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DEVELOPMENT OF A MATHEMATICAL MODEL FOR OPTIMAL PLANNING OF BIOFUEL SUPPLY CHAIN

MARYAM VALIZADEH

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DEVELOPMENT OF A MATHEMATICAL MODEL FOR OPTIMAL PLANNING OF BIOFUEL SUPPLY CHAIN

By

MARYAM VALIZADEH

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Master of Science

October 2014

DEDICATION

I would like to dedicate this thesis to my adorable parents whose affection, love, encouragement and support have sustained me throughout the challenges of my life. I also dedicate this thesis to my beloved brothers, Ali and Amin, for their patience and encouragement. I am truly thankful for having you in my life.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirements for the degree of Master of Science

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October 2014

Chairman : S. Syafiie, PhD
Faculty : Engineering

Biofuels have attracted the attention of researchers, due to their potential to mitigate climate changes. Biodiesel is a type of biofuel that can be used as an alternative fuel for diesel engines. The three main problems with biodiesel production are, high production costs, environmental, and social impact over the entire supply chain.

The main objective of this thesis is to propose a method for optimal planning and operation of biodiesel supply chain. An additional objective is to understand the capability of a modern heuristic method for optimal planning of the chain.

In this study, a methodology is presented to optimize the full supply chain for producing biodiesel. A Multi-Objective Linear Programming (MOLP) model is developed, which takes into account the economic, environmental and social concerns that are related to the biodiesel supply chain. The model aims to minimize total operational cost, greenhouse gas (GHG) emission, and edible feedstock consumption. The proposed model is solved using a simple Multi-Objective Particle Swarm Optimization (MOPSO) method, to overcome the difficulties related to classical methods for solving multi-objective optimization problems. The performance of this method is compared with a well-known classical method, Ɛ-constraint, to study the capability of the MOPSO method.

The proposed model and solving strategy was used to evaluate biodiesel production from palm oil and jatropha, based on existing biodiesel plants in Malaysia. The results show that the MOPSO method has a good ability for finding the approximation of optimal solutions. The model determined the optimal annual operational cost, GHG emission, edible feedstock consumption, quantity of feedstock to be harvested, transportation schedules, and quantity of biodiesel to be produced at bio-refineries, for the selected case study in Malaysia. The model was also compared with an economic and environmental-economic optimization models.

The results show the effectiveness of the proposed MOLP model at providing decisions with better economic, environmental, and social performances. Furthermore, a sensitivity analysis, based on the availability of jatropha, demonstrated the impact of a reduction of jatropha availability, on total emission and edible feedstock consumption.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan Ijazah Master Sains

PERKEMBANGAN MODEL MATEMATIK UNTUK PERANCANGAN OPTIMUM RANTAIAN BEKALAN BIOFUEL

Oleh

MARYAM VALIZADEH

Oktober 2014

Pengerusi : S. Syafiie, PhD
Fakulti : Kejuruteraan

Biofuel telah menarik perhatian penyelidik kerana potensinya untuk mengurangkan kesan perubahan iklim. Biodiesel adalah sejenis biofuel yang boleh digunakan sebagai bahan api alternatif untuk enjin diesel. Tiga masalah utama dengan pengeluaran biodiesel adalah kos pengeluaran yang tinggi, dan kesan alam sekitar dan sosial ke atas rantaian bekalan keseluruhannya.

Objektif utama projek ini adalah untuk mencadangkan suatu kaedah untuk perancangan dan operasi optimum rantaian bekalan biodiesel. Objektif tambahannya adalah untuk memahami keupayaan kaedah heuristik moden untuk perancangan optimum rantai tersebut.

Kajian ini membentangkan kaedah untuk mengoptimumkan rantaian bekalan sepenuhnya untuk menghasilkan biodiesel. Suatu model Pengaturcaraan Linear Pelbagai Objektif (MOLP) dibangunkan, dengan mengambil kira aspek-aspek ekonomi, alam sekitar dan sosial yang berkaitan dengan rantaian bekalan biodiesel. Model ini bertujuan untuk mengurangkan jumlah kos operasi, pelepasan gas rumah hijau (GHG), dan penggunaan bahan mentah yang boleh dimakan. Model yang dicadangkan itu diselesaikan dengan menggunakan kaedah Pengoptimuman Partikel Swarm Pelbagai Objektif (MOPSO) yang mudah, untuk mengatasi kesukaran yang berkaitan dengan kaedah-kaedah klasik untuk menyelesaikan masalah pengoptimuman pelbagai objektif. Prestasi kaedah ini dibandingkan dengan kaedah klasik terkenal, kekangan-Ɛ, untuk mengkaji keupayaan kaedah MOPSO itu.

Model dan strategi penyelesaian yang dicadangkan ini telah digunakan untuk menilai pengeluaran biodiesel daripada minyak kelapa sawit dan jarak berdasarkan kilang biodiesel yang sedia ada di Malaysia. Hasil kajian menunjukkan bahawa kaedah MOPSO mempunyai keupayaan yang baik untuk mencari penghampiran penyelesaian yang optimum. Model ini menentukan kos operasi tahunan yang optimum, pelepasan GHG, penggunaan bahan mentah yang boleh dimakan, kuantiti bahan mentah untuk dituai, jadual pengangkutan, dan kuantiti biodiesel yang harus dikeluarkan oleh kilang penapis bio, untuk kajian kes yang dipilih di Malaysia. Model ini juga dibandingkan dengan model-model pengoptimuman ekonomi dan ekonomi alam sekitar.

Hasil kajian menunjukkan keberkesanan model MOLP yang dicadangkan untuk menyediakan keputusan dengan prestasi ekonomi, alam sekitar, dan sosial yang lebih baik. Tambahan pula, analisis sensitiviti berdasarkan ketersediaan jarak menunjukkan kesan pengurangan ketersediaan jarak ke atas jumlah pengeluaran dan penggunaan bahan mentah yang boleh dimakan.

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I would also like to express my wholehearted thanks to my family for their generous support provided me throughout my life.

I certify that a Thesis Examination Committee has met on 30 October 2014 to conduct the final examination of Maryam Valizadeh on her thesis entitled "Development of a Mathemtical Model for Optimal Planning of Biofuel Supply Chain" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Master of Science.

Members of the Thesis Examination Committee were as follows:

Mohd Halim Shah Ismail, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Salmiaton binti Ali, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Mohd Noriznan bin Mokhtar, PhD
Ing
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Lee Keat Teong, PhD
Associate Professor
Universiti Sains Malaysia
Malaysia
(External Examiner)

ZULKARNAIN ZAINAL, PhD
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 23 January 2015

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Dr. S. Syafiie. The members of the Supervisory Committee were as follows:

S. Syafiie, PhD
Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Intan Salwani Ahamad, PhD
Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Member)

BUJANG BIN KIM HUAT, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

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Committee: ______________________

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LIST OF ABBREVIATIONS

NPC	National Petroleum Council
GHG	Greenhouse gas
MOPSO	Multi- Objective Particle Swarm Optimization
MOLP	Multi-Objective Linear Programming
PSO	Particle Swarm Optimization
MINLP	Mixed Integer Non-Linear Programming
MILP	Mixed Integer Linear Programming
CBGTL	Coal, Biomass and Natural Gas to Liquids
LCA	Life Cycle Assessment
UK-RFA	UK Renewable Fuels Agency
EIA	United States Energy Information Administration
APEC	Asia-Pacific Economic Cooperation
FAO	Food and Agriculture Organization of the United Nations
JO	Jatropha Oil
FFB	Fresh Fruit Bunches
MPOB	Malaysia Palm Oil Board
CPO	Crude Palm Oil
APOC	American Palm Oil Council
PPI	Producer Price Index
MEIH	Malaysia Energy Information Hub
MYR	Malaysian Ringgit

NOTATIONS

Indices

i	Type of feedstock
l	Feedstock resource
w	Biorefinery
n	Demand zone

Parameters

$C_{i,l}^{har}$	Production and harvesting cost of feedstock type *i* from resource *l*
C_i^{pre}	Pre-processing cost of feedstock type *i*
$T1_i^r$	Transportation cost of feedstock type *i* via road
$D_{l,w}$	Road distance between resource *l* and biorefinery *w*
$T1_i^s$	Transportation cost of feedstock type *i* via ocean
	Production cost of biodiesel from feedstock *i* at biorefinery *w*
$T2_i^r$	Transportation cost of biodiesel via road
$D'_{w,n}$	Road distance between biorefinery *w* and demand zone *n*
$T2_i^s$	Transportation cost of biodiesel via ocean

η_i	Conversion factor for pre-processing of feedstock type *i*
E_i^p	Emission factor for production and harvesting of feedstock type *i*
E_i^{pre}	Emission factor for pre-processing of feedstock type *i*
Et_i^r	Emission factor for transportation of feedstock type *i* via road
Et_i^S	Emission factor for transportation of feedstock type *i* via ocean
$Ds_{l,w}$	Ocean distance between resource *l* and biorefinery *w*
E_i^c	Emission factor for conversion of feedstock *i* to biodiesel
Ed_i^r	Emission factor for distribution of biodiesel via road
Ed_i^S	Emission factor for distribution of biodiesel via ocean
$D's_{w,n}$	Ocean distance between biorefinery *w* and demand zone *n*
β_i	Binary variable which is equal to 1 if feedstock is edible, otherwise equals 0
$Y_{i,l}$	Maximum availability of feedstock type *i* at resource *l*
α_i	Conversion factor for biodiesel production from feedstock type *i*
Ref_w	Capacity of biorefinery *w*
D_n	Biodiesel demand at demand zone *n*

Decision variables

$Q_{i,l}$	Quantity of feedstock type *i* to be harvested from resource *l*
$X_{i,l,w}$	Quantity of pre-processed feedstock type i shipped from resource *l* to biorefinery *w*
$X_{i,w}^f$	Amount of biodiesel produced from feedstock *i* at biorefinery *w*
$Q_{i,w,n}^f$	Quantity of biodiesel which is produced from feedstock *i* and shipped from biorefinery *w* to demand zone *n*

CHAPTER 1

INTRODUCTION

Recently, issues such as energy demand growth, interest in cutting down energy consumption as well as the related emissions, have led to the use of renewable energy resources. It has been predicted that the world's demand for energy will increase by 50% to 60% until 2030, as a result of population growth and the pursuit of higher living standards. Additionally, biomass has been considered as a good substitute for meeting the demands, due to the increasing prices of petroleum and the uncertainty of its availability (Santibañez-Aguilar et al., 2011; National Petroleum Council [NPC], 2007; Rosegrant et al., 2006).

To satisfy future energy demands, renewable energy generated from wind, biomass, and solar resources has great potential for growing (Drapcho et al., 2008). Biofuel energy is considered as a type of renewable energy produced from biomass resources.

Biofuels such as bioethanol, biodiesel, biogas, and syngas are produced from variety of sources and are classified into three categories (An et al., 2011):

Sugar, oil crops, starch crops and animal fats are sources of the first generation biofuels. Edible feedstocks are the main source of the first generation biofuels, which could affect the global food crisis (Rosegrant et al., 2006).
Non-edible crops, residues of crops and other lignocellulosic materials, are sources of the second generation biofuels.
Algae are considered as the source of the third generation biofuels.

Biofuels are capable of reducing greenhouse gas (GHG) emissions. However, biofuels' potential for reducing climate changes depends on feedstock type and the way it is produced and the technologies used for processing of biomass and biofuels as well (Santibañez-Aguilar et al., 2011; Timilsina & Shrestha, 2011).

From an economic point of view, the production cost of biofuels in large scale is high comparing to fossil fuels (United Nations, 2006). Production cost of biofuels varies based on factors such as feedstock type, process, plant size, and region. The price of feedstock is the major factor in overall costs (Demirbas, 2009; Timilsina & Shrestha, 2011).
Another challenge lies in the issue that some of biofuel's feedstocks, such as soybean, oil palm, and corn are food sources for humans or animals. Growing demand for agricultural crops, which are sources of food, to produce biofuel has been one of the factors in increasing food prices. Furthermore, increase in

demand for these crops may lead to deforestation due to the area required for cultivation of energy crops, which will result in GHG emissions (FAO, 2008). Management of plant, production and transportation and optimization of biofuel supply chain could improve the biofuel production.

Among all the biofuels, biodiesel has received considerable attention due to the similarities to petroleum diesel (Lam et al., 2009).

1.1 Problem Definition

Biodiesel is considered as renewable energy and has the potential to reduce GHG emissions (Panwar et al., 2011). However, climate change mitigation potential of biodiesel depends on other factors such as biomass cultivation process as well as feedstock to biodiesel processing technologies (Timilsina & Shrestha, 2011). In addition, production costs of biodiesel are high compared to petroleum diesel. Another issue is management of crops used for production of biodiesel, as more than 95% of biodiesel is made from edible oil derived from agricultural crops. This issue is along with the reduction of food resources which can bring global imbalance to the food supply and the market demand. Furthermore, deforestation and destruction of ecosystems are among the negative impacts of biodiesel derived from edible oils (Yusuf et al., 2011).

According to the previous descriptions, an effective strategy is needed for production of sustainable biodiesel. Planning of biodiesel supply chain is one of the most important aspects of biodiesel production, since the methods of production and consumption of energy as well as the way it is supplied influence the environment (Tran et al., 2011). An optimal biofuel supply chain will lead to the efficient delivery of biofuel to the end users (Hamelinck et al., 2005).

Optimization problems in biofuel supply chains are formulated in form of mathematical models. Some of the optimization problems, like the problem in hand, deal with multiple objectives. Depending on complexity of supply chain, the optimization of chain could become difficult to handle with classical methods (Silva & Coelho, 2007). Therefore, a proficient method is required for solving the biodiesel supply chain optimization problem.
The aim of this contribution is improvement of biodiesel production by taking into account economic, environmental, and social criteria through the development of a mathematical model. Subsequently, a heuristic method will be used to study the capability of the heuristic method for solving the optimization problem in hand.

1.2 Research Questions

In order to improve biodiesel production, a series of questions need to be addressed.How to reach a solution for optimal planning of biodiesel supply chain considering economic, environmental and social concerns?

- How to overcome difficulties associated with classical methods for solving multi-objective optimization problems?
- What are the optimal quantity of feedstock to be harvested, feedstock and biodiesel transportation schedules, and quantity of biodiesel produced at biorefineries?
- What are the optimal operational cost, GHG emissions, and edible feedstock consumption for production of biodiesel over the specified planning horizon?

1.3 Research Objectives

Based on the research questions, the research objectives are:

- To develop a mathematical model for optimal planning of biodiesel supply chain under the economic, environmental, and social criteria
- To evaluate the capability of a heuristic method for solving the multi-objective optimization problem in biodiesel supply chain
- To specify the optimal quantity of feedstock to be harvested, feedstock and biodiesel transportation schedules, and quantity of biodiesel produced at biorefineries based on the proposed model
- To determine the optimal operational cost, GHG emissions, and quantity of edible feedstock consumption for production of biodiesel over the planning horizon based on the proposed optimization model.

1.4 Research Scope

This study focuses on optimal planning of biodiesel supply chain based on available resources and facilities through development a mathematical model. It considers the minimization of annual operational cost, GHG emissions in form of CO2 equivalent, and quantity of edible feedstock consumption for production of biodiesel over the entire supply chain. It should be noted that capital costs are not included in this study. The model also takes into account optimal selection of feedstock, harvesting and transportation schedules as well as biodiesel production at biorefineries.

The proposed model is applied to a case study for production of biodiesel from palm oil and jatropha in Malaysia. The planning horizon has been set to one year. The simple multi-objective particle swarm optimization (MOPSO) method is applied to solve the optimization problem and it is compared with the Ɛ-constraint method. These methods are implemented in MATLAB software.

1.5 Methodology Framework

To obtain an optimal plan for operation of biodiesel supply chain, a five-step methodology has been proposed. This methodology has been briefly presented in Figure 1.1. Identifying the decision variables and parameters that should be used in the model is the first step. The decision variables are shown in Figure 1.2.

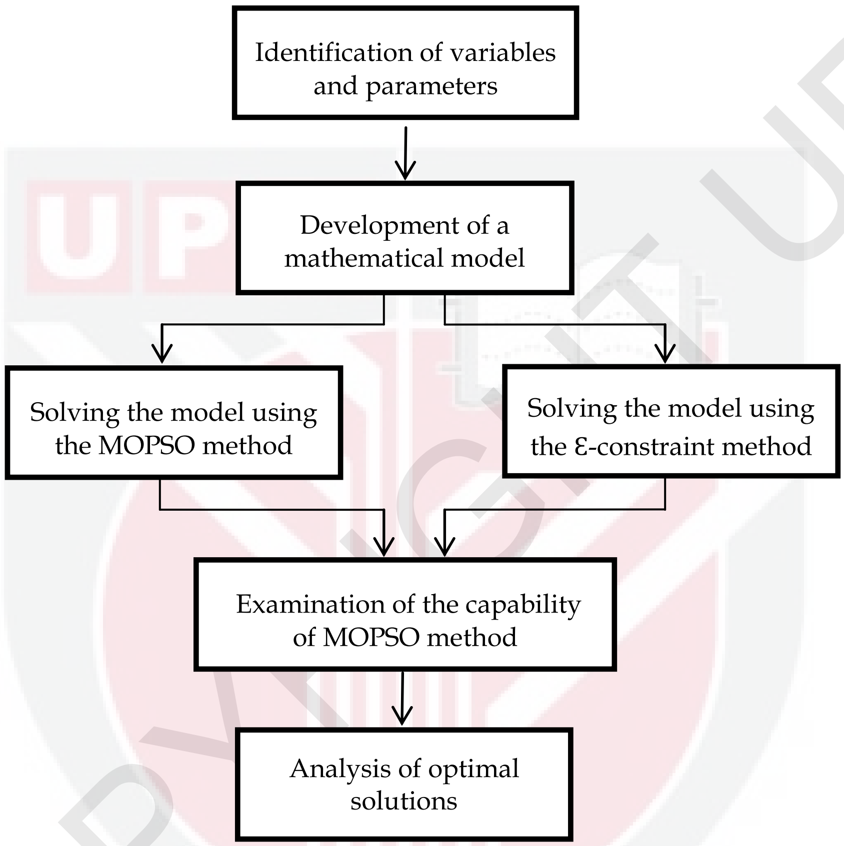

Figure 1.1.Steps of methodology

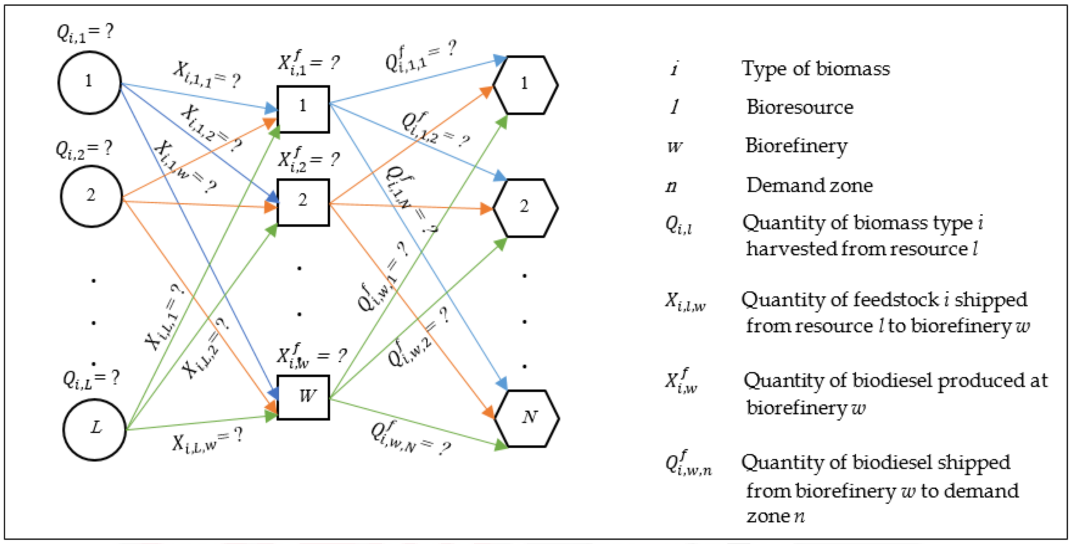

Figure 1.2.Structure of biodiesel supply chain and optimization decision variables

A mathematical model will be developed in the next step. The model is linear and considers the economic, environmental, and social objectives related to biodiesel supply chain. Therefore, the proposed model is a multi-objective linear programming (MOLP) model. The economic objective represents the total operational cost. GHG emissions (CO_2 equivalent) over the entire supply chain are used to measure the environmental objective. Likewise, quantity of edible feedstock consumption for production of biodiesel is measured as the social objective.

