A HYBRID MODEL OF SYSTEM DYNAMICS AND GENETIC ALGORITHM TO INCREASE CRUDE PALM OIL PRODUCTION IN MALAYSIA

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Abstrak

Industri kelapa sawit di Malaysia sedang menghadapi perkembangan yang statik dalam pengeluaran minyak sawit mentah jika dibandingkan dengan Indonesia disebabkan tiga isu iaitu; (i) kekurangan kawasan tanaman; (ii) buruh yang terhad; dan (iii) peningkatan permintaan daripada industri biodiesel berasaskan minyak sawit. Dengan mengfokuskan isu tersebut, kajian terdahulu telah menggunakan pelbagai pendekatan. Walaubagaimanapun, penggunaan metod tanpa hibrid ini mempunyai beberapa kekurangan dan boleh ditambah baik dengan kaedah hibrid. Oleh itu, objektif kajian ini adalah untuk menentu pilihan polisi yang optimum bagi meningkatkan pengeluaran minyak sawit mentah di Malaysia. Dalam kajian ini, sebuah model hibrid sistem dinamik dan algoritma genetik telah dibangunkan untuk menentu polisi yang optimum bagi meningkatkan pengeluaran minyak sawit mentah di Malaysia. Lima pembolehubah polisi iaitu kadar penggunaan mesin, purata penanaman semula, mandat biodiesel di sektor pengangkutan, industri, dan 4 sektor yang relevan bagi mengenalpasti nilai polisi yang optimum. Lima pembolehubah polisi ini diuji dalam tiga scenario: tahun 2017, tahun 2020, dan berfasa sehingga tahun 2050. Daripada semua senario, optimisasi secara berfasa didapati paling berkesan dalam menghasilkan nilai pembolehubah polisi yang sesuai untuk mendapatkan pengeluaran minyak sawit mentah yang terbaik pada tahun 2050 setakat 20 larian populasi GA. Hybrid SD-GA melalui optimisasi secara berfasa mampu untuk mencadangkan polisi yang meyakinkan untuk dilaksana bagi mengelakkan kejutan yang tidak diingini kepada industri. Tambahan lagi, model hibrid ini juga berupaya untuk mengenalpasti pembolehubah polisi yang berkaitan dengan fungsi objektif pada sesuatu tempoh masa yang spesifik. Daripada perspektif pengurusan, kajian ini boleh membantu pihak pemegang taruh dalam industri minyak sawit ke arah pembuatan keputusan pelaburan yang lebih baik.

Kata kunci: Pengeluaran minyak sawit mentah, Sistem dinamik, Algoritma genetik, model hibrid SD-GA, polisi minyak sawit mentah

Abstract

Palm oil industry in Malaysia is facing a stagnant growth in terms of crude palm oil (CPO) production as compared to Indonesia due to three issues namely (i) the scarcity of plantation area, (ii) labour shortage, and (iii) the rising demand from palm-based biodiesel industry. Focusing on these issues, previous studies have been adopted various approaches. However, these non-hybridized methods have some shortcomings and can be improved by hybridization method. Hence, the objective of this research is to determine the optimal policy options to increase CPO production in Malaysia. In this research, a hybrid model of system dynamics (SD) and genetic algorithm (GA) was developed to determine the optimal policy in increasing the CPO production in Malaysia. Five policy variables namely mechanization adoption rate, average replanting, biodiesel mandates in transportation, industrial and 4 other relevant sectors were examined to determine optimal policy values. These five policy variables were tested in three scenarios: year 2017, year 2020, and in phases until 2050. From all the scenarios, the phase optimization emerged as the most effective in producing suitable policy variable values in order to obtain the best possible value of CPO production in year 2050 up to 20 GA population runs. The hybrid of SD-GA through phase optimization process is capable to recommend policies that are plausible to be implemented to avoid unwarranted shock to the industry. Furthermore, the hybrid model provides the ability of identifying the policy variables related to the objective function at any specific time line. From the managerial perspectives, this research helps the stakeholders in palm oil industry towards making a better future investment decision.