In the third step, the MOPSO method, which is improved form of particle swarm optimization (PSO) approach for handling multi-objective problems, is applied to solve the optimization problem. PSO approach is a modern heuristic method which has been successfully applied to several supply chain problems (Izquierdo et al., 2008; Sinha et al., 2009; Wei, 2011; Song et al., 2011). The Ɛ-constraint method, a well-known classical method that is usually used for solving the multi-objective optimization problems, is applied to the proposed model as well.

In the next step, the MOPSO method and the Ɛ-constraint method are compared in order to investigate the capability of the heuristic method (MOPSO) for solving the multi-objective optimization problem in biodiesel supply chain.

In the last step, optimal solutions resulting from optimization process are analyzed in order to select an appropriate solution.

1.6 Thesis Structure

After the introduction provided in this chapter, Chapter 2 reveals a literature review of relevant works, including the mathematical modeling of biofuel supply chain and multi-objective optimization solving methods. A detailed description of the methodology for optimal planning of biodiesel_supply chain is given in Chapter 3. Chapter 4 presents the results through the illustration of proposed model in a case study for the optimal planning of biodiesel supply chain in Malaysia. Chapter 5 draws the conclusion and provides the discussion of potential research extensions.

CHAPTER 2

LITERATURE REVIEW

In recent years, considerable attention has been devoted to biofuel and biofuel supply chain optimization (Kim et al., 2011). The modeling and optimization of biofuel supply chain have been the subject of a relatively large number of works. This chapter presents the basic principles of biomass, biofuel and biodiesel. Furthermore, it provides an overview of mathematical modeling of biofuel supply chain and it presents the works most relevant to this study based on articles and reports. A review of the advantages and disadvantages of employing multi-objective optimization methods has also been undertaken in this chapter.

2.1 Biomass Characteristics

Biomass is a biological material regarded as a renewable source of energy. Biomass is derived from living organisms or their remains and includes both plant and animal derived materials. The organic compounds are absorbed and stored in plants using solar energy through the photosynthetic process. Organic compounds that make up living things are a potential source of energy that can be used as biofuel. Plant materials are converted into animal biomass when they are eaten by animals. The biomass materials are classified into five categories (Drapcho et al., 2008; Biomass Energy Center, 2012):

- Wood
- Agricultural residues
- Energy crops
- Food waste
- Industrial waste

2.2 Biofuel Characteristics

Biofuel is a fuel derived from biomass sources. Therefore, the nature of biofuel refers to plants. Biofuels are produced from variety of feedstocks through different processing technologies. Biodiesel and bioethanol are the most common biofuels which can be used in transportation and industry (Drapcho et al., 2008, Demirbas, 2009).

2.3 Biodiesel

Biodiesel is generally referred to a renewable fuel derived from vegetable oils or animal fats that meets the standards for using in diesel engines. Technically speaking, biodiesel is a mono-alkyl ester with a long chain of fatty acids derived from natural oils (Demirbas, 2009).

2.3.1 Biodiesel as an Alternative Fuel

Biodiesel, as a product of chemical reaction of oil or fat with an alcohol, has received considerable attention among all the biofuels due to the similarities to petroleum diesel. Another advantage of biodiesel is adaptability to existing models of engines, so no alteration of diesel engines is needed (Demirbas, 2007; Lam et al., 2009).

2.3.2 Biodiesel Characteristics

The unique property of biodiesel among the biofuels is its good combustion in conventional engines while it is blended with petroleum fuel. Oil seed crops can be used as a source for production of biodiesel. Compared to petroleum diesel, the risks of handling, transportation, and storage of biodiesel are much lower due to the high flash point. Biodiesel could be used alone or in the form of blended with petroleum diesel in any ratio (Demirbas, 2007). Table 2.1 shows the properties of biodiesel (Demirbas, 2009).

Table 2.1. Technical properties of biodiesel

Parameter	Description
Common name	Biodiesel
Common chemical name	Fatty acid methyl ester
Chemical formula range	C_{14}-C_{24} methyl ester or $C_{15-25}H_{28-48}O_2$
Kinematic viscosity range (mm^2/s, at 313 K)	3.3-5.2
Density range (kg/m^3, at 288 K)	860-890
Boiling point range (K)	>457
Flash point range (K)	420-450
Distillation range (K)	470-600
Vapor pressure (mm Hg, at 295 K)	<5
Solubility in water	Insoluble in water
Physical appearance	Light to dark yellow, clear liquid
Odor	Light musty/soapy odor
Biodegradability	More biodegradable than petroleum diesel
Reactivity	Stable, but avoid strong oxidization agents

(Source: Demirbas, 2009)

Due to the high viscosity, the direct use of pure vegetable oils as fuels is problematic (Demirbas, 2009). To resolve such problems posed by the high fuel viscosity, transesterification appears to be the most commonly used process for converting oil into biodiesel (Barnwal & Sharma, 2005). Transesterification is the reaction of an alcohol with a triglyceride such as vegetable oil or animal fat in presence of a catalyst. The viscosity of the oil is reduced by transesterification; as a result, its combustion improves (Demirbas, 2007).

2.3.3 Biodiesel Feedstock

Despite the diversity of oil crops identified, a few oil crops have been used for the production of biodiesel worldwide; such as soybean, palm, peanut and sunflower oil. Cotton seed, jatropha and calophyllum inophyllum oil are among the plant oils that are under consideration.

The availability of the crops in each region is the main factor for choosing the biodiesel feedstock; for example, palm oil and coconut oil are commonly used for production of biodiesel in coastal countries such as Malaysia, Indonesia and Thailand. Oil palm has the highest oil yield among the oil crops (Ong et al., 2011).

2.3.4 Biodiesel in Malaysia

Malaysia is one of the countries that produces a large volume of biodiesel (Johnston & Holloway, 2007). There are various kinds of feedstock that could be used as source for biodiesel production. Over 95% of biodiesel is currently produced from edible oil (Yusuf et al., 2011). The production of biodiesel in Malaysia has been increased from 1.1 thousand barrels per day in 2006 to 4.5 thousand barrels per day in 2009, being mainly produced from edible sources (United States Energy Information Administration [EIA]; Demirbas, 2007).

2.3.5 Palm Oil Biodiesel

As a tropical perennial plant, oil palm grows well in lowland and humid areas. Hence, Malaysia is a suitable place for cultivation of this plant (Lam et al., 2009). In large and tight female bunches, the fleshy orange reddish colored fruits grow. Each fruit bunch weighs up to 10-40 kg and holds up to 2000 fruitlets (Ong et al., 2011). The density of oil palm plantation in Malaysia is 148 palms per hectare (Yusoff, 2006). Economically speaking, the life of each oil palm tree is about 20 to 25 years (Singh et al., 2010). By annually producing an average of nearly 4 to 5 tons of oil per hectare, oil palm fruit is regarded as the highest oil yield crop (Sumathi et al., 2008). Palm oil, being an edible vegetable oil, is the major feedstock for producing biodiesel in Malaysia (Asia-Pacific Economic Cooperation [APEC], 2008).

It is expected that producing biodiesel on a large scale from edible oil can lead to a global imbalance of the supply and demand market for the food (Monbiot, 2004). Reports have stated that jatropha is one of the best choices for producing future biodiesel. Jatropha resolves the dilemma of food against fuel, since it is a non-edible vegetable oil (Lim & Teong, 2010).

2.3.6 Jatropha Biodiesel

Jatropha Curcas is a tropical plant with various names; in Malaysia this plant is called *Jarak Pagar*. It can be grown in low and high rainfall and temperature range of 18-28 °C, so it can be produced in most parts of Malaysia (Gour, 2006;

Behera et al., 2010; Mofijur et al., 2012). Even though humidity results in better crop production, this plant can grow in all types of soils and can be adapted to dry conditions. It has also the potential for growing on marginal soils (Gour, 2006; Ong et al., 2011). Jatropha seeds are sources of jatropha oil (JO). About 0.8 kg/m^2 of jatropha seeds are produced per year. The seeds' oil content ranges from 30% to 40%. The lifespan of jatropha plant can be up to 50 years (Banapurmath et al., 2008). JO solves the dilemma of food against fuel.

2.4 Biofuel Supply Chain

A supply chain is a system comprised of facilities and distribution centers responsible for procuring raw materials, turning them into intermediate and final products, and distributing final products to the end users. A supply chain includes all activities, tasks and facilities producing and delivering a service or a product which some consumers and suppliers are involved in (Papapostolou et al., 2011).

The optimal planning and management of supplier and demand, preparation and production schedules for products or services accompanied by schedule of transportation, storage, inventory control, and distribution are among the major tasks of supply chain management (Papapostolou et al., 2011).

Biofuel supply chain typically includes the following elements (Papapostolou et al., 2011):

- A set of feedstock resources where feedstock types are cultivated and harvested
- A set of production sites where feedstock converted to biofuels
- Distribution networks.

2.5 Biofuel Supply Chain Optimization

Considered as a candidate for reducing oil dependence and environmental impacts, biofuels have recently attracted special attention (An et al., 2011). The general structure of biofuel production network is influenced by the supply chain modeling and optimization for biofuel systems, as well as supply chain decisions (Kim et al., 2011). Decision-making in this field takes into account many aspects, including economic, energy, and environmental considerations; and in some cases, social acceptability are considered. This type of decision-making influences and forms the structure, design, and operation of biofuel supply chain (Papapostolou et al., 2011). In order to boost the efficiency of the entire system, an effective supply chain planning is required.

2.6 Optimization using Mathematical Modeling

Optimization is defined as a process of finding the best and feasible solution based on the constraints. One of the most important methods for optimization and decision making, is mathematical programming. The best or worst solution is determined according to the objective of the problem. In some optimization problems, like the problem in hand, multiple objectives are considered. These problems, in which the objective function is multi-client, are known as multi-objective optimizations. A multi-objective optimization problem defined as:

$$\begin{aligned} \text{minimize or maximize} \quad & f(x) = (\, f_1(x), f_2(x), \dots, f_k(x)), \\ & x = (x_1, x_2, \dots, x_n) \\ \text{subject to} \quad & g_m(x) \le 0, \quad m = 1,2, \dots, n_g \\ & h_m(x) = 0, \quad m = 1,2, \dots, n_h \\ & \forall\, x \in R^n \end{aligned} \tag{2.1}$$

where $f(x)$ is the objective function vector, k is the number of objective functions, x is the decision vector, n_g and n_h are the number of inequality and equality constraints respectively.

In contrast to single objective optimization, typically there is no single global solution to multi-objective problem and it is often required a set of solutions in feasible region (Marler & Arora, 2004). In multi-objective optimization, a set of alternatives with different trade-offs, is termed *Pareto optimal* solutions.

2.7 Mathematical Modeling of Biofuel Supply Chain

A variety of models exist that present the optimal design and planning of biofuel supply chain. These models that consider different objectives can be classified into three categories:

- Modeling under economic objectives
- Modeling under economic and environmental objectives
- Modeling under economic, environmental and social objectives.

In the subsequent section, some related works are reviewed.

2.7.1 Modeling under Economic Objectives

Several research works have focused on development of mathematical models for improving biofuels' economic performance through minimization of total costs (Gunnarsson et al., 2004; Dunnett et al., 2007; Ekşioğlu et al., 2009).

Parker et al. (2010) proposed a mixed integer non-linear programming (MINLP) model to find the efficient configuration of biofuel supply chain considering the annual profit as an objective. They evaluated the optimal production and distribution of biohydrogen from agricultural residues. They gave a case study in California using rice straw and found that biohydrogen produced from agricultural wastes can be delivered to the end market at costs similar to hydrogen produced from natural gas.

A multistage mixed integer linear programing (MILP) model was addressed by Huang et al. (2010) for strategic planning of bioethanol supply chain to minimize the total system cost throughout the planning horizon. The model was applied to a case study in California to design the bioethanol supply chain from bio-waste resources and it was observed that bioethanol can be produced for $ 1.1 per gallon through careful network plan. The model also determines the size and location of new refineries and also supplemental capacities and material flows of feedstock and bioethanol; however, it only takes into account the economic aspect of bioethanol supply chain.

MILP model was also used by Akgul et al. (2011), Elia et al. (2011) and Leão et al. (2011) for planning an optimized biofuel supply chain. Akgul et al. (2011) presented an optimization model for a hybrid first-second generation of bioethanol supply chain. The model determines the optimal biomass cultivation rate, locations of facilities, biomass flows, biofuel flows and modes of transportation in a way that minimizes the total costs of supply chain. The model was used to evaluate the bioethanol production in the UK. The optimal configuration of bioethanol supply chain network was determined through the proposed model.

The analysis of the United States energy supply chain considering hybrid coal, biomass and natural gas to liquids (CBGTL) facilities was reported by Elia et al. (2011) using a developed optimization model. The model selects the optimal feedstock combination, feedstock and product flows, locations and size of CBGTL facilities as to minimize the overall production costs. The proposed model is capable to supply fuels (gasoline, diesel and kerosene) at a cost between $ 76.55 and $ 112.91 per crude oil barrel in the United States.

Planning and optimization of biodiesel supply chain based on small family farms was investigated in the work of Leão et al. (2011). The model was applied to a biodiesel production case study from castor oil in Brazil for selection of optimal number, type and locations of crushing units as well as configuration of production zones. The objective of this model was minimization of the total costs of supply chain. The minimum total cost found was $ 200 million which gives an estimate of $ 1,630 per ton of castor oil produced.

Some researchers have used mathematical models to maximize the profit of biofuel network (An et al., 2011; Corsano et al., 2011). An et al. (2011) proposed a mathematical model for optimization of lignocellulosic biofuel supply chain in order to prescribe the locations and capacities of facilities, material flows, and technologies. The model was applied to a case study in Central Texas to design a profitable biofuel supply chain. Corsano et al. (2011) considered the optimization of sugar-bioethanol supply chain. They used a MINLP model for optimal design and analysis of bioethanol supply chain produced from sugar cane.

Similar to Akgul et al., Kim et al. (2011) and Papapostolou et al. (2011) have used MILP models for optimal planning of biofuel supply chain. Kim et al. (2011) presented a model to determine the optimal number, locations, and sizes of processing facilities and the logistics of transportation over the selected planning horizon. The model was used to optimize the biogasoline and biodiesel production from forestry resources in the southeastern of the United States while the overall profit was maximized. Optimization results showed that the total profit for the distributed design is higher than that for the centralized design. The goal of the model proposed by Papapostolou et al. (2011) was maximization of the total value of the biofuel supply chain. The model was used to evaluate the biodiesel production from energy crops in Greece as a case study. The optimal decisions for operating the biodiesel supply chain, such as the quantity of raw material to be cultivated, the quantity of biodiesel to be produced and the best solution for the optimal design of biodiesel supply chain, were carried out from the optimization process.

Papapostolou et al. (2011) developed a generic mathematical model for optimal production of heat, power and biofuel from biomass feedstock as well. The main goal of their model was identification of the best solution for optimal operation and design of the biofuel and biomass supply chain to maximize the total value. The model was implemented in a case study in Greece for production of heat, power and bioethanol. It was found that the maximum profit from the production of heat, power and bioethanol is €16,689,859.

Recently, a multi-period MILP model framework has been used for optimal design and planning of biodiesel supply chain based on sunflower, energy crops and soybean in Argentina (Andersen et al., 2012). The model considers alternative raw materials and land competition and takes into account intermediate and final products, production plants, and distribution centers while maximizes the net present value of the supply chain. Optimization results showed that development of biodiesel supply chain in Argentina obliges an expanding utilization of area to produce oil for satisfying demands.

The studies described in previous paragraphs have focused on economic aspects of biofuel supply chain. These methodologies have not considered other characteristics of the system. Some studies have been conducted to consider the environmental performance of the biofuel supply chain in addition to economic performance.

2.7.2 Modeling under Economic and Environmental Objectives

In a study by Mele et al. (2009), a multi-objective MILP model was presented which addresses the design of sugar and ethanol supply chain while minimizes the total cost of the system and environmental impacts as well. The capabilities of the model were highlighted through a case study in Argentina. The proposed model identified *Pareto* alternatives that lead to environmental savings. They also proposed another model taking into consideration economic and environmental performances of the sugar and ethanol production chain (Mele et al., 2011). The environmental function of this model is measured based on the life cycle assessment (LCA) approach. The goal of the study is to design the bioethanol network and determine associated planning decisions in a way that the net value maximized and the environmental impacts minimized. The capability of the model was illustrated through a case study in Argentina. The model recommended different options prompting environmental improvements. It was demonstrated that significant environmental savings can be achived by altering the operating conditions.

Like Mele et al., Giarola et al. (2011) have used a multi-objective MILP framework for strategic design and planning of bioethanol supply chain and optimization of the environmental and financial performances through the first and second generation process. The model is multi-period and provides decisions assessing the economic and environmental performances of the supply chain. A biomass-based ethanol production supply chain in Italy was used as a case study to demonstrate the capability of the model. Results demonstrated the efficiency of the optimization model at finding the design configuration.

A multi-objective multi-period MILP approach for design and operation of biomass to liquid supply chain by taking into consideration the economic and environmental criteria was described in the work of You and Wang (2011). The model seeks to minimize the total annualized cost and GHG emissions and determines the optimal network, facility locations, process technology, capital cost, level of inventory, and logistics decisions. The application of this model was shown in a case study for production of gasoline and diesel for the state of Iowa. The optimization model showed that the liquid fuels can be produced for $ 3.68 per gasoline-equivalent gallon with the total GHG emissions at 4,502 kton CO_2 equivalent.