Keywords: Crude palm oil production, System dynamics, Genetic algorithm, SD-GA hybrid model, CPO policy

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List of Abbreviations

2SLS	Two Stage Least Squares
ABM	Agent-Based Modeling
AIDS	Acquired Immune Deficiency Syndrome
ARDL	Auto Regressive Distribution Lag
ARIMA	Auto Regressive Moving Average
CPO	Crude Palm Oil
DES	Discrete Event Simulation
DO	Dynamic Optimization
DSS	Decision Support System
EPP	Entry Point Project
ETP	Economic Transformation Program
GA	Genetic Algorithm
GHG	Green-House Gasses
GNI	Gross National Income
ISIS	Information Society Integrated System
MAPA	Malayan Agricultural Producers Association
MOO	Multiple Objective Optimization
MPOB	Malaysian Palm Oil Board
MSPO	Malaysian Sustainable Palm Oil
MyGAP	Malaysian Good Agricultural Practices
N2SLS	Nonlinear Two Stage Least Squares
NKEA	National Key Economic Area
OLS	Ordinary Least Squares
PPO	Processed Palm Oil
PRN	Partial Recurrent Network
RNN	Recurrent Neural Network
SCOR	Supply Chain Operational Reference
SD	System Dynamics
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

VB	Visual Basics
VensimDLL	Vensim Direct Link Library

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CHAPTER ONE
INTRODUCTION

Vegetable oils have been an important commodity in the world oils and fats market. In the recent decade, it has become the main substitutes of animal fats as the source of cooking oils and fats. Among the seven highly traded vegetable oil in the world market, palm oil has been significantly increased in terms of its production and consumption. This is hugely attributing to its economic viability in oil palm plantation and palm oil production vis-à-vis other vegetable oil. Currently, the world largest producer of palm oil is Indonesia followed by Malaysia, with the combination of these two countries the total production of palm oil contributes approximately eighty percent of the world palm oil production (MPOB, 2016; GAPKI, 2016).

1.1 Palm Oil Industry in Malaysia at a Glance

The important role of palm oil as one of the Malaysia's main economic contributor cannot be denied, as this industry has been studied from many perspectives. For instance in the general economic perspective (Shamsudin, Mohamed, & Arshad, 1988; Shamsudin, Arshad, Mohammad, & Rahman, 1995; Mohammad, Mohd Fauzi, & Ramli, 1999); palm-based biodiesel industry (Yahaya, Sabri, & Kennedy, 2006; Shri Dewi, Ali, & Alias, 2014; Azadeh, Arani, & Dashti, 2014); production planning (Tan & Fong, 1998; Nwawe, Akintola, Ikpi, & Rahji, 2008; Banitalebi, Aziz, Aziz, & Nasir, 2016); and environment (Diban, Aziz, Foo, Jia, Li, & Tan, 2016). Palm oil also is an important economic stimulus as there are many affiliates industries such as food, cosmetics and alternative fuel that also contribute to the economic growth in Malaysia. In 2016, a total of RM41.44 billion of export value was contributed by palm oil industry which accounts for 5.3 percent of total Malaysia's export value (MATRADE, 2017).

Thus, it is very important for Malaysia to retain a vigorous palm oil industry with promising growth prospect in long term future, particularly the supply and demand sector.

Palm oil industry not only produce crude palm oil (CPO) as main product, but also other palm oil products such as palm kernel oil, palm kernel cake, oleo chemicals, finished products and biodiesel. Among this, biodiesel is the latest rising prospect as palm oil affiliated industry in energy sector. This is particularly because it plays an important role in supporting the green environment campaign promoted by the government through the international treaties on environment such as Kyoto Protocol (Shri Dewi, Arshad, Shamsudin & Yusop, 2009; Yusoff, Abdullah, Sultana, & Ahmad, 2013). Kyoto Protocol is an international legal binding treaty between participating countries in an effort to reduce the greenhouse gas (GHG) emission. Furthermore, in the period of high fossil fuel price, the demand for biofuel significantly increase as the world is looking for alternative fuel. This is true especially when the price of CPO is sufficiently low and opens the opportunity for producer to utilize the excess CPO stock as palm-based biodiesel feedstock (Yahaya et al., 2006). Even though in 2016 the world was suffering with low crude oil price due to the glutting supplies, expert has found this as the end of the fossil fuel era particularly with the participation of 200 countries in signing the Paris Climate Summit 2016 (The Guardian, 2015). This has been non-other a signal for biofuel to prevail as greener and renewable alternative fuel.