Recently, Akgul et al. (2012) have addressed a multi-objective MILP model for optimization of hybrid first-second generation biofuel supply chain. Their model determines the optimal biomass cultivation rate, locations and size of facilities, biomass and biofuel flows, transportation mode, and GHG emissions for each stage of the life cycle. The objectives of the optimization model are minimization of the total daily cost of biofuel supply chain and total GHG emissions. Bioethanol production in the UK was used as a case study. The optimization results demonstrated that total GHG savings are increased from 62% to 69% whereas total cost increased by 11%.

Modeling of biofuel supply chain needs other considerations to become more sustainable, such as social criteria. Limited works have been conducted to investigate social issues in optimization of biofuel supply chain in addition to economic and environmental criteria.

2.7.3 Modeling under Economic, Environmental and Social Objectives

Consideration of a social objective related to biofuel supply chain was presented in the work of You et al. (2012). They proposed an approach for the optimal design and operation of cellulosic bioethanol supply chain. They developed a multi-objective MILP model under economic, environmental and social criteria. The number of local jobs was taken into account as the social objective and life cycle of GHG emissions measured as the environmental objective. The model considers the availability and diversity of biomass, deterioration of feedstock, the economy of region and government incentives, process technologies, and byproducts. It determines the optimal design and plan of supply chain, locations of facilities, capital investment, and inventory and logistics decisions. The proposed model was applied to two county level case studies for the state of Illinois. It was found that ethanol could be produced for $ 3.243 per gallon through the optimization process.

It should be noted that all the multi-objective optimization problems reviewed above, have used Ɛ-constraint method to obtain the optimal solutions.

As previously mentioned, food versus fuel conflict is the other important social issue in production of biofuels and specially biodiesel. Some feedstocks used for biofuel production are sources of food for humans or animals and compete with food crops. Furthermore, using more crops leads to increase of food prices. Modeling of biofuel supply chain by taking into account this social issue leads to more sustainable biofuel production.

According to the reviewed articles and reports, modeling and optimization of biodiesel supply chain by taking into consideration economic, environmental and social concerns while food crisis investigated as a social concern, and also capability of the heuristic methods, such as MOPSO, for solving the optimization problems in biofuel supply chain have not been considered to date.

2.8 Multi-Objective Optimization Solution Strategies

In order to solve multi-objective optimization models, there are several methods that could be used. These methods have been classified into three categories by Hwang and Masud (1979) as follows:

- Priori methods
- Interactive methods
- Posteriori methods.

Goal attainment, goal programming and lexicographic methods are among the first category, in which decision is made prior to the search. Tchebycheff method, light beam search and reference points methods are examples of interactive techniques which the decision maker provides priorities during the optimization process. Weighted metrics method, Ɛ-constraint method and normal boundary intersection are related to the third category in which optimization is done without providing information beforehand (Zitzler, 1999; Jaimes et al., 2011). It seems that posterior methods are more desirable, as they do not require any information prior to the search.

2.9 Modern Methods for Solving Multi-Objective Optimization Problems

In most of the traditional methods, a single objective is produced through combining all the objectives into a single one. As in traditional methods, one solution is produced during each run; they must be repeated several times to reach the *Pareto optimal* set. Another issue with traditional methods is that for some techniques there is the need to problem knowledge which may not exist (Zitzler, 1999; Jaimes et al., 2011).

Such difficulties necessitate the presence of some alternatives to solve multi-objective optimization problems (Jaimes et al., 2011). Some examples of the novel techniques aimed at finding good approximation of the *Pareto optimal* set are neural networks, particle swarm optimization, simulated annealing, genetic algorithms, and ant colony optimization.

Particle swarm optimization (PSO) method is an algorithm based on population. Simplicity of implementation and good convergence ability have made this method popular (Talukder, 2011).

2.9.1 PSO Method

Inspired by simulation of the social behavior of organisms in a group like birds flocking and fish schools, Eberhart and Kennedy introduced the PSO in 1995. Animal's activities for finding the food sources are the basis of this method for finding the optimal solutions. In this method, each member of population which indicates a solution in searching space, called a *particle,* and the population, called *swarm*. Going through the searching boundary, each particle remembers its best past positions and its neighbors. To achieve an optimal solution, particles rearrange their positions and velocities and share good positions to each other (Talukder, 2011).

Compared to other methods, the PSO method has some advantages. This method is less dependent on initial values, and the optimal solution is obtained after the movement of all particles. Furthermore, it is not very sensitive or dependent on the objective function. Other advantages of this method include easy implementation and simple settings (Lee & Jong-Bae, 2006).

To solve multi-objective problems, the basic PSO cannot be used. Researchers have extended the basic PSO and introduced some methods to apply PSO for handling multi-objective optimization problems (Parsopoulos &Vrahatis, 2002; Coello et al., 2004; Pulido & Coello, 2004; Cagnina et al., 2005).

2.9.2 PSO for Optimization of Supply Chain

Depending on nature and intricacy of supply chain network, handling the related optimization problems with classical methods can become difficult (Silva & Coelho, 2007). As a modern heuristic method, the PSO approach has been applied to several supply chain problems effectively (Izquierdo et al., 2008; Sinha et al., 2009; Wei, 2011; Song et al., 2011). According to the study conducted by Kadadevaramath et al. (2009), PSO has a good capability for solving the supply chain optimization problems.

As mentioned before, the basic PSO cannot be used for multi-objective problems. In this study, the simple MOPSO method proposed by Cagnina et al. (2005) is applied to solve the optimization problem. The results are compared with the Ɛ-constraint method, a well-known classical approach, to show the capability of the heuristic method.

2.10 Summary

This chapter provided a brief overview of most relevant works to mathematical modeling and optimization of biofuel supply chain. The multi-objective optimization solving methods were reviewed as well. According to the papers and reports provided in this chapter, limited works have focused on optimization of biofuel supply chain considering social criteria in addition to economic and environmental criteria. On the other hand, the food versus fuel conflict has not been well studied. Modeling and optimization of biofuel supply chain by taking into account this issue, can lead to the sustainable biofuel production. Implementation of modern methods for solving multi-objective optimization problems related to biofuel supply chain has not been considered too.

CHAPTER 3

RESEARCH METHODOLOGY

As mentioned in Chapter 2, a few works have focused on optimal planning of biofuel supply chain under social concerns in addition to economic and environmental concerns. The optimal planning of biodiesel supply chain considering the food versus fuel conflict and also consideration of the capability of heuristic methods for solving multi-objective optimization problems in biofuel supply chain have not been well studied. This chapter aims to describe a methodology based on a mathematical formulation for the optimal planning of biodiesel supply chain by taking into account the economic, environmental and social concerns. The objective functions are minimization of total operational cost, GHG emissions and edible feedstock consumption over the entire supply chain. The proposed methodology is applied to a case study for production of biodiesel from palm oil and jatropha in Malaysia. The MOPSO method and the Ɛ-constraint approach are used to solve the proposed multi-objective model.

3.1 Mathematical Programming Approach

One of the most important methods for quantitative decision making in supply chain network is mathematical programming. Mathematical programming describes the problem related to supply chain using a mathematical model. The aim of mathematical programming is to find an optimal solution (Chandra & Grabis, 2007).

Mathematical formulation of an optimization problem includes determining the parameters and decision variables, determining the objective function, specifying the constraints and developing the formulation.

In this study, a biodiesel supply chain system is described using mathematical equations. The optimization problem is to determine the harvesting and production plan and material flows as well, such that the total operational cost, GHG emissions and edible feedstock consumption are minimized over the specific planning horizon. The planning horizon has been set to one year.

3.2 Biodiesel Supply Chain Structure

The general structure of biodiesel supply chain network considered in this research was depicted in Figure 1.2. It includes a set of feedstock resources and pre-processing facilities, a set of biorefineries and a set of demand zones. It is assumed that pre-processing facilities are located nearby resources and all harvested feedstocks are pre-processed as soon as possible after harvesting.

The paths connecting the nodes represent sequences of material flows that ensure biodiesel is produced and delivered to the demand zones.

3.3 Input Data and Decision Variables

The optimization problem has be ed in form of a MOLP model, as described in section 2.6. The bas n of the model inputs are stated below. The given parameters are as follows:

- Set of feedstock types
- Set of feedstock resources and pre-processing facilities
- Set of biorefineries
- Set of demand zones
- The planning horizon
- Production, harvesting, pre-processing and transportation costs for each type of feedstock
- Road and ocean distance between facilities
- Production and transportation costs of biodiesel
- Maximum available amount of feedstock
- Biodiesel demand at each demand zone
- Conversion factors for pre-processing of feedstock and biodiesel production
- Emission factor for each stage of biodiesel supply chain.

The decision variables related to the optimization problem are as follows:

- Quantity of feedstock to be harvested from each resource
- Quantity of feedstock transported to each biorefinery
- Quantity of biodiesel produced at each biorefinery
- Quantity of biodiesel shipped to demand zones.

A detailed description of indices, decision variables, and parameters has been given in the Abbreviation section at the beginning of this thesis.

3.4 Mathematical Formulation

The proposed MOLP model aims to describe the biodiesel supply chain through linear equations and it searches for minimization of the total operational cost, GHG emissions, and quantity of edible feedstock consumption for production of biodiesel. The formulation reflects the main characteristics of the system. The model objectives and constraints are described as follows.

3.4.1 Economic Objective

The economic objective to be minimized is the total system operational cost throughout the planning horizon. The planning horizon is set to one year. The total operational cost includes feedstock production and harvesting cost (C_1), feedstock pre-processing cost (C_2), feedstock transportation cost (C_3), biodiesel production cost (C_4), and distribution cost (C_5). Figure 3.1 illustrates the terms of the economic objective.

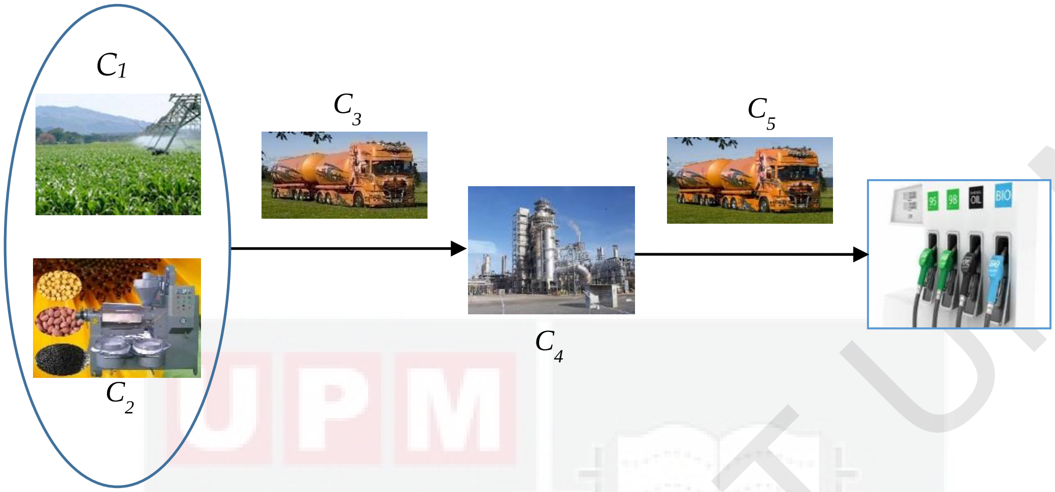

Figure 3.1. Components of economic objective

It should be noted that capital costs are not included in this study. The economic terms are stated as follows:

The production and harvesting cost of feedstock (C_1), as stated in equation (3.1), equals the sum of the all feedstock types harvested from all resources multiplied by their associated production and harvesting cost. $Q_{i,l}$ is amount of feedstock type i harvested from resource l, and $C_{i,l}^{har}$ represents the production and harvesting cost of feedstock type i at resource l.

$$C_1 = \sum_{i=1}^{I} \sum_{l=1}^{L} Q_{i,l} \,.\, C_{i,l}^{har} \tag{3.1}$$

C_2 represents the pre-processing cost of feedstock. It should be noted that all harvested feedstock types are pre-processed after harvesting; so the pre-processing cost of feedstock is equal to the sum of the all feedstock types which are pre-processed at all resources multiplied by their relevant pre-processing cost. This term is stated in equation (3.2). C_i^{pre} is pre-processing cost of feedstock type i.

$$C_2 = \sum_{i=1}^{I} \sum_{l=1}^{L} Q_{i,l} . C_i^{pre} \tag{3.2}$$

The feedstock transportation cost (C_3) takes into account both road and ocean transportation. It is equal to the sum of all pre-processed feedstocks shipped from all resources to all biorefineries multiplied by distance-dependent road transportation cost and ocean freights. Equation (3.3) presents the feedstock transportation cost. $X_{i,l,w}$ is quantity of pre-processed feedstock type i shipped from resource l to biorefinery w. $T1_i^r$ and $D_{l,w}$ are transportation cost via road and distance between resource l and biorefinery w, respectively. $T1_i^S$ is the transportation cost of feedstock type i via ocean.

$$C_3 = \sum_{i=1}^{I} \sum_{l=1}^{l} \sum_{w=1}^{W} X_{i,l,w}. \left[\left(T1_i^r . D_{l,w} \right) + T1_i^S \right] \tag{3.3}$$

C_4 is production cost of biodiesel at biorefineries and it is equal to the sum of all biodiesel produced at all biorefineries multiplied by relevant production cost. This term is defined in equation (3.4), where $X_{i,w}^f$ is the amount of biodiesel produced from feedstock type i at biorefinery w, and $C_{i,w}^p$ presents the production cost of biodiesel from feedstock i at biorefinery w.

$$C_4 = \sum_{i=1}^{I} \sum_{w=1}^{W} X_{i,w}^f . C_{i,w}^p \tag{3.4}$$

Similar to feedstock transportation cost, distribution cost of biodiesel (C_5) includes both road and ocean transportation cost. Biodiesel distribution cost that is defined in equation (3.5), equals the sum of the all biodiesel shipped from biorefineries to all demand zones multiplied by distance-dependent road transportation cost and ocean freights. In equation (3.5), $Q_{i,w,n}^f$ is quantity of biodiesel, which is produced from feedstock i, shipped from biorefinery w to demand zone n. $T2_i^r$, $D'_{w,n}$ and $T2_i^S$ represent biodiesel transportation cost via road, distance between biorefinery w and demand zone n, and transportation cost of biodiesel via ocean respectively.

$$C_5 = \sum_{i=1}^{I} \sum_{w=1}^{W} \sum_{n=1}^{N} Q_{i,w,n}^f . \left[\left(T2_i^r . D'_{w,n} \right) + T2_i^S \right] \tag{3.5}$$

The total annual operational cost (C^{Total}), which is the economic objective in this study, has been expressed as the summation of production and harvesting cost of feedstock, feedstock pre-processing cost, feedstock transportation cost, biodiesel production cost, and biodiesel distribution cost.

$$C^{Total} = C_1 + C_2 + C_3 + C_4 + C_5 \tag{3.6}$$

3.4.2 Environmental Objective

The environmental objective is minimization of GHG emissions (CO_2 equivalent) over the entire biodiesel supply chain. In this research, GHG emissions resulting from biodiesel supply chain are calculated based on a method drawn from the study conducted by the UK Renewable Fuels Agency (UK-RFA). This method evaluates environmental impacts associated with all the stages of biofuel supply chain. Total GHG emissions are reported in terms of CO_2 equivalent.

The UK-RFA approach includes all significant sources of GHG emissions. It contains the default values for reporting the emissions of biofuels derived from various types of energy crops. The approach uses common modules which make up fuel chain and covers the activities starting from the cultivation of biomass and ending with delivery of biofuel to demand zones. These modules are illustrated in Figure 3.2.

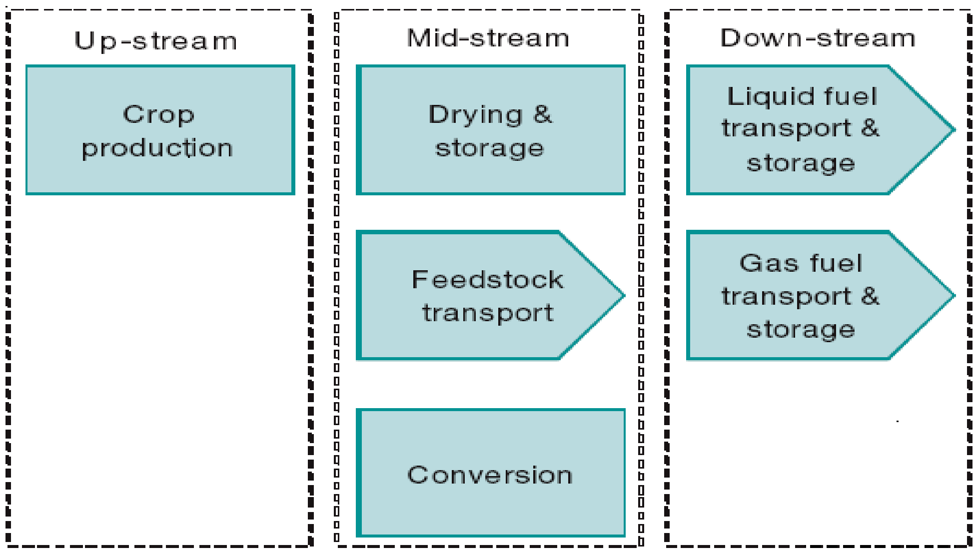

Figure 3.2. Module used to define a biofuel chain
(Source: UK-RFA, 2010)

The terms of the environmental objective are depicted in Figure 3.3.