Malaysia has launched the National Biofuel Policy in 2006, aimed to stimulate the biofuel industry growth in Malaysia. The policy mission includes the promotion of palm-based biodiesel usage in Malaysia industrial sector to reduce the high dependability on fossil fuel. The implementation of biodiesel blend mandate worked as a stimulus for palm-based biodiesel demand (Yahaya et al., 2006). This program regulated the blending of certain percentage of palm oil with petrol diesel to produce palm-based biodiesel. Malaysia has launched B5 in 2011 and B7 programme in 2014 (Yusoff et al., 2013). In the latest announcement in 2016, government has launched B10 for transportation sector and B7 for industrial sector (Adnan, 2016). Apart from that, the palm biodiesel industry is aimed to utilize the palm oil excess stock and help to mitigate palm oil price (Yahaya et al., 2006; Shri Dewi et al., 2009; Yusoff et al., 2013). This highlights the importance interdependencies between the industry and its biodiesel sector as price stabilizing mechanism.

1.1.1 Palm Oil Industry Issues in Malaysia

Malaysia was once the largest producer of CPO followed by its neighbour Indonesia. However, starting from 2004 Indonesia's CPO production has surpassed Malaysia as shown in Figure 1.1. Further, by looking at the CPO production pattern, Malaysia exhibit a stagnant growth as compared to vibrant growth of Indonesia. Malaysia has since been left behind Indonesia and yet to recover due to several issues. In the long term, this could jeopardize Malaysia's position in world palm oil market. Vigorous CPO production is needed for Malaysia to secure its export revenue and also fulfilling increasing demand of palm oil both locally and globally in the future (Adnan, 2016; PEMANDU 2016; Oil World, 2017).