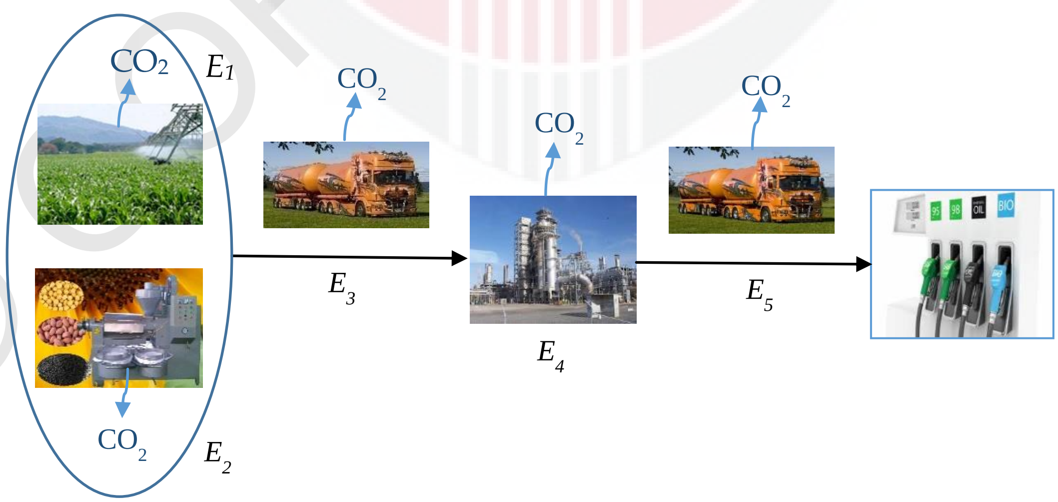

Figure 3.3. Components of environmental objective

The environmental objective is defined as follows:

The total emission from production and harvesting of feedstock (E_1), equals the sum of the all feedstock types harvested from all resources ($Q_{i,l}$) multiplied by their related production and harvesting emission factors (E_i^p).

$$E_1 = \sum_{i=1}^{I} \sum_{l=1}^{L} Q_{i,l} \, . \, E_i^p \tag{3.7}$$

E_2, the emission from pre-processing of feedstock, is equal to the sum of the all feedstock types harvested from all resources ($Q_{i,l}$) multiplied by relevant pre-processing conversion factor (η_i), and pre-processing emission factor (E_i^{pre}).

$$E_2 = \sum_{i=1}^{I} \sum_{l=1}^{L} (Q_{i,l} . \eta_i) . E_i^{pre} \tag{3.8}$$

The total emission from transportation of feedstocks from resources to biorefineries is defined in equation (3.9). This term is equal to the sum of the pre-processed feedstocks that shipped from all resources to all biorefineries ($X_{i,l,w}$) multiplied by their associated distance-dependent emission factor for transportation via road and ocean. In this equation, Et_i^r and Et_i^S are road transportation and ocean transportation emission factors, respectively. $D_{l,w}$ describes the road distance between resource l and biorefinery w and $Ds_{l,w}$ shows the ocean distance between resource l and biorefinery w.

$$E_3 = \sum_{i=1}^{I} \sum_{l=1}^{L} \sum_{w=1}^{W} X_{i,l,w} . (Et_i^r \, . \, D_{l,w} + Et_i^S \, . \, Ds_{l,w}) \tag{3.9}$$

The total emission from conversion of feedstocks to biodiesel (E_4) is stated in equation (3.10). It is equal to sum of the biodiesel produced at all biorefineries ($X_{i,w}^f$) multiplied by emission factors for conversion of feedstocks to biodiesel. E_i^c represents the emission factor for conversion of feedstock type i to biodiesel.

$$E_4 = \sum_{i=1}^{I} \sum_{w=1}^{W} X_{i,w}^f . E_i^c \tag{3.10}$$

E_5 presents the total emission from distribution of biodiesel from biorefineries to demand zones. This term, which is given by equation (3.11), equals the sum of the biodiesel produced at all biorefineries and shipped to all demand zones ($Q_{i,w,n}^f$) multiplied by distance-dependent emission factors for distribution of biodiesel via road and ocean. Ed_i^r and Ed_i^S are distance-dependent emission factors for distribution of biodiesel via road and ocean. $D'_{w,n}$ is a road distance between biorefinery w and demand zone n, and $D's_{w,n}$ indicates the ocean distance between biorefinery w and demand zone n.

$$E_5 = \sum_{i=1}^{I} \sum_{w=1}^{W} \sum_{n=1}^{N} Q_{i,w,n}^{f} . (Ed_i^r . D'_{w,n} + Ed_i^S . D's_{w,n}) \tag{3.11}$$

Therefore, the total GHG emission resulting from biodiesel supply chain (E^{Total}) is defined as the summation of emission from production and harvesting of feedstock (E_1), emission from pre-processing of feedstock (E_2), emission from transportation of feedstock (E_3), emission from biodiesel production (E_4), and emission from distribution of biodiesel (E_5).

$$E^{Total} = E_1 + E_2 + E_3 + E_4 + E_5 \tag{3.12}$$

3.4.3 Social Objective

Biodiesel development has several social issues such as poverty reduction potential, effects on water utility systems and impacts on land and crops (Awudu & Zhang, 2012). However, in this study the food versus fuel conflict is studied as a social concern and consideration of other social issues is beyond the scope of this research. The social objective of this study is minimization of total amount of edible feedstock used for biodiesel production (Qe^{Total}). Edible feedstocks are feedstocks which are common between human food resources and feedstocks used for biofuel production. Equation (3.13) represents the social term:

$$Qe^{Total} = \sum_{i=1}^{I} \sum_{l=1}^{L} Q_{i,l} . \beta_i \tag{3.13}$$

where β_i is equal to 1 if feedstock is edible, otherwise it equals 0.

3.4.4 Constraints

The following constraints are inherent to the problem. The constraints take into consideration the major characteristics of biodiesel supply chain such as feedstock and facility availability, biorefinery capacity and biodiesel demand.

3.4.4.1 Resource Constraints

For the reason that it is not possible to harvest feedstock more than available quantity, the total amount of feedstock type i collected from feedstock resource l ($Q_{i,l}$) cannot exceed its maximum availability ($Y_{i,l}$).

$$Q_{i,l} \leq Y_{i,l} \qquad \forall\, i \in I, l \in L \tag{3.14}$$

It has been assumed that pre-processing facilities are located nearby the fields and resources and all harvested feedstock types are pre-processed as soon as possible after harvesting. All the pre-processed feedstocks are shipped to biorefineries.

$$Q_{i,l} \,.\, \eta_i = \sum_{w=1}^{W} X_{i,l,w} \qquad \forall i \in I, l \in L \quad (3.15)$$

where η_i is the pre-processing conversion factor for feedstock type i.

3.4.4.2 Biorefinery Constraints

The total amount of biodiesel produced from feedstock i at each biorefinery w, equals the amount of transported feedstock type i from all resources to biorefinery w multiplied by relevant conversion factor.

$$X_{i,w}^{f} = \sum_{l=1}^{L} X_{i,l,w} \,.\, \alpha_i \qquad \forall i \in I, w \in W \quad (3.16)$$

where $X_{i,w}^{f}$ is the amount of biodiesel produced from feedstock type i at biorefinery w, and α_i is the conversion factor for biodiesel production from feedstock i.

Total amount of biodiesel produced from all types of feedstocks at biorefinery w should not exceed the refinery capacity.

$$\sum_{i=1}^{I} X_{i,w}^{f} \leq Ref_w \qquad \forall w \in W \quad (3.17)$$

Ref_w is the capacity of biorefinery w.

3.4.4.3 Demand Zone Constraints

All amount of biodiesel produced at each biorefinery from each type of feedstock is shipped to demand zones.

$$\sum_{n=1}^{N} Q_{i,w,n}^{f} = X_{i,w}^{f} \qquad \forall i \in I, w \in W \quad (3.18)$$

Constraint (3.19) shows the demand satisfaction at each demand zone. Total quantity of biodiesel shipped from all biorefineries to each demand zone should fulfill the demand.

$$\sum_{i=1}^{I} \sum_{w=1}^{W} Q_{i,w,n}^{f} \geq D_n \qquad \forall n \in N \quad (3.19)$$

D_n represents the biodiesel demand at demand zone n.

3.5 Solution Strategy

As mentioned before, there are several methods for solving multi-objective optimization models. In this study, two methods are applied to solve the problem. The first one is the Ɛ-Constraint strategy which is a well-known classical method. The second strategy is the simple MOPSO method which is a heuristic method. Both of the methods are applied to the problem to find the optimal solutions.

The Ɛ-Constraint strategy is one of the most widely used methods for multi-objective optimization problems in finding adequate optimal solutions (Mavrotas, 2009). This method is based on the aggregation of multi-objective optimization problems into single-objective problems. Although Ɛ-Constraint method is capable of finding the optimal solutions (Diwekar, 2008), it must be run several times to find solutions and takes high computational time according to complexity of the problem.

As a solution to such difficulties, the simple MOPSO method, which is a heuristic method, is proposed to solve the multi-objective optimization problem. MOPSO is an improved form of PSO method for solving multi-objective optimization problems.

3.5.1 Ɛ-Constraint Method

Ɛ-Constraint method is a classical method. In this method, one of the objectives is considered as the main objective while the others are transformed to constraints. The set of *Pareto* solutions is obtained by solving the following single objective problem for different values of Ɛ.

$$
\begin{aligned}
\text{Minimize} \quad & f_1(x) \\
& x = (x_1, x_2, \dots, x_p) \\
\text{Subject to} \quad & f_2(x) \le \varepsilon_2 \\
& \quad \vdots \\
& f_n(x) \le \varepsilon_n \\
& g_m(x) \le 0, \quad m = 1,2,\dots,n_g \\
& h_m(x) = 0, \quad m = 1,2,\dots,n_h
\end{aligned}
\tag{3.20}
$$

where $f(x)$ is the objective function, x is the decision vector, $g_m(x)$ and $h_m(x)$ denotes inequality and equality constraints, respectively.

The steps of Ɛ-Constraint method are as follows (Diwekar, 2008):

1. One of the objectives is chosen as the main objective function
2. The upper bound of parameter Ɛ is determined by solving the optimization problem for the main objective which is chosen in the first step.
3. The problem is solved according to each sub-objective function, separately. Value of each objective obtained by optimization, represents the lower bound of parameter Ɛ.

4. The *Pareto* optimal set is defined by running the model with the main objective function and different values of Ɛ which are between the lower and upper bounds.

3.5.2 MOPSO Method

PSO is a heuristic method based on the behavior of the birds within a flock. This method simulates the social behavior of organisms within a group, such as birds, fish schools, and so on. In PSO, each proposed solution, called a *Particle* which is a point in the search space of the optimization problem.

The algorithm used in this study is the simple MOPSO, proposed by Cagnina et al. (2005). In this algorithm, a policy is defined to maintain the dominant solutions in iterations. Non-dominated solutions saved in an external archive. The mutation operator was adapted to prevent premature convergence due to the high convergence speed.

Suppose that the search space has D dimension. Each particle is placed in the $X_i = [x_{i1}; \dots; x_{iD}]$ with the velocity of $V_i = [v_{i1}; \dots; v_{iD}]$. Each particle moves to the best position has experienced ($pbest_i$). Velocity of each particle in each dimension and iteration is updated according to the *pbest*, position of the best particle (*gbest*) and certain velocity (equation 3.21).

$$v_i^{it} = \omega v_i^{it-1} + c_1 r_1 \left(pbest_i^{it-1} - x_i^{it-1}\right) + c_2 r_2 \left(gbest^{it-1} - x_i^{it-1}\right) \tag{3.21}$$

where it and ω are number of iterations and inertia weight respectively. c_1 and c_2 are acceleration constants. r_1 and r_2 are random numbers between 0 and 1.

Position of each particle in each dimension is also updated in every iteration according to the equation (3.22).

$$x_i^{it} = x_i^{it-1} + v_i^{it} \tag{3.22}$$

The steps of algorithm used in this study are as follows:

1. Initialization of population and velocities
2. Evaluation of particles based on objective functions
3. Update the fitness vector
4. Keeping non-dominated particles in an external archive
5. Selection of global best
6. Update velocity and positions according to equations 3.21 and 3.22
7. Apply mutation
8. Evaluation of positions
9. Update best position and fitness vector
10. Update external archive
11. Update global best
12. Repetition of step 6 to 11 until the termination criteria are met.

The global best is randomly selected from non-dominated particles in the external archive. In this study, the process is stopped if there is no significant improvement after the specified number of iterations.

3.6 Examination of the MOPSO Method

As previously mentioned, the Ɛ-Constraint method is able to find the optimal solutions (Diwekar, 2008). However, this method must be run several times to obtain a set of *Pareto* solutions. In this study, the MOPSO method is used to solve the multi-objective optimization problem. In order to study the capability of the MOPSO method, it is compared with the Ɛ-Constraint method in terms of finding the best result for each objective and computational running time. The Ɛ-Constraint method is implemented using optimization toolbox in MATLAB. The MOPSO method is coded in MATLAB environment as well. Appendix A1 shows MATLAB code for the MOPSO method. The evaluation of the MOPSO method is as follow:

Firstly, the Ɛ-constraint method is applied to the model to obtain the *Pareto* optimal solutions. In this study, the economic objective is considered as the main objective, and environmental and social criteria are transformed to constraints. Determination of the lower and upper bound of Ɛ for each objective function is the next step in this method. The lower bound of Ɛ is determined by minimizing the environmental and social objectives subject to the constraints separately. The upper bound is determined by minimizing the economic objective. In the last step, Ɛ is fixed to 10 values between the lower and upper bounds for each sub-objective and added as a constraint to the model. In this way, one optimal solution is obtained in each run. A set of *Pareto* optimal solutions has been defined by running the model for different values of Ɛ.

The second optimization method applied to the model is the simple MOPSO method. The MOPSO approach used in this study has been proposed by Cagnina et al. (2005). According to the experimental study regarding the MOPSO method, conducted by Coello et al. (2004), using 100 particles is recommended when there is no pre-knowledge about the optimal solution; so the simple MOPSO implementation initialized with the population size of 100 particles. c_1 and c_2, the acceleration coefficients, are typically static. Studies show when $c_1 = c_2$ and both of them are positive the attraction of particles is towards the average of $pbest_i$ and $gbest$. Empirical research have proposed the acceleration coefficient of $c_1 = c_2 = 2$. ω, the inertia weight, controls the momentum of particles. In order to control the local and global optima, normally the inertia weight decreases from 0.9 to 0.4 over the entire algorithm run (Talukder, 2011). In this study, the process is stopped if there is no significant improvement after 200 iterations. The mutation rate is set to 0.5

based on empirical research. The size of external archive has been set to 10. The MOPSO parameters are summarized in Table 3.1.

Table 3.1.MOPSO parameters

Parameter	Value
Number of particles	100
Number of iterations	200
c_1	2
c_2	2
Mutation rate	0.5
External archive size	10
ω	0.9

The simple MOPSO method is compared with the Ɛ-constraint method so as to evaluate the capability of the heuristic method for solving the biodiesel supply chain optimization problem. In order to measure the errors resulting from the MOPSO method, the results obtained for each objective by implementing this method are compared with the results obtained by the Ɛ-constraint method (equation 3.23).

$$error = \left|\frac{S_{MOPSO} - S_{\varepsilon}}{S_{\varepsilon}}\right| \tag{3.23}$$

where S_{ε} is the best result for each objective function among the optimal solutions obtained by the Ɛ-constraint method, and S_{MOPSO} is the best result for each objective function among the optimal solutions obtained by the MOPSO method. These two methods are compared in terms of running time as well.

3.7 Case Study

The proposed MOLP model and solving strategy have been applied to the case study in Malaysia for optimal production of biodiesel from palm oil and jatropha in order to show the capability of the proposed methodology. Malaysia is an equatorial country with the average rainfall of 250 cm a year and the daily temperatures fluctuate between 20°C and 30°C (Swee-Hock, 2007). The country has two parts, Peninsular Malaysia in the west, and East Malaysia in the east ("Geography of Malaysia," 2012). A detailed description of case study is as follows.

3.7.1 Feedstock Resource

Malaysia has 13 states and 3 federal territories. 11 states and 2 federal territories are located in Peninsular Malaysia and 2 states are in East Malaysia ("States and federal territories of Malaysia," 2012). In this study, each state is considered as a feedstock resource. Since the resources are spread across the states, in order to calculate the distances, it is assumed that resources are lumped at one point in each state. These states and configuration of the supply chain for one of the resources (Kedah) are both illustrated in Figure 3.4.

Figure 3.4 States of Malaysia and configuration of the supply chain for Kedah
(Adapted from Malaysia travel guide, 2012)

3.7.2 Feedstock Data

3.7.2.1 Palm Oil Data

The annual fresh fruit bunch (FFB) yield in each state in 2012 and area under mature oil palm plantation in Malaysia have been obtained from Malaysian Palm Oil Board (MPOB, 2012). These data are shown in Tables 3.2 and 3.3. It has been assumed that no FFB is harvested from Perlis due to the small area under mature oil palm plantation.

Table 3.2. Annual yield of FFB

State	yield (t/ ha)
Johor	19.02
Kedah	21.43
Kelantan	11.89
Malacca	23.30
N. Sembilan	19.88
Pahang	18.94
Penang	16.88
Perak	21.35
Selangor	20.91
Terengganu	15.35
Sabah	20.40
Sarawak	16.51

(Source: MPOB, 2012)

Table 3.3. Area under mature oil palm plantation

State	Oil palm planted area (ha)
Johor	618,353
Kedah	76,181
Kelantan	91,182
Malacca	48,718
N. Sembilan	143,580
Pahang	595,799
Penang	13,264
Perak	338,100
Selangor	124,080
Terengganu	136,509
Sabah	1292,757
Sarawak	874,152

(Source: MPOB, 2012)

The average yield of crude palm oil (CPO) in 2012 was 20.35% by weight (MPOB, 2012). Production and harvesting cost of FFB that is provided by Wahid and Simeh (2009) is MYR 214/t FFB. Production cost of FFB consists of up-keeping, fertilizer application, harvesting, in-field transportation and_general charges. The extraction cost of CPO from FFB was estimated at MYR 36.25/t FFB by Ying Man and Baharum (2011) for large-scale palm oil mills.

3.7.2.2 Jatropha Data

Malaysia has good climate condition for cultivation of jatropha. The potential area for cultivation of jatropha is given in Table 3.4.

Table 3.4. Potential area for cultivation of jatropha

Region	Area (million acres)
Peninsular Malaysia	8.5
Sabah	10.4
Sarawak	14

(Source:" *Jatropha Curcas* Grower Murabahah Programme,"2012)

Since jatropha grows in all types of soils, even marginal lands (Gour, 2006; Ong et al., 2011); it has been assumed that area under jatropha plantation in each state is proportional to the state area. The area of each state is presented in Appendix B1. According to the Bionas jatropha biodiesel project, per acre yield of 3.6 metric tons of fruits in the first three years. Jatropha oil is (JO) obtained from jatropha seeds. The oil content of jatropha seed is around 33% (BIONAS, 2013). The production cost of jatropha was estimated at MYR 535/t seed based on Puteh and Sivapragasam presentation (2008). Crushing cost of jatropha seeds has been reported at USD 40/t seed (Global NRG Ltd, 2013).

It should be noted that appropriate producer price index (PPI), as presented in Appendix B2, is used to inflate the costs. Appendix B3 shows the calculation of inflation using PPI. All the costs are converted to Malaysian Ringgit (MYR) as well and are summarized in Table 3.5.

Table 3.5. Feedstock related costs

Cost items	Unit	FFB	Jatropha
Production and harvesting	MYR/t feedstock	214	650.56
Pre-processing of feedstock(oil extraction)	MYR/ t feedstock	43.68	121.2

Adapted from (Wahid & Simeh, 2009; Ying Man & Baharum, 2011; Puteh & Sivapragasam, 2008; Global NRG Ltd, 2013)

3.7.3 Biorefinery Locations

According to the MPOB and American Palm Oil Council (APOC) presentation in 2010, 12 biodiesel plants are in operation and 4 plants have completed construction in Malaysia. These plants are located in 6 states. Each state is considered as a biorefinery location. It has been presumed that biorefineries are located at the center of each state and each biorefinery handles JO as well as CPO. Table 3.6 shows the location and capacity of the plants.

Table 3.6. Locations and capacity of biodiesel plants

State	In operation		Completed construction	
	No	Capacity (t/year)	No	Capacity (t/year)
Sabah	2	250000	-	-
Johor	5	780000	-	-
Selangor	2	190000	2	72000
Pahang	1	99000	1	100000
Perak	2	153000	-	-
N. Sembilan	-	-	1	18000

(Source: MPOB & APOC, 2010)

3.7.4 Transportation

It is assumed that transportation in West Malaysia is performed by diesel truck and transportation between the east and west is performed by ship. All the items in the west for transporting to East Malaysia, are transferred to Port Klang and shipped to Kota Kinabalu in Sabah and Kuching in Sarawak. The distance between each pair of states and ports was obtained from Google Maps and Ports website. Appendix B4 shows the ports distances. Cost of transportation by truck is based on data reported by Kim et al. (2011). The ocean freights were obtained from Malaysia Logistics Buzz (VK, 2013).

Similar to feedstock related costs, costs of transportation via truck are inflated using appropriate PPI. Transportation costs are summarized in Table 3.7.

Table 3.7. Transportation costs

Transportation mode	Transportation cost
Diesel truck	0.19 (MYR/ t · km)
Ship (Klang to Kuching)	220 (MYR/t)
Ship (Klang to Kota Kinabalu)	230 (MYR/t)

Adapted from (Kim et al., 2011; VK, 2013)

3.7.5 Biodiesel Production

Biodiesel produced from different ways. The most common method for biodiesel production is transesterification (Barnwal & Sharma, 2005). According to the study by Singh et al. (2006), the optimal yield of biodiesel using alkaline catalyst, which is normally used for biodiesel production, is 95.8%.

Production cost of biodiesel from CPO was estimated at MYR 460/t biodiesel by Malaysian Biofuel Association in 2007, when the operating costs were taken into account (Pio Lopez and Laan, 2008). It has been assumed that production cost of biodiesel from JO is similar to the production cost of biodiesel from CPO. Biodiesel production cost was inflated as well.

3.7.6 Demand Data

According to data obtained from Malaysia Energy Information Hub (MEIH), the final demand for biodiesel in Malaysia in 2012 was 115 ktoe (Kilotons of oil equivalent). Figure 3.5 illustrates the final demand for fossil diesel and biodiesel in 2012.

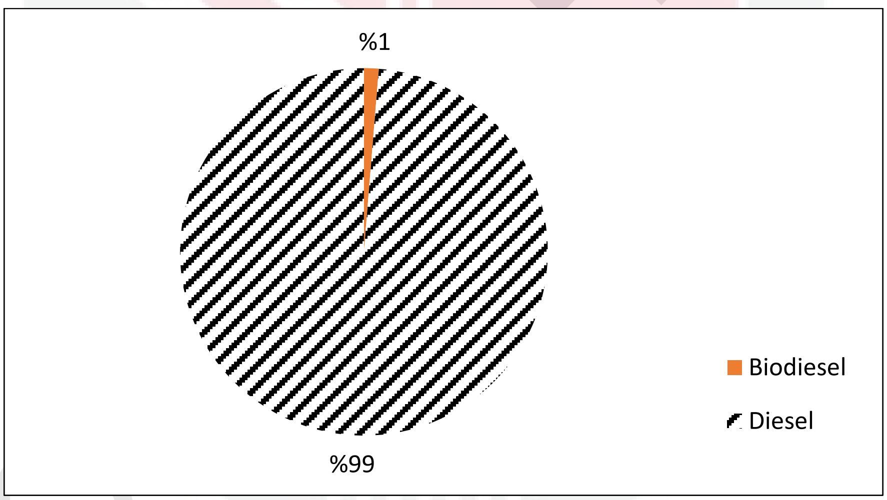

Figure 3.4. Final biodiesel and diesel demand
(Source: MEIH, 2012)

In this study, each state is considered as a demand zone, and it is assumed that demand of each state is proportional to its population which is given in Appendix B5. Appendix B6 shows the demand calculation using proportion. Demand of each state is presented in Table 3.8.

Table 3.8. Biodiesel demand by state

State	Biodiesel demand (ktoe per year)
Johor	13.60
Kedah	7.91
Kelantan	6.25
Malacca	3.33
N. Sembilan	4.14
Pahang	6.09
Perak	9.54
Perlis	0.93
Pinang	6.33
Selangor	22.16
Terengganu	4.22
Sabah	13.03
Sarawak	10.03

3.7.7 Emission Factors

The emissions data were obtained from the method specified by the UK renewable fuel agency (UK-RFA, 2010). The total GHG emissions resulting from biodiesel supply chain is reported in terms of CO_2 equivalent. Emission factors for palm oil and jatropha are summarized in Tables 3.9 and 3.10.

Table 3.9. Palm oil to biodiesel emissions

Stage of supply chain	Emission factor
Crop production	81.34 (kg CO_2/t FFB)
Feedstock pre-processing	516.6 (kg CO_2/t CPO)
Feedstock transportation (road)	0.15 (kg CO_2/t · km)
Feedstock transportation (ship)	0.02 (kg CO_2/t · km)
Conversion	471 (kg CO_2/t biodiesel)
Fuel transportation (road)	0.15 (kg CO_2/t · km)
Fuel transportation (ship)	0.02 (kg CO_2/t · km)

(Source: UK-RFA, 2010)

Table 3.10. Jatropha to biodiesel emissions

Stage of supply chain	Emission factor
Crop production	42.78 (kg CO_2/t seed)
Feedstock pre-processing	43.24 (kg CO_2/t JO)
Feedstock transportation (road)	0.15 (kg CO_2/t · km)
Feedstock transportation (ship)	0.02 (kg CO_2/t · km)
Conversion	471 (kg CO_2/t biodiesel)
Fuel transportation (road)	0.15 (kg CO_2/t · km)
Fuel transportation (ship)	0.02 (kg CO_2/t · km)

(Source: UK-RFA, 2010)

3.8 Summary

This chapter presented an optimization strategy based on the mathematical formulation. A MOLP model was proposed to measure the economic, environmental, and social objectives related to the biodiesel supply chain. The optimality was defined with respect to the total operational cost, GHG emissions, and edible feedstock consumption. The MOPSO method and the ε-Constraint method were proposed for solving the MOLP model. A biodiesel supply chain in Malaysia was selected as a case study to illustrate the capability of the proposed methodology.

CHAPTER 4

RESULTS AND DISCUSSION

The methodology provided in Chapter 3 has been used to improve the economic, environmental and social performances of biodiesel production from palm oil and jatropha in Malaysia. The proposed MOLP model and optimization strategy aim to minimize the total annual operational cost, GHG emissions, and edible feedstock consumption for production of biodiesel in Malaysia. A detailed description of the case study was presented in the previous chapter. In this chapter, the computational results of the case study will be presented and the computational performance comparison between the Ɛ-constraint and the simple MOPSO methods will be discussed.

4.1 Computational Results

The resulting MOLP model for the Malaysia case study has been solved with the Ɛ-constraint and the simple MOPSO methods as described in Chapter 3. Table 4.1 demonstrates the optimal solutions obtained by the Ɛ-constraint method. In this table, each row represents an optimal solution for planning of biodiesel supply chain in Malaysia.

Table 4.1. Optimal solutions obtained by Ɛ-constraint method

Solution	Total annual cost (MYR)	GHG emissions (t CO_2)	Edible feedstock consumption (t)
S_1	384,460,000	99,017	64,972
S_2	368,840,000	106,760	131,110
S_3	355,410,000	117,510	203,240
S_4	341,550,000	123,260	251,240
S_5	326,990,000	146,000	340,440
S_6	311,850,000	157,750	410,632
S_7	298,120,000	167,500	459,771
S_8	282,810,000	187,250	521,892
S_9	268,290,000	196,990	607,030
S_{10}	254,510,000	204,630	685,420

Comparing the optimal solutions reveals that decreasing the operational cost causes an increase in edible feedstock consumption and GHG emissions.The optimal solutions obtained by the MOPSO method are presented in Table 4.2.

Similar to Table 4.1, each row presents a solution for optimal planning of biodiesel supply chain in Malaysia.

Table 4.2. Optimal solutions obtained by MOPSO method

Solution	Total annual cost (MYR)	GHG emissions (t CO_2)	Edible feedstock consumption (t)
S_1	390,610,000	99,046	61,920
S_2	372,100,000	110,800	123,400
S_3	359,700,000	122,530	186,070
S_4	341,600,000	134,280	256,690
S_5	322,270,000	146,030	329,130
S_6	309,970,000	157,760	391,120
S_7	289,590,000	169,530	466,050
S_8	279,700,000	181,260	522,860
S_9	265,020,000	191,690	584,310
S_{10}	254,740,000	199,950	630,100

According to the optimization results shown in Tables 4.1 and 4.2, as the optimal annual operational cost decreases from MYR 384,460,000 to MYR 254,510,000 among the optimal solutions obtained by the Ɛ-constraint method, the total GHG emission and edible feedstock consumption increase from 99,017 t CO_2 equivalent to 204,630 t CO_2 and 64,972 t edible feedstock to 685,420 t, respectively. Likewise, the optimal annual operational cost, obtained through the MOPSO method, reduces from MYR 390,610,000 to MYR 254,740,000 while the total GHG emission and edible feedstock consumption increase from 99,046 t CO_2 equivalent to 199,950 t CO_2 and 61,920 t edible feedstock to 630,100 t.

Since all the optimal solutions in a *Pareto* solutions set are equally good, the decision maker can take the one from the set of solutions that best fits the necessities.

4.2 Computational Performance Comparison

In order to study the capability of the MOPSO method for solving the optimization problem in hand, the best result for each objective function among the *Pareto* solutions obtained by the Ɛ-constraint and the MOPSO methods, the total running time and error percentage of MOPSO method, as described in section 3.6, are measured and presented in Tables 4.3 to 4.5.

Table 4.3. Best results obtaind by Ɛ-constraint and MOPSO methods

Objective function	The best result obtained by Ɛ-constraint method	The best result obtained by MOPSO method
First objective (Operational cost)	254,510,000 (MYR)	254,740,000 (MYR)
Second objective (GHG emissions)	99,017 (t CO_2)	99,046 (t CO_2)
Third objective (Edible feedstock Consumption)	64,972 (t)	61,920 (t)

Table 4.4. Running time of Ɛ-constraint and MOPSO methods

Method	Running time (s)
Ɛ-constraint	2123.67
MOPSO	436.22

Table 4.5. Error percentage of MOPSO method

Objective function	Error percentage (%)
First objective (Operational cost)	0.09
Second objective (GHG emissions)	0.02
Third objective (Edible feedstock consumption)	4.7

Table 4.5 shows that the error percentage of the MOPSO method in finding the best result for each bjective function is small. The error percentage of MOPSO method for each solution is also measured. The average error percentage of objective functions are 1%, 2.5% and 4.2% respectively.

4.3 Remarks

The results of implementation of the proposed optimization model and solving strategy are considered under five sections. In section 4.3.1, capability of the MOPSO method is discussed. In section 4.3.2, optimal solutions for the production of biodiesel in Malaysia, which were given in Tables 4.1 and 4.2, will be considered and discussed. In section 4.3.3, the optimal results for biodiesel production in Malaysia under two optimization criteria are presented. These two criteria include optimization under economic objective and optimization under environmental-economic objectives. The results of these optimization cases are compared with the results of optimization model proposed in this study in order to show the effectiveness of the model. In section 4.3.4, results of a sensitivity analysis will be presented.

4.3.1 Capability of the MOPSO Method

According to section 4.2, quality of the results provided by the MOPSO method is acceptable and the average error percentage of the case study is low. Results show that the MOPSO method is able to find the approximation of *Pareto* solutions in less computational time. Figure 4.1 shows the *Pareto* curves obtained by the Ɛ-constraint and the MOPSO methods for the selected case study.

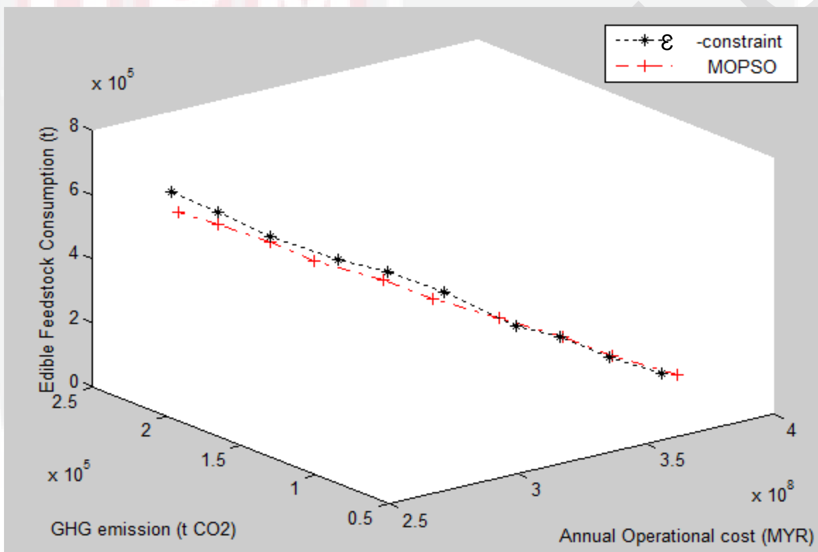

Figure 4.1. Pareto curves for the case study

It could be seen that MOPSO method is able to find the approximation of the optimal solutions.

4.3.2 Discussion on Optimal Solutions for the Malaysia Case Study

The optimal solutions for the production of biodiesel in Malaysia are discussed as follow:

4.3.2.1 Low Cost Scenario

As shown in Table 4.1, the minimum cost solution obtained by Ɛ-constraint method has the operational cost of MYR 254,510,000. The total GHG emission and edible feedstock consumption of this solution are 204,630 t CO_2 and 685,420 t feedstock respectively. The low cost solution obtained through the MOPSO method, as shown in Table 4.2, has the operational cost of MYR 254,740,000.

Figure 4.2 illustrates the quantity of feedstock consumed for the production of biodiesel under the low cost scenario for both methods.

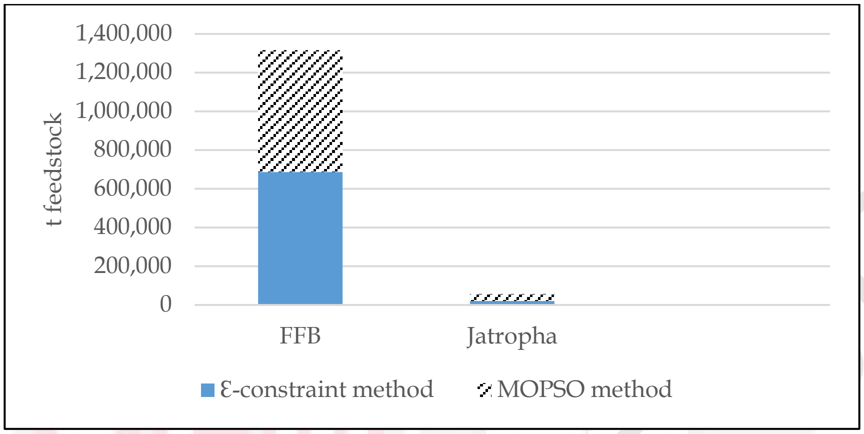

Figure 4.2. Feedstock consumption under the low cost scenario

This figure represents, in the low cost scenario, biodiesel is mainly produced from palm oil derived from FFB, which could impact food resources. Figure 4.3 illustrates GHG emission from different stages of biodiesel supply chain under the low cost scenario. It can be observed that conversion of feedstock to biodiesel (biodiesel production stage) is the main factor in GHG emissions.

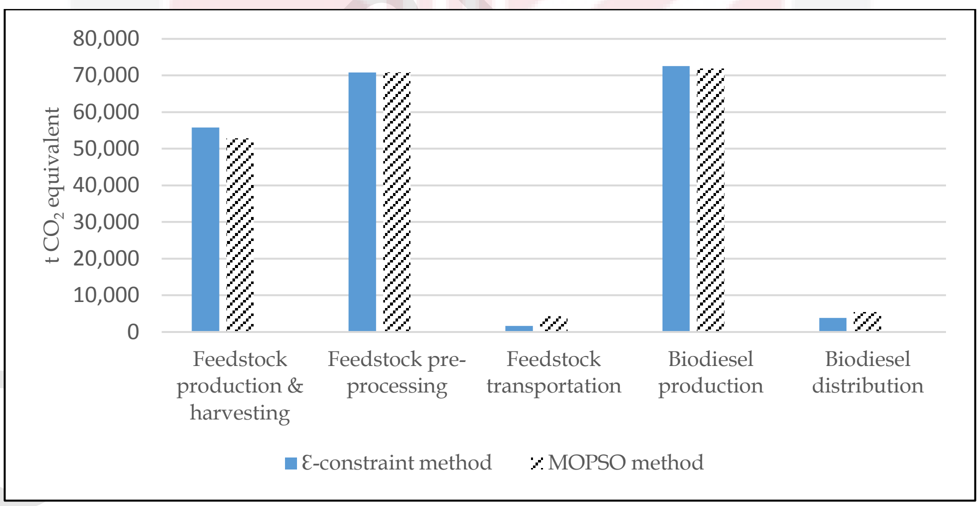

Figure 4.3. GHG emission from different stages of biodiesel supply chain under the low cost scenario

4.3.2.2 High Cost Scenario

According to the obtained optimal solutions, Tables 4.1 and 4.2, the highest annual operational cost of biodiesel production in Malaysia, obtained by Ɛ-constraint method, is MYR 384,460,000. The total GHG emission and edible feedstock consumption for this scenario are 99,017 t CO_2 and 64,972 t edible feedstock, respectively. The highest cost solution obtained by MOPSO method, as presented in Table 4.2, has the operational cost of MYR 390,610,000. This cost is equivalent to 99,046 t CO_2 emission and 61,920 t edible feedstock consumption. The GHG emission from each stage of the biodiesel supply chain, under the high cost scenario, is depicted in Figure 4.4. Similar to the low cost scenario, biodiesel production stage has the major contribution in GHG emissions over the entire biodiesel supply chain.