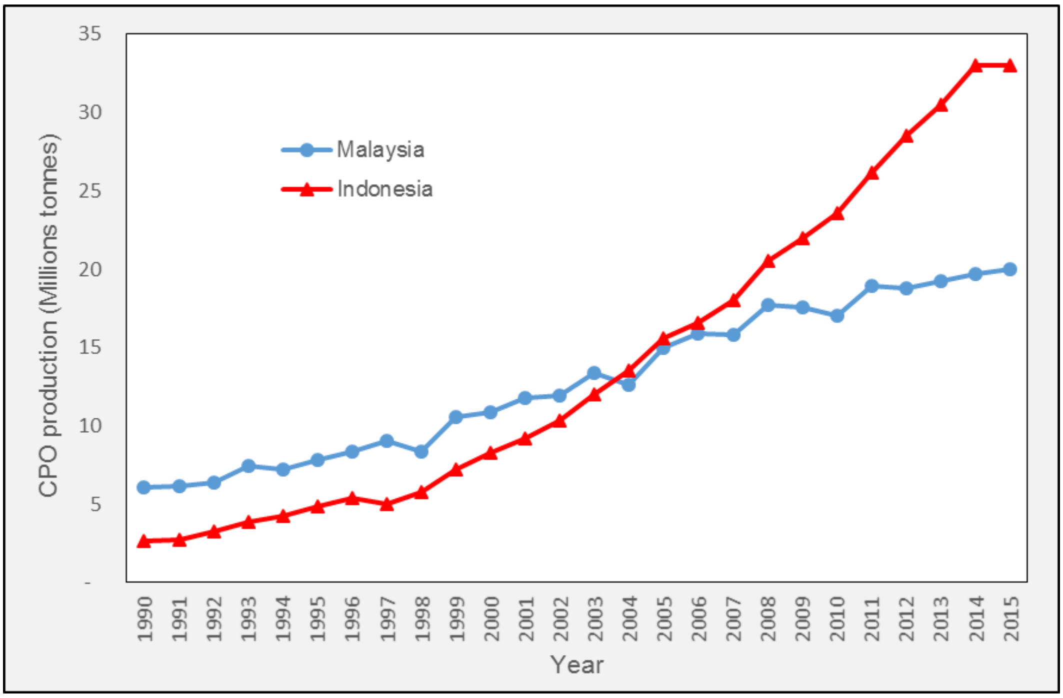

Figure 1.1. Malaysia and Indonesia crude palm oil production from 1990 – 2015 (source: MPOB, 2016)

There are several issues related to palm oil industry in Malaysia that contribute to the stagnant growth in CPO production. These include the land constraint, labour shortage, demand surge from energy sector, adverse weather, and uncertainty in world economics trend as addressed by the director General of Malaysia Palm Oil Board (MPOB) and other renowned analyst in Palm Oil Economic Review Seminar in Kuala Lumpur on 17th January 2017. In fact, the same issue has been reiterated by experts in every economic conferences related to palm oil like the annual Palm Economic Review and Outlook Seminar (PALMEROS) and bi-annual International Palm Oil Congress and Exhibition (PIPOC) organized by MPOB (MPOB, 2016). As the adverse weather and the world economic trends are external factors which are deemed incontrollable, this research however will weigh it focus on three compounding issues which are the land constraint, labour shortage and demand surge from energy sector.

1.1.1.1 Scarcity of Plantation Land

The first issue in Malaysia palm oil industry is the scarcity of plantation land. History has recorded that in 1960, total oil palm plantation area was only 55,000 hectares (MPOB, 2016). Then, under the government's agricultural diversification programs, there were rapid expansion of the oil palm plantation area where it has been recorded of approximately 1 million hectares of oil palm plantation land in 1980. However, the oil palm plantation area expansion has been growing at slower rate and plummeting in year 2000 as shown in Figure 1.2. This statistic suggests the fact that Malaysia palm oil industry has started to face land constraint as there are lesser land available for oil palm plantation expansion[1]. Another reason for the low plantation area growth rate is due to the competition faced by oil palm with other crops for the balance of agriculture land in Malaysia, and also due to the industrial or residential areas where land converted to these purposes (Abdullah & Wahid, 2011). There lies the option for land expansion abroad but these involve substantial monetary cost and conscientious geo-political issues. Sufficient plantation area is critical to establish a production capable of coping with the growing demand in the future.

[1] Anonymous informational interview with Malaysian palm oil research body.