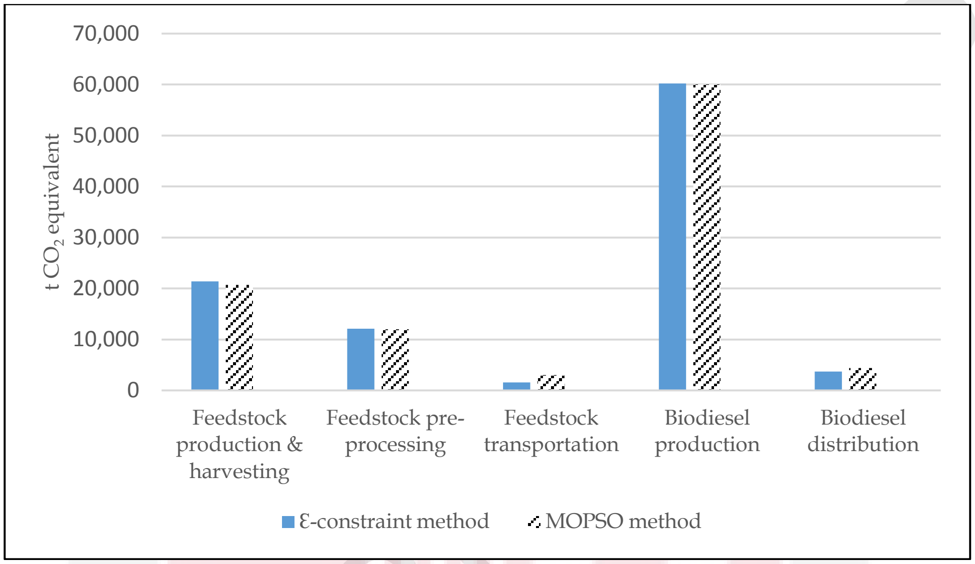

Figure 4.4. GHG emission from different stages of biodiesel supply chain under the high cost scenario

Quantity of feedstock consumption for production of biodiesel under the high cost scenario, obtained by both solving methods, is depicted in Figure 4.5.

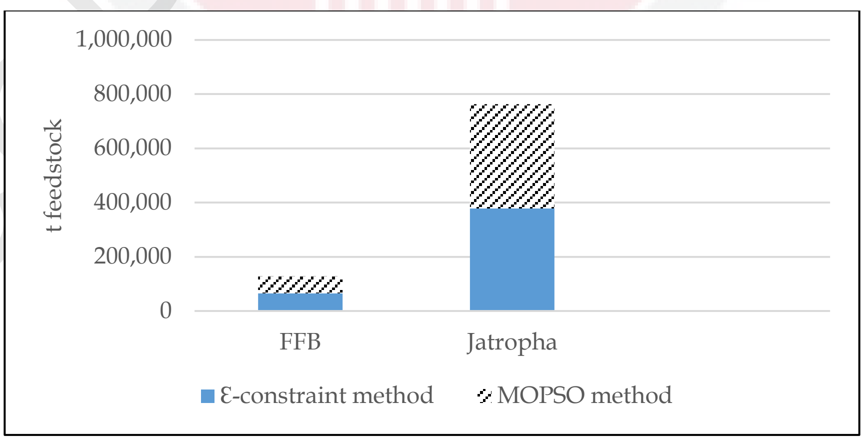

Figure 4.5. Feedstock consumption under the high cost scenario

It is obvious that jatropha, which is a non-edible crop, is the main feedstock for production of biodiesel under the high cost scenario.

By comparing Figures 4.3 and 4.4, it can be seen that GHG emissions from production and harvesting and pre-processing of feedstock under the high cost scenario are much lower than those for the low cost scenario. The reason is that production and harvesting and also pre-processing of jatropha that is the main feedstock in the high cost scenario, emit less GHG than those for the FFB in the low cost scenario.

The total annual operational costs, feedstock production and harvesting costs, feedstock pre-processing costs, feedstock transportation costs, biodiesel production costs, biodiesel distribution costs, total GHG emission, and quantity of edible feedstock consumption for biodiesel production under the low cost and the high cost scenarios, obtained by Ɛ-constraint and MOPSO methods, are summarized in Table 4.6.

Table 4.6. Summary of results for the low cost and the high cost scenarios

	Low cost scenario		High cost scenario	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Production and harvesting cost of feedstock (MYR)	147,430,000	147,594,170	259,230,000	260,890,100
Pre-processing cost of feedstock (MYR)	30,078,000	30,093,230	48,543,000	48,986,900
Transportation cost of feedstock (MYR)	2,168,600	2,171,500	2,003,800	2,446,800
Production cost of Biodiesel (MYR)	69,971,000	69,983,100	69,959,000	69,981,00
Distribution cost of Biodiesel (MYR)	4,823,200	4,898,000	4,721,900	4,912,200
Total annual operational cost (MYR)	254,510,000	254,740,000	384,460,000	390,610,000
Total GHG emission (t CO_2)	204,630	199,950	99,017	99,046
Quantity of edible feedstock consumption (t)	685,420	630,100	64,972	61,920

Table 4.6 shows that the total GHG emission and edible feedstock consumption for the low cost scenario are much higher than those for the high cost scenario. It can be attributed to the emissions from production and pre-processing of FFB, as the main feedstock in the low cost scenario, that are higher than those for jatropha.

The results of the low cost and the high cost scenarios show that these scenarios could not be good solutions for biodiesel production in Malaysia. The reason is that in the low cost scenario biodiesel is mainly produced from palm oil, which could affect the food supply. In addition, GHG emission is very high. On the other hand, in the high cost solution, although biodiesel is mainly produced from non-edible feedstock and GHG emission is very low, the total operational cost is very high.

4.3.2.3 Promising Solution

Considering above descriptions, a rather promising scenario for production of sustainable biodiesel in Malaysia is needed. According to Table 4.1, comparing the optimal solutions reveals that decreasing the operational cost, causes an increase in edible feedstock consumption and GHG emissions. Based on the obtained solutions, the total annual operational cost at MYR 326,990,000 could be selected as a good choice among the optimal solutions. The reason is that based on Malaysian Biofuel Association calculation in 2007, the palm oil biodiesel could be produced for MYR 2,960 per tonne at biorefineries (Pio Lopez and Laan, 2008), whereas the cost of biodiesel produced at biorefineries from a combination of palm oil and jatropha for the selected optimal solution at operational cost of MYR 326,990,000 is MYR 2,575 per tonne. On the other hand, about 38% of feedstock for biodiesel production under the selected scenario is supplied by jatropha which leads to reduction in GHG emissions and edible feedstock consumption compared to palm oil biodiesel. Similarly, the operational cost at MYR 322,270,000 obtained by MOPSO method could be selected as a good solution for production of biodiesel, since biodiesel could be produced for less than MYR 2,960 at this point.

The break-down of the total operational cost for the selected optimal solutions, which were obtained by the Ɛ-constraint and MOPSO methods, are shown in Figure 4.6. This figure shows that production and harvesting cost of feedstock is the major factor in total operational cost.

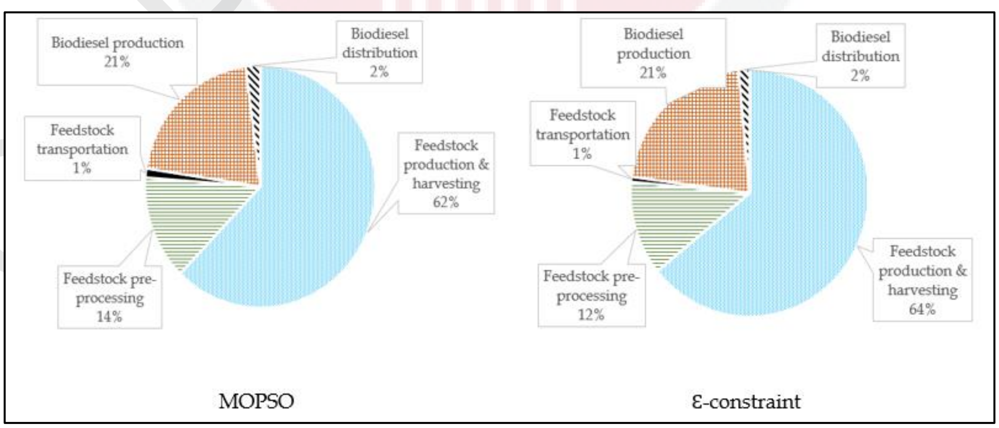

Figure 4.6. Break-down of annual operational cost for the promising solution

Figure 4.7 illustrates GHG emission from different stages of biodiesel supply chain for the selected optimal solutions. It can be observed that conversion of feedstock to biodiesel, similar to the low cost and high cost results, is the major factor in GHG emissions over the entire biodiesel supply chain.

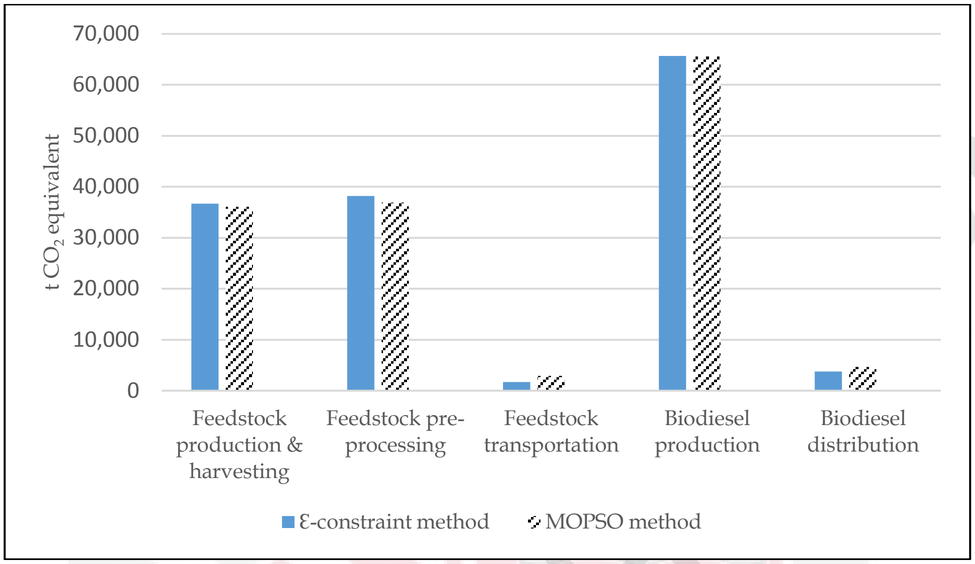

Figure 4.7. GHG emissions from different stages of biodiesel supply chain under the promising scenarios

The decisions related to the promising solutions for biodiesel production in Malaysia are presented as follows.

Table 4.7 presents the quantity of feedstock to be harvested from each resource based on the selected good solutions.

Table 4.7. Optimal quantity of feedstock to be harvested from each resource ($Q_{i,l}$)

	FFB		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	50,575	43,979	23,244	27,631
Kedah	545	584	334	342
Kelantan	724	790	438	453
Malacca	2,662	3,404	1,412	1,701
Negeri Sembilan	29,394	30,514	18,469	17,516
Pahang	9,712	9,753	5,366	5,253
Penang	9,712	9,000	482	503
Perak	97,212	95,488	58,083	58,854
Perlis	0	0	210	239
Terengganu	3,648	3,562	2,030	1,996
Selangor	82,948	87,444	49,430	46,652
Sabah	62,051	63,839	50,583	48,914
Sarawak	183	186	113	116

Unit: tonne

We can see from this table that FFB is the main feedstock harvested for production of biodiesel under the selected solutions in order to reduce the production and harvesting cost of feedstock which is the major factor in operational cost. However, a part of feedstock is supplied by jatropha to reduce GHG emissions and edible feedstock consumption. The quantity of FFB harvested from Perlis is equal to 0, because it has been assumed that no FFB is harvested from this state due to the small area under oil palm plantation. This table also represents that feedstocks are mainly harvested from states with biodiesel plants. As a result, feedstock transportation cost and related emissions are reduced.

Tables 4.8 to 4.13 demonstrate the optimal quantity of feedstock transported from resources to biorefineries.

Table 4.8. Optimal quantity of feedstock transported from resources to Perak biorefineries ($X_{i,l,w}$)

	Palm oil		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	13	13	15	14
Kedah	44	52	45	47
Kelantan	47	57	47	49
Malacca	19	20	19	20
Negeri Sembilan	21	22	18	20
Pahang	23	25	24	25
Penang	84	107	86	92
Perak	19,358	19,013	19,084	19,336
Perlis	0	0	24	30
Terengganu	19	19	17	19
Selangor	52	65	50	52
Sabah	5	6	6	6
Sarawak	5	5	5	6

Unit: tonne

Table 4.9. Optimal quantity of feedstock transported from resources to Selangor biorefineries ($X_{i,l,w}$)

	Palm oil		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	26	25	24	25
Kedah	20	20	19	20
Kelantan	29	30	27	29
Malacca	64	76	62	69
Negeri Sembilan	83	103	84	90
Pahang	39	42	39	43
Penang	24	24	23	24
Perak	30	30	27	29
Perlis	0	0	13	16
Terengganu	16	17	16	16
Selangor	16,405	17,278	16,132	15,205
Sabah	7	7	7	8
Sarawak	6	6	6	7

Unit: tone

Table 4.10. Optimal quantity of feedstock transportedfrom resources to Pahang biorefineries ($X_{i,l,w}$)

	Palm oil		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	44	43	40	42
Kedah	15	15	15	16
Kelantan	32	33	31	32
Malacca	53	57	50	53
Negeri Sembilan	101	113	93	102
Pahang	1,825	1,827	1,651	1,611
Penang	15	16	15	15
Perak	18	17	17	18
Perlis	0	0	10	12
Terengganu	662	644	600	589
Selangor	41	42	39	41
Sabah	5	6	6	6
Sarawak	5	6	6	5

Unit: tonne

Table 4.11. Optimal quantity of feedstock transported from resources to Negeri Sembilan biorefineries ($X_{i,l,w}$)

	Palm oil		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	33	35	33	33
Kedah	15	16	16	17
Kelantan	21	20	21	21
Malacca	329	457	273	358
Negeri Sembilan	5,637	5,827	5,861	5,530
Pahang	33	34	34	35
Penang	18	17	18	18
Perak	21	21	21	22
Perlis	0	0	11	13
Terengganu	16	15	16	16
Selangor	68	80	66	73
Sabah	7	7	7	8
Sarawak	6	6	7	7

Unit: tonne

Table 4.12. Optimal quantity of feedstock transportedfrom resources to Johor biorefineries ($X_{i,l,w}$)

	Palm oil		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	9,993	8,675	7,555	8,999
Kedah	10	10	11	10
Kelantan	11	12	13	12
Malacca	60	64	56	58
Negeri Sembilan	31	30	31	54
Pahang	17	17	18	17
Penang	11	12	12	11
Perak	11	12	13	12
Perlis	0	0	7	8
Terengganu	13	13	15	14
Selangor	18	18	20	19
Sabah	5	6	6	6
Sarawak	5	5	5	6

Unit: tonne

Table 4.13. Optimal quantity of feedstock transported from resources to Sabah biorefineries ($X_{i,l,w}$)

	Palm oil		Jatropha	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor	5	6	5	6
Kedah	5	4	5	5
Kelantan	5	6	5	5
Malacca	7	7	6	7
Negeri Sembilan	6	6	6	7
Pahang	5	5	5	6
Penang	5	6	5	5
Perak	5	6	5	5
Perlis	0	0	4	3
Terengganu	4	5	5	6
Selangor	6	6	6	6
Sabah	12,381	12,737	16,661	16,109
Sarawak	9	8	8	8

Unit: tonne

It can be observed that each biorefinery is mainly supplied by resources which are located at the same state in order to reduce transportation costs and related GHG emissions. Quantity of FFB that transported from Perlis to biorefineries equals 0, because based on the assumption no FFB is harvested from Perlis due to the small oil palm plantation area.

The optimal biodiesel production plan at biorefineries, which has been obtained by both methods, is shown in Table 4.14.

Table 4.14. Optimal quantity of biodiesel produced at biorefineries ($X_{i,w}^{f}$)

	Palm oil biodiesel		Jatropha biodiesel	
	Ɛ-constraint	MOPSO	Ɛ-constraint	MOPSO
Johor biorefineries	9,269	8,075	7,062	8,369
Negeri Sembilan biorefinery	5,645	5,948	5,808	5,594
Pahang biorefineries	2,564	2,565	2,341	2,315
Perak biorefineries	17,919	17,656	17,694	17,943
Selangor biorefineries	15,240	16,067	14,996	14,176
Sabah bioefineries	11,323	11,649	15,220	14,722

Unit: tonne

Table 4.14 shows that biodiesel is mainly produced in states with relatively large biodiesel demand. Such biodiesel production decisions lead to lower distribution cost of biodiesel and GHG emissions as well.

The optimal solutions for distribution of biodiesel in Malaysia, carried out by both methods, are presented in Tables 4.15 to 4.18.

Table 4.15. Optimal quantity of palm oil biodiesel distributed from biorefineries to demand zones obtained by Ɛ-constraint method ($Q^f_{i,w,n}$)

	Kedah	Penang	Perak	Kelantan	Terengganu	Selangor	Pahang	Negeri Sembilan	Melaka	Johor	Sabah	Sarawak	Perlis
Johor biorefineries	13	13	13	16	33	23	34	32	126	8,927	6	20	10
Negeri Sembilan biorefinery	22	21	23	35	36	91	1,361	2,212	1,714	33	9	72	17
Pahang biorefineries	12	11	12	11	2,414	20	11	14	15	17	5	12	10
Perak biorefineries	4,439	3,514	5,454	3,530	53	70	44	18	17	13	6	17	745
Selangor biorefineries	29	28	30	58	32	12,849	2,018	58	50	22	7	40	18
Sabah biorefineries	4	4	5	5	4	5	5	5	5	4	6,872	4,399	4

Table 4.16. Optimal quantity of palm oil biodiesel distributed from biorefineries to demand zones obtained by MOPSO method ($Q^{f}_{i,w,n}$)

	Kedah	Penang	Perak	Kelantan	Terengganu	Selangor	Pahang	Negeri Sembilan	Melaka	Johor	Sabah	Sarawak	Perlis
Johor biorefineries	14	14	22	18	38	26	39	38	149	7,684	7	25	10
Negeri Sembilan biorefinery	23	23	23	44	41	13	1,548	2,217	1,709	31	9	133	14
Pahang biorefineries	12	11	12	12	2,417	20	10	15	16	12	6	14	9
Perak biorefineries	4,540	3,648	5,497	3,481	60	68	49	19	18	12	7	19	405
Selangor biorefineries	32	29	32	70	36	13,584	2,055	67	59	18	8	61	14
Sabah biorefineries	5	6	5	5	4	6	5	5	5	4	6,488	5,108	4

Table 4.17. Optimal quantity of jatropha biodiesel distributed from biorefineries to demand zones obtained by Ɛ-constraint method ($Q^{f}_{i,w,n}$)

	Kedah	Penang	Perak	Kelantan	Terengganu	Selangor	Pahang	Negeri Sembilan	Melaka	Johor	Sabah	Sarawak	Perlis
Johor biorefineries	14	13	14	16	34	26	35	32	132	6,710	6	21	10
Negeri Sembilan biorefinery	22	21	22	32	35	65	1,410	2,352	1,730	32	8	64	17
Pahang biorefineries	12	11	12	16	2,179	19	18	15	15	17	5	12	10
Perak biorefineries	4,598	3,693	5,474	3,492	51	53	44	17	17	13	6	16	219
Selangor biorefineries	28	27	29	54	31	12,541	2,098	55	49	22	6	37	19
Sabah biorefineries	5	4	5	5	4	6	5	5	5	5	8,215	6,953	4

Table 4.18. Optimal quantity of jatropha biodiesel distributed from biorefineries to demand zones obtained by MOPSO method ($Q^{f}_{i,w,n}$)

	Kedah	Penang	Perak	Kelantan	Terengganu	Selangor	Pahang	Negeri Sembilan	Melaka	Johor	Sabah	Sarawak	Perlis
Johor biorefineries	14	14	14	17	37	28	38	36	155	7,975	7	26	10
Negeri Sembilan biorefinery	22	21	22	38	39	44	1,263	2,315	1,666	29	9	99	15
Pahang biorefineries	13	11	12	15	2,139	21	31	15	16	13	6	14	9
Perak biorefineries	4,549	3,658	5,427	3,500	57	56	47	19	18	12	7	19	573
Selangor biorefineries	30	31	31	63	34	11,779	1,993	63	56	19	7	56	16
Sabah biorefineries	5	5	5	5	5	6	5	5	5	6	8,591	6,077	4

It can be observed that biodiesel demand at each state is mainly satisfied by the biodiesel produced at the biorefinery located in that state. For those states that do not have biorefineries, the biodiesel demand is mainly fulfilled by the nearest existing biorefinery. As a result, distribution costs and related GHG emissions can be reduced.

4.3.3 Comparison of the Malaysia Biodiesel Supply Chain under Different Criteria

In this section, the optimal biodiesel production in Malaysia under the proposed mathematical model is compared with two different optimization criteria, provided in literature review, in order to show the effectiveness of the proposed model. These optimization criteria are economic optimization and environmental-economic optimization.

4.3.3.1 Economic Optimization

In this case, the optimal production of biodiesel from palm oil and jatropha in Malaysia under the economic criterion is considered. The objective function is minimization of the total cost of supply chain similar to the criterion proposed by Leao et al. (2011). The optimization model aims to minimize the total annual operational cost (equation 3.6) through the entire biodiesel supply chain. The resulting single-objective linear programming model was solved using the linear programming solver in MATLAB.

The minimum annual operational cost found was MYR 264,330,000. The corresponding GHG emission and edible feedstock consumption are 208,780 t CO_2 and 685,780 t edible feedstock respectively, whereas GHG emission resulting from the proposed MOLP model ranges between 99,046 t CO_2 and 199,950 t CO_2 and the quantity of edible feedstock consumption fluctuates between 61,920 t and 630,100 t as well. Since the GHG emission and edible feedstck consumption of the MOLP model are lower than those corresponding to the economic optimization, the proposed MOLP model leads to the production of biodiesel which is more sustainable.

4.3.3.2 Environmental-Economic Optimization

In this case, the optimal planning of biodiesel supply chain in Malaysia under the economic and environmental criteria, similar to the criteria studied by You and Wang (2011), is investigated. The economic objective is measured by the total annual operational cost (equation 3.6) and the total GHG emission over the entire biodiesel supply chain is measured as the environmental objective (equation 3.12). The resulting MOLP model, which has two objectives, is solved using the MOPSO method. The optimization results are listed in Table 4.19.

Table 4.15. Environmental-economic optimization results

	Minimum amount	Maximum amount
Annual operatinal cost (MYR)	240,760,000	387,210,000
GHG emission (t CO_2)	99,037	203,130

Although this two-objective model reveals the trade-offs between the economic and environmental objectives, the food versus fuel conflict is not considered in this model. The corresponding edible feedstock consumption in this case fluctuates between 98,292 t feedstock and 748,920 t feedstock, whereas edible feedstock consumption range of the proposed MOLP model, which considers three objectives, is between 61,920 t and 630,100 t. It implies that the proposed MOLP model with three objectives is able to improve the social performance of the biodiesel supply chain.

4.3.4 Sensitivity Analysis

In this section, a sensitivity analysis is made based on the availability of jatropha, considering a reduction from 100% to 60% using 20% points intervals. The reason for studying the availability of jatropha is that the current land under jatropha cultivation in Malaysia has not been well identified and this study has been conducted based on the potential area for cultivation of jatropha.

Table 4.20 presents the minimum and maximum of annual operational cost, GHG emission in terms of CO_2 equivalent and edible feedstock consumption for various values of the availability of jatropha.

Table 4.16. Sensitivity analysis results

	Jatropha availability		
	100%	80%	60%
Minimum cost (MYR)	254,740,000	248,390,000	246,340,000
Maximum cost (MYR)	390,610,000	363,620,000	353,100,000
Minimum GHG emission (t CO2)	99,046	117,080	124,450
Maximum GHG emission (t CO2)	199,950	204,983	205,342
Minimum edible feedstock consumption (t)	61,920	159,610	202,790
Maximum edible feedstock consumption (t)	630,100	685,842	690,371

This table shows that the decrease in availability of jatropha leads to a reduction in the total operational cost, whereas the total GHG emission and edible feedstock consumption increased. This happened because when the availability of jatropha reduced, palm oil has to be used for production of biodiesel. As a result, the use of this feedstock yields an increase in total GHG emission and edible feedstock consumption. These results also imply that availability of jatropha could improve environmental and social performances of biodiesel supply chain in Malaysia.

4.4 Summary

This chapter illustrated the results of application of the proposed MOLP model to the biodiesel supply chain in Malaysia. The optimal solutions resulting from implementation of the MOPSO method and comparison with the Ɛ-constraint method showed that the MOPSO method is able to find the approximation of optimal solutions. Comparison of the proposed MOLP model with the economic and environmental-economic optimization models showed that the proposed model has better results for improvement of the performance of biodiesel supply chain.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this section, the research findings related to the research objectives are summarized. The research objectives were (i) to develop a mathematical model for optimal planning of biodiesel supply chain under economic, environmental, and social criteria, (ii) to evaluate the capability of a heuristic method for solving the multi-objective optimization problem in biodiesel supply chain, (iii) to specify the optimal quantity of feedstock to be harvested, feedstock and biodiesel transportation schedules, and quantity of biodiesel produced at biorefineries based on the proposed model, and (iv) to determine the optimal operational cost, GHG emission, and quantity of edible feedstock consumption for production of biodiesel over the planning horizon based on the proposed model.

The major findings of the research, based on the selected case study, are as follows.

- A MOLP model was proposed that takes into account economic, environmental and social objectives. The economic objective was measured by total annual operational cost. The environmental, and social objectives were measured by total amount of GHG emission, and edible feedstock consumption, respectively.
- Results obtained by implementation of the Ɛ-constraint and the MOPSO methods for the MOLP problem related to the case study showed that the MOPSO method, which is a heuristic method, is able to find the approximation of optimal solutions in less computational time compared to the Ɛ-constraint method.
- The optimal quantity of feedstock to be harvested, quantity of feedstock to be transported, amount of biodiesel produced at each biorefinery, and quantity of biodiesel to be delivered to demand zones for the case study and selected scenarios were given in Chapter 4.
- The optimization results for the Malaysia case study revealed that biodiesel production with the annual operational cost of MYR 326,990,000 is a promising optimal solution. The total GHG emission, and edible feedstock consumption for this solution are 146,000 t CO_2 and 340,440 t edible feedstock respectively. Similarly, operational cost at MYR 322,270,000 which was obtained by MOPSO method, the nearest point to MYR 326,990,000 solution, was selected as a good solution for production of biodiesel in Malaysia as well. The total GHG

- emission and edible feedstock consumption related to this solution are 146,030 t CO_2 and 329,130 t feedstock respectively.

5.2 Recommendations

There are several directions for optimal planning of biofuel supply chain. Study the capability of the proposed model and solving strategy for optimal planning of other types of biofuel supply chains is the issue that could be considered in future. The reason is that the general structure of biofuel supply chain is almost similar.

In real world situations, there are some uncertainties such as supply, demand and operation uncertainties that could impact the performance of supply chain. Improving the proposed model in order to consider the uncertainty could be a future extension of this research.

Extending the model to multi-period one, for the robust optimization and planning of biodiesel supply chain, is another future research direction.

Several issues must be taken into account to achieve a sustainable biodiesel supply chain. GHG emission and food-versus-fuel conflict were considered in this study. Impacts of biodiesel production on land and water resources are issues that should be incorporated in future research.