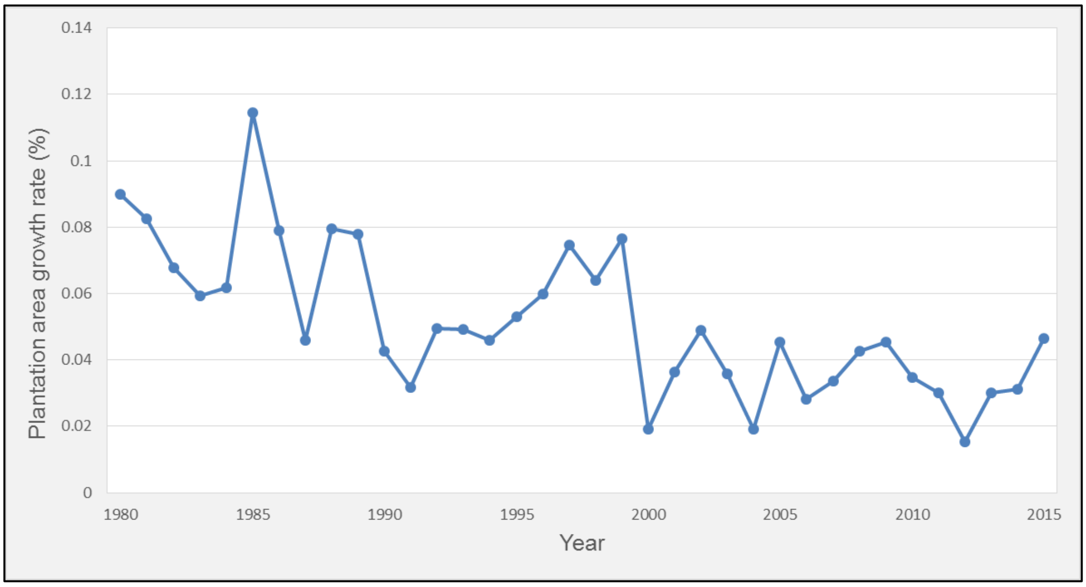

Figure 1.2. Malaysian oil plantation area growth rate (Source: MPOB, 2016)

1.1.1.2 Labour Shortage

The second issue in palm oil industry in Malaysia is labour shortage. As a highly labour-intensive industry, shortage of labours will significantly affect the performance of the industry, as palm oil estates rely heavily on immigrant Indonesian workers. Skilled labour shortages have plagued some regions, reducing harvest activity by fifty percent and leaving ripe but unharvested fruit rotting on the plantation (Amatzin, 2006; Abdullah, Ismail, & Rahman, 2011; Koswanage, 2011). At the same time, robust growth in Indonesia are creating lots of jobs for skilled plantation workers. This caused acute competition for the labour which resorted into a lower application from Indonesian to become part of the workforce in Malaysia oil palm plantations (Raghu, 2014). Wage pressure is reportedly hitting oil palm plantations in Malaysia as they compete for needed manpower. Given future growth prospects in the palm oil industry in Indonesia, this problem will continue for Malaysian producers unless wages and benefits rise significantly (Hai, 2000; MPOC, 2015).

1.1.1.3 Demand Surge from Palm-based Biodiesel Sector

Besides land constraint and labour shortage, there is also factor from the demand side which affecting palm oil industry in Malaysia. The demand for CPO to produce palm-based biodiesel pressures Malaysia for the need of having better supply of palm oil in the future. The implementation of B5 programme in 2011 for transportation sector by government has stimulated the palm oil demand as main feedstock for palm biodiesel production. It is estimated that 0.5 million tonne of CPO is needed as biodiesel feedstock with the implementation of B5 program (Yahaya et al., 2006, Wahid, Abdullah, & Shariff, 2010). The implementation of B5 program is aimed to utilize the excess stock of palm oil (Yahaya et al., 2006; Shri Dewi et al., 2009; Yusoff et al., 2013). Later, the blend mandates programme has been increased to B7 in 2014 and recently in 2016, government has announced the latest mandate with B10 increased for transportation sector and the introduction of B7 in industrial sector (Adnan, 2016). The increase of blend mandate will further demand for higher consumption of CPO as its feedstock. Moreover, the biodiesel programme is a long term commitment by the government to reduce dependency on fossil fuel, thus further increase of blend mandates in the future is anticipated. Further, there is an emerging market of palm-based biodiesel in India as the country started to venture into biodiesel sector as reported by Malaysia Performance Management and Delivery Unit (PEMANDU) director in his address during Palm Oil Trade Seminar (POTS) 2016 in Kuala Lumpur. (PEMANDU, 2016). This emerging biodiesel market further urge the need for our palm oil industry to secure strong CPO production in the future.

Leading palm oil analyst, Thomas Mielke, in his address in Price Outlook Conference held in Kuala Lumpur in March 2017, reported that it is forecasted that the world will need additional 25 tonne of palm oil annually for another 10 years which signal the global dependence on palm oil will continue to rise (Oil World, 2017). On this account, it is possible that Malaysia will face supply shortage with the current production rate, exacerbated by the latest increasing palm oil demand from biodiesel industry. This situation will only lead to CPO price surge which in turn lowering the motivation for replanting the highly productive oil palm tree (replacing the less productive ageing tree) due to the short term profit target, especially among the smallholders (PEMANDU, 2015). Hence, the palm oil