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APPENDICES

Appendix A1

MOPSO Code

```
%% Detremination of parameters and objective functions
function Z = CaseStudy( X )
Q=reshape(X(1:26),2,13);
xoil=reshape(X(27:182),2,13,6);
Xfuel=reshape(X(183:194),2,6);
Qfuel=reshape (X(195:350),2,6,13);

%Transportation Cost(1)
%D1 Distance of milling L from biorefinery j(km)
D1=zeros(2,13,6);
for i=1:2
    for l=1:13
        for j=1  %perak
                D1(:,:,j)=[229 153 68.2 207 367 162 293
                319 361 491 479 793 287;229 153 68.2 207
                367 162 293 319 361 491 479 793 287];
        end
    end
end

for i=1:2
    for l=1:13
        for j=2  %selangor
                D1(:,:,j)=[412 336 251 302 437 62.1 207
                132 160 291 278.4 592.4 487;412 336 251
                302 437 62.1 207 132 160 291 278.4 592.4
                487];
        end
    end
end

for i=1:2
    for l=1:13
        for j=3  %pahang
                D1(:,:,j)=[601 571 486 375 178 297 172
                216 277 296 507 821 689;601 571 486 375
                178 297 172 216 277 296 507 821 689];
        end
    end
end

for i=1:2
    for l=1:13
```

```
        for j=4  %N.S
                D1(:,:,j)=[479 403 318 364 431 129 211
                57.9 83 218 246.9 560.9 559;479 403 318
                364 431 129 211 57.9 83 218 246.9 560.9
                559];
        end
    end
end

for i=1:2
    for l=1:13
        for j=5  %Johor
                D1(:,:,j)=[668 592 507 549 459 319 367
                217 142 33.7 437 751 823;668 592 507 549
                459 319 367 217 142 33.7 437 751 823];
        end
    end
end

for i=1:2
     for l=1:13
         for j=6  %Sabah

                D1(:,:,j)=[795 718 635 692 805 464 644
                426 444 576 121 1038 822;795 718 635 692
                805 464 644 426 444 576 121 1038 822];
         end
     end
end

%T1c: Transprtation cost of bio-oil from milling L to
biorefinery j
T1c=zeros(2,13,6);
for i=1:2
    for l=1:13
        for j=1:6
                T1c(i,l,j)=0.19;
        end
    end
end

%Shipping cost(1)
T11=zeros(2,13,6);
for i=1:2
    for l=1:13
        for j=1
                T11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 230 220
```

```
                    0;0 0 0 0 0 0 0 0 0 0 230 220 0];
            end
        end
    end

    for i=1:2
        for l=1:13
            for j=2
                    T11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 230 220
                    0;0 0 0 0 0 0 0 0 0 0 230 220 0];
            end
        end
    end

    for i=1:2
        for l=1:13
            for j=3
                    T11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 230 220
                    0;0 0 0 0 0 0 0 0 0 0 230 220 0];
            end
        end
    end

    for i=1:2
        for l=1:13
            for j=4
                    T11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 230 220
                    0;0 0 0 0 0 0 0 0 0 0 230 220 0];
            end
        end
    end

    for i=1:2
        for l=1:13
            for j=5
                    T11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 230 220
                    0;0 0 0 0 0 0 0 0 0 0 230 220 0];
            end
        end
    end

    for i=1:2
        for l=1:13
            for j=6
                    T11(:,:,j)=[230 230 230 230 230 230 230
                    230 230 230 0 0 230;230 230 230 230 230
                    230 230 230 230 230 0 0 230];
```

```
        end
    end
end

%Transportation Cost(2)
%D2:Distance of biorefinery j from demand zone n
D2=zeros(2,6,13);
for i=1:2
    for j=1:6
        for n=1
                D2(:,:,n)=[229 412 601 479 668 795 ;229
                412 601 479 668 795 ];   %n1:Kedah
        end
    end
end

for i=1:2
    for j=1:6
        for n=2
                D2(:,:,n)=[153 336 571 403 592 718 ;153
                336 571 403 592 718  ];  %n2:Penang
        end
    end
end

for i=1:2
    for j=1:6
        for n=3
                D2(:,:,n)=[68.2 251 486 318 507 635 ;68.2
                251 486 318 507 635  ]; %n3:Perak
        end
    end
end

for i=1:2
    for j=1:6
        for n=4
                D2(:,:,n)=[207 302 375 364 549 692 ; 207
                302 375 364 549 692 ];   %n4:Kelantan
        end
    end
end

for i=1:2
    for j=1:6
        for n=5
                D2(:,:,n)=[367 437 178 431 459 805; 367
```

```
                437 178 431 459 805 ];     %n5:Terrenganu
        end
    end
end

for i=1:2
    for j=1:6
        for n=6
                D2(:,:,n)=[162 62.1 297 129 319 464 ;162
                62.1 297 129 319 464 ];  %n6:Selangor
        end
    end
end

for i=1:2
     for j=1:6
         for n=7
                D2(:,:,n)=[293 207 172 211 367 644 ;293
                207 172 211 367 644 ];  %n7:Pahang
         end
     end
end

for i=1:2
     for j=1:6
         for n=8
                D2(:,:,n)=[319 132 216 57.9 217 426 ;319
                132 216 57.9 217 426 ];
                %n8:Negeri sembilan
         end
     end
end

for i=1:2
     for j=1:6
         for n=9
                D2(:,:,n)=[361 160 277 83 142 444 ;361
                160 277 83 142 444 ];  %n9:Melaka
         end
     end
end

for i=1:2
     for j=1:6
         for n=10
                D2(:,:,n)=[491 291 296 218 33.7 576 ;491
                291 296 218 33.7 576 ]; %n10:Johor
```

```
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=11
                        D2(:,:,n)=[399 278.4 507 246.9 437 121
                        ;399 278.4 507 246.9 437 121 ];
                        %n11:Sabah
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=12
                        D2(:,:,n)=[793 592.4 821 560.9 751 1038
                        ;793 592.4 821 560.9 751 1038 ];
                        %n12:Sarawak
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=13
                        D2(:,:,n)=[319 132 216 57.9 217 426 ;319
                        132 216 57.9 217 426 ];  %n13:Perlis
            end
        end
    end

    %T2c:Transportation cost of biodiesel from biorefinery j to
    demand zone n
    T2c=zeros(2,6,13);
    for i=1:2
      for j=1:6
        for n=1:13
                        T2c(i,j,n)=0.19;
        end
      end
    end

    T22=zeros(2,6,13);
    for i=1:2
        for j=1:6
```

```
            for n=1
                     T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                     230 ];  %n1:Kedah
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=2
                     T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                     230 ];  %n2:Penang
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=3
                      T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                      230 ]; %n3:Perak
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=4
                      T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                      230 ];  %n4:Kelantan
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=5
                      T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                      230 ];  %n5:Terrenganu

            end
        end
    end

    for i=1:2
         for j=1:6
             for n=6
```

```
                    T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                    230 ];  %n6:Selangor
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=7
                    T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                    230 ];   %n7:Pahang
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=8
                    T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                    230 ];   %n8:Negeri sembilan
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=9
                    T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                    230 ];   %n9:Melaka
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=10
                    T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                    230 ];   %n10:Johor
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=11
                    T22(:,:,n)=[230 230 230 230 230 0
                    ;230 230 230 230 230 0 ];  %n11:Sabah
```

```
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=12
                           T22(:,:,n)=[220 220 220 220 220 0
                           ;220 220 220 220 220 0 ];%n12:Sarawak
            end
        end
    end

    for i=1:2
        for j=1:6
            for n=13
                           T22(:,:,n)=[0 0 0 0 0 230 ;0 0 0 0 0
                           230 ];  %n13:Perlis
            end
        end
    end

    %Harvesting cost
    har=zeros(2,13);
    for i=1:2
        for l=1:13
                      if i==1
                           har(i,l)=214 ;
                      else
                           har(i,l)=650.56;
                      end
        end
    end

    %Pre-processing cost
    Cpre=zeros(2,13,6);
    for i=1:2
        for l=1:13
            for  j=1:6
                 if i==1
                 Cpre(i,l,j)=43.68;
                 else
                 Cpre(i,l,j)=121.2;
                 end
            end
        end
    end
```

```
%Production cost of biodiesel at biorefinery
Pc=zeros(2,6);
for i=1:2
  for j=1:6
            Pc(i,j)=559.36;
  end
end

%Maximum Yield
S=[ 21.43 16.88 21.35 11.89 15.35 20.91 18.94 19.88 23.30
19.02 20.40 16.51 0; 3.6 3.6 3.6 3.6 3.6 3.6 3.6 3.6 3.6
3.6 3.6 3.6 3.6];

%A(area under plantation)
A=[76181 13265 338100 91182 136509 124080 595799 143580
48718   618353   1292757   874152   197;610175.35   67311.97
1351056.75   969793.50   837224.84   520511.71   2321042.93
429435.12 106877.05 1233838.86 10400000 14000000 456];

Y=S.*A ;     %Maximum Yield

% Constraints
V1=sum(sum(((Q-Y)+abs(Q-Y))/2));

eta=zeros(2,13);
for i=1:2
    for li=1:13
            if i==1
             eta(i,li)=0.20;
            else
             eta(i,li)=0.33;
            end
    end
end

a=zeros(2,13);
for i=1:2
    for li=1:13
            a(i,li)=sum(xoil(i,li,:));
    end
end

V3=sum(sum((a-(Q.*eta)).^2));

e1=zeros(2,6);
for i=1:2
    for w=1:6
```

```
            e1(i,w)=sum(xoil(i,:,w));
        end
end

alfa=zeros(2,6);
for i=1:2
    for w=1:6
            alfa(i,w)=0.95 ;
    end
end

V4= sum(sum((Xfuel-(e1.*alfa).^2)));

e6=zeros(6,1);
for w=1:6
            e6(w)=sum(Xfuel(:,w));
end

Ref=zeros(6,1);
for w=1:6
       if w==1
        Ref(w)=153000;  %Perak
        else if w==2
        Ref(w)=262000;    %Selangor
            else if w==3
                Ref(w)=199000; %Pahang
                else if w==4
                    Ref(w)=18000;    %N.S
                    else if w==5
                          Ref(w)=780000; %Johor
                        else
                             Ref(w)=250000;    %Sabah
                        end
                    end
                end
            end
     end
end

V6=sum(((e6-Ref)+(abs(e6-Ref)))/2);

e8=zeros(2,6);
for i=1:2
    for w=1:6
            e8(i,w)=sum(Qfuel(i,w,:));
    end
end
```

```
V7=sum(sum((e8-Xfuel).^2));

e10=zeros(13,1);
for n=1:13
            e10(n)=sum(sum(Qfuel(:,:,n)));
end

%Demand at each demand zone
D=zeros(13,1);
for n=1:13
    if n==1
     D(n)=9197.67;    %Kedah
      else if n==2
       D(n)=7360.46;    %Penang
        else if n==3
         D(n)=11093.02;    %Perak
          else if n==4
           D(n)=7267.44;    %Kelantan
            else if n==5
             D(n)=4906.98;   %Terengganu
              else if n==6
               D(n)=25767.44; %Selangor
                else if n==7
                 D(n)=7081.39;    %Pahang
                  else if n==8
                   D(n)=4813.95;    %N.S
                    else if n==9
                      D(n)=3872.09;   %Melaka
                       else if n==10
                         D(n)=15813.95;  %Johor
                          else if n==11
                           D(n)=15151.16;   % Sabah
                            else if n==12
                             D(n)=11662.79;    %Sarawak
                                else
                                  D(n)=1081.39; %Perlis
                                end
                             end
                          end
                       end
                     end
                   end
                end
              end
            end
          end
        end
      end
```

```
   end
end

V8=sum( ((-e10+D)+ (abs(-e10+D)))/2);

%Distance via ship
D11=zeros(2,13,6);
for i=1:2
    for l=1:13
        for j=1  %Perak
                D11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0;0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0];
        end
    end
end

for i=1:2
    for l=1:13
        for j=2  %Selangor
                D11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0;0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0];
        end
    end
end

for i=1:2
    for l=1:13
        for j=3 %Pahang
                D11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0;0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0];
        end
    end
end

for i=1:2
    for l=1:13
        for j=4 %N.S
                D11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0;0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0];
        end
    end
end
```

```
for i=1:2
    for l=1:13
        for j=5 %Johor
                D11(:,:,j)=[0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0;0 0 0 0 0 0 0 0 0 0 1663.54
                1014.11 0];
        end
    end
end

for i=1:2
     for l=1:13
         for j=6 %Sabah
                D11(:,:,j)=[1663.54 1663.54 1663.54
                1663.54 1663.54 1663.54 1663.54 1663.54
                444 1663.54 0 0 1663.54;1663.54 1663.54
                1663.54 1663.54 1663.54 1663.54 1663.54
                1663.54 444 1663.54 0 0 1663.54];
         end
     end
end

% Transportation of biodiesel via ship
D22=zeros(2,6,13);
for i=1:2
    for j=1:6
        for n=1
                D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0 0
                1663.54 ];    %n1:Kedah
        end
    end
end
for i=1:2
    for j=1:6
        for n=2
                 D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                 0 1663.54 ];    %n2:Penang
        end
    end
end

for i=1:2
    for j=1:6
        for n=3
                 D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                 0 1663.54 ];    %n3:Perak
        end
```

```
    end
end

for i=1:2
    for j=1:6
        for n=4
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];   %n4:Kelantan
        end
    end
end

for i=1:2
    for j=1:6
        for n=5
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];    %n5:Terrenganu
        end
    end
end

for i=1:2
     for j=1:6
         for n=6
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];    %n6:Selangor
         end
     end
end

for i=1:2
     for j=1:6
         for n=7
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];   %n7:Pahang
         end
     end
end

for i=1:2
     for j=1:6
         for n=8
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];   %n8:Negeri sembilan
         end
     end
end
```

```
for i=1:2
     for j=1:6
         for n=9
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];   %n9:Melaka
         end
     end
end

for i=1:2
     for j=1:6
         for n=10
                  D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                  0 1663.54 ];   %n10:Johor
         end
     end
end

for i=1:2
     for j=1:6
         for n=11
                  D22(:,:,n)=[1663.54 1663.54 1663.54
                  1663.54 1663.54 0 ;1663.54 1663.54
                  1663.54 1663.54 1663.54 0 ];
                  %n11:Sabah
         end
     end
end

for i=1:2
     for j=1:6
         for n=12
                   D22(:,:,n)=[1014.11 1014.11 1014.11
                   1014.11 1014.11 0 ;1014.11 1014.11
                   1014.11 1014.11 1014.11 0 ];
                   %n12:Sarawak
         end
     end
end

for i=1:2
     for j=1:6
         for n=13
                   D22(:,:,n)=[0 0 0 0 0 1663.54 ;0 0 0 0
                   0 1663.54 ];  %n13:Perlis

         end
```

```
        end
    end

    % emission factors
    Ep=zeros(2,13);      %emission factor for production
    for i=1:2
        for l=1:13
                    if i==1
                      Ep(i,l)=81.34;
                    else
                      Ep(i,l)=42.78;
                    end
         end
    end

    Epre=zeros(2,13,6);  %emission factor for pre-processing
    for i=1:2
        for l=1:13
            for j=1:6
                    if i==1
                      Epre(i,l,j)=516.6;
                    else
                      Epre(i,l,j)=43.24;
                    end
            end
        end
    end
    Ec=zeros(2,6);
    for i=1:2
        for j=1:6
                    if i==1
                      Ec(i,j)=580;
                    else
                      Ec(i,j)=471;
                    end
         end
    end

    ETr=zeros(2,13,6);   %emission factor for transportation
                          via truck
    for i=1:2
        for l=1:13
            for j=1:6
                     ETr(i,l,j)=0.15;
            end
        end
    end
```

```
ETs=zeros(2,13,6);    %emission factor for transportation
                       via ship
for i=1:2
    for l=1:13
        for j=1:6
                 ETs(i,l,j)=0.02;
        end
    end
end

%Transportation of biodiesel

EDr=zeros(2,6,13);     %emission factor for transportation
                        via truck (biodiesel)
for i=1:2
    for j=1:6
        for n=1:13
                 EDr(i,j,n)=0.15;
        end
    end
end

EDs=zeros(2,6,13);     %emission factor for transportation
                        via ship (biodiesel)
for i=1:2
    for j=1:6
        for n=1:13
                 EDs(i,j,n)=0.02;
        end
    end
end

% Parameters

%Omega:binary parameter
Omega=zeros(2,13);
for i=1:2
    for li=1:13
            if i==1
                Omega(i,li)=1;   %palm oil
            else
                Omega(i,li)=0;  %jatropha
            end
    end
end

% Objective Functions
```

```
Z1=sum(sum(Q.*har))+sum(sum(sum(xoil.*(Cpre+(T1c.*D1)+T11))
))+sum(sum(Xfuel.*Pc))+sum(sum(sum(Qfuel.*T2c.*D2+Qfuel.*T2
2)))+V1+V3+V4+V6+V7+V8;

Z2=sum(sum(Q.*Omega));

Z3=sum(sum(Ep.*Q))+sum(sum(sum(xoil.*(Epre+(ETr.*D1)+(ETs.*
D11)))))+sum(sum(Xfuel.*Ec))+sum(sum(sum(Qfuel.*((EDr.*D2)+
(EDs.*D22))))));

Z=[Z1 Z2 Z3]';

End

%% Creation of particles
function particle=CreateEmptyParticle(n)
    if nargin<1
        n=1;
    end
    empty_particle.Position=[];
    empty_particle.Velocity=[];
    empty_particle.Cost=[];
    empty_particle.Dominated=false;
    empty_particle.Best.Position=[];
    empty_particle.Best.Cost=[];
    empty_particle.GridIndex=[];
    empty_particle.GridSubIndex=[];

    particle=repmat(empty_particle,n,1);
end

%%Domination
function dominate=Dominates(x,y)
    if isstruct(x)
        x=x.Cost;
    end
    if isstruct(y)
        y=y.Cost;
    end
    dominate=all(x<=y) && any(x<y);
end

%%Domination determination
function pop=DetermineDomination(pop)
    npop=numel(pop);
    for i=1:npop
        pop(i).Dominated=false;
```

```
        for j=1:i-1
            if ~pop(j).Dominated
                if Dominates(pop(i),pop(j))
                    pop(j).Dominated=true;
                elseif Dominates(pop(j),pop(i))
                    pop(i).Dominated=true;
                    break;
                end
            end
        end
    end
end

%% Grid
function G=CreateHypercubes(costs,ngrid,alpha)
    nobj=size(costs,1);
    empty_grid.Lower=[];
    empty_grid.Upper=[];
    G=repmat(empty_grid,nobj,1);
    for j=1:nobj
        min_cj=min(costs(j,:));
        max_cj=max(costs(j,:));
        dcj=alpha*(max_cj-min_cj);
        min_cj=min_cj-dcj;
        max_cj=max_cj+dcj;
        gx=linspace(min_cj,max_cj,ngrid-1);
        G(j).Lower=[-inf gx];
        G(j).Upper=[gx inf];
    end
end

% Getting the grid
function [Index SubIndex]=GetGridIndex(particle,G)
    c=particle.Cost;
    nobj=numel(c);
    ngrid=numel(G(1).Upper);
    str=['sub2ind('
    mat2str(ones(1,nobj)*ngrid)];
    SubIndex=zeros(1,nobj);
    for j=1:nobj
        U=G(j).Upper;
        i=find(c(j)<U,1,'first');
        SubIndex(j)=i;
        str=[str ',' num2str(i)];
    end
    str=[str ');'];
    Index=eval(str);
```

```
end

%% Cost
function costs=GetCosts(pop)
    nobj=numel(pop(1).Cost);
    costs=reshape([pop.Cost],nobj,[]);
end


%% Non-dominated particles
function nd_pop=GetNonDominatedParticles(pop)
    ND=~[pop.Dominated];
    nd_pop=pop(ND);
end

%% Select the Gbest from repository
 function rep_h=SelectLeader(rep,beta)
    if nargin<2
        beta=1;
    end
    [occ_cell_index
     occ_cell_member_count]=GetOccupiedCells
     (rep);
     p=occ_cell_member_count.^(-beta);
     p=p/sum(p);
     selected_cell_index=occ_cell_index
     (RouletteWheelSelection(p));
     GridIndices=[rep.GridIndex];
     selected_cell_members=find
     (GridIndices==selected_cell_index);
     n=numel(selected_cell_members);
     selected_memebr_index=randi([1 n]);
     h=selected_cell_members
     (selected_memebr_index);
     rep_h=rep(h);
end

%% Mutation
function xnew=Mutate(x,pm,VarMin,VarMax)
    nVar=numel(x);
    j=randi([1 nVar]);
    dx=pm*(VarMax-VarMin);
    lb=x(j)-dx;
    if lb<VarMin
        lb=VarMin;
    end
    ub=x(j)+dx;
```

```
    if ub>VarMax
        ub=VarMax;
    end
    xnew=x;
    xnew(j)=unifrnd(lb,ub);
end

%% Delete the extra particles from repository
function rep=DeleteFromRep(rep,EXTRA,gamma)
    if nargin<3
        gamma=1;
    end
    for k=1:EXTRA
        [occ_cell_index
         occ_cell_member_count]=GetOccupiedCells
        (rep);
         p=occ_cell_member_count.^gamma;
         p=p/sum(p);
         selected_cell_index=occ_cell_index
        (RouletteWheelSelection(p));
         GridIndices=[rep.GridIndex];
         selected_cell_members=find
        (GridIndices==selected_cell_index);
         n=numel(selected_cell_members);
         selected_memebr_index=randi([1 n]);
         j=selected_cell_members
        (selected_memebr_index);
         rep=[rep(1:j-1); rep(j+1:end)];
    end
end

%% MOPSO
        CostFunction=@(X) CaseStudy2(X);
        nVar=350;
VarSize=[1 nVar];
VarMin= input ('varmin:');
VarMax=input ('varmax:');

%Settings
nPop=100;
nRep=10;
MaxIt=200;
w=0.9;
wdamp=0.99;
c1=2;
c2=2;
alpha=0.1;
```

```
nGrid=10;
beta=4;
gamma=2;
mu=0.5;

%Initialization
tic;
particle=CreateEmptyParticle(nPop);
for i=1:nPop
    particle(i).Velocity=0;
    particle(i).Position=unifrnd
   (VarMin,VarMax,VarSize);
    particle(i).Cost=CostFunction
   (particle(i).Position);
    particle(i).Best.Position=
    particle(i).Position;
    particle(i).Best.Cost=particle(i).Cost;
end

particle=DetermineDomination(particle);
rep=GetNonDominatedParticles(particle);
rep_costs=GetCosts(rep);
G=CreateHypercubes(rep_costs,nGrid,alpha);
for i=1:numel(rep)
    [rep(i).GridIndex
    rep(i).GridSubIndex]=GetGridIndex(rep(i),G);
end

%Main Loop
for it=1:MaxIt
    for i=1:nPop
        rep_h=SelectLeader(rep,beta);
        particle(i).Velocity=
        w*particle(i).Velocity ...
        +c1*rand*(particle(i).Best.Position -
        particle(i).Position) ...
        +c2*rand*(rep_h.Position -
        particle(i).Position);
        particle(i).Velocity=
        min(max(particle(i).Velocity,-VelMax)
        ,+VelMax);
        particle(i).Position=
        particle(i).Position +
        particle(i).Velocity;
        flag=(particle(i).Position<VarMin |
        particle(i).Position>VarMax);
        particle(i).Velocity(flag)=-
```

```
        particle(i).Velocity(flag);
        particle(i).Position=min
       (max(particle(i).Position,VarMin)
        ,VarMax);
        particle(i).Cost=CostFunction
       (particle(i).Position);

% Mutation
        pm=(1-(it-1)/(MaxIt-1))^(1/mu);
NewSol.Position=Mutate(particle(i).Position,pm,VarMin,VarMa
x);
NewSol.Cost=CostFunction(NewSol.Position);
        If Dominates(NewSol,particle(i))
           particle(i).Position=NewSol.Position;
           particle(i).Cost=NewSol.Cost;
        elseif Dominates(particle(i),NewSol)
        else
            if rand<0.5
               particle(i).Position=
               NewSol.Position;
               particle(i).Cost=NewSol.Cost;
            end
        end
        if
Dominates(particle(i),particle(i).Best)
particle(i).Best.Position=particle(i).Position;
particle(i).Best.Cost=particle(i).Cost;
        elseif Dominates(particle(i).Best,particle(i))
        else
            if rand<0.5
particle(i).Best.Position=particle(i).Position;
particle(i).Best.Cost=particle(i).Cost;
            end
        end
end
    particle=DetermineDomination(particle);
    nd_particle=GetNonDominatedParticles
   (particle);
    rep=[repnd_particle];
    rep=DetermineDomination(rep);
    rep=GetNonDominatedParticles(rep);
    for i=1:numel(rep)
        [rep(i).GridIndex rep(i).GridSubIndex]=
        GetGridIndex(rep(i),G);
    end
    if numel(rep)>nRep
        EXTRA=numel(rep)-nRep;
```

```
            rep=DeleteFromRep(rep,EXTRA,gamma);
            rep_costs=GetCosts(rep);
            G=CreateHypercubes
           (rep_costs,nGrid,alpha);
        end
        disp(['Iteration ' num2str(it) ': Number of
        Repository Particles = '
        num2str(numel(rep))]);
        w=w*wdamp;
    end
    costs=GetCosts(particle);
    rep_costs=GetC
```

Appendix B1

Area Density

Table B1.1. Area density by state

State	Area (km^2)
Johor	19,210
Kedah	9,500
Kelantan	15,099
Malacca	1,664
Negeri Sembilan	6,686
Pahang	36,137
Penang	1,048
Perak	21,035
Perlis	821
Terengganu	13,035
Selangor	8,104
Sabah	73,631
Sarawak	124,450

(Source: Department of Statistics Malaysia, 2010)

Appendix B2

Producer Price Index (PPI) 2007-2012

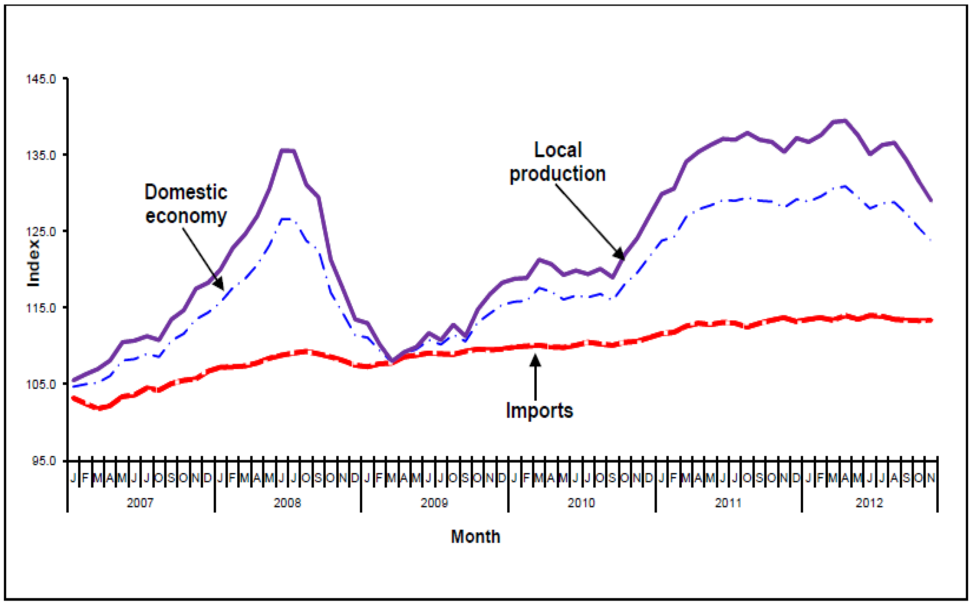

Figure B2.1. Producer Price Index (year-on-year) percentage change-Domestic economy, local production and imports, 2007-2012
(Source: Department of Statistics Malaysia, 2012)

Appendix B3

Inflation Calculation using PPI

A PPI in earlier year
B PPI in current year
C Price in earlier year
D Final price in current year

$$Inflation\ rate = \frac{(B - A)}{A} * 100$$
$$D = (C * Inflation\ rate) + C$$

Appendix B4

Ocean Distances

Table B4.1. Ocean distance between ports

	Port Klang
Port Kota Kinabalu	1,188
Port Kuching	735

unit: Nautical mile
1 nautical mile = 1852 m
(Source: Ports web site)

Appendix B5

Malaysia Population

Table B5.1. Population distribution by state

State	Population
Johor	3,233,434
Kedah	1,890,098
Kelantan	1,459,994
Malacca	788,706
Negeri Sembilan	997,071
Pahang	1,443,365
Penang	1,520,143
Perak	2,258,428
Perlis	227,025
Terengganu	1,015,776
Selangor	5,411,324
Sabah	3,120,040
Sarawak	2,420,009

(Source: Department of Statistics Malaysia, 2010)

Appendix B6

Demand Calculation using Proportion

E Total population
F Population of state x
G Total demand
H Demand of state x

$$\frac{F}{E} = \frac{H}{G} \quad \rightarrow \quad H = \frac{(F * G)}{E}$$

BIODATA OF STUDENT

Maryam Valizadeh was born in Iran in 1987. She obtained her BSC in Chemical Engineering-Food Processing from Azad University Dezful, Iran in 2009.

She joined the Department of Chemical and Environmental Engineering of University Putra Malaysia in September 2011 for her MSC in Chemical Engineering. Her areas of interest include biofuels, renewable energy, and process optimization.

PUBLICATIONS

Valizadeh, M., Syafiie, S., & Ahamad, I. S. (2014). Multi-Objective Particle Swarm Optimization for Optimal Planning of Biodiesel Supply Chain in Malaysia. In T. Herawan, R. Ghazali & M. M. Deris (Eds.), *Recent Advances on Soft Computing and Data Mining* (Vol. 287, pp. 293-302): Springer International Publishing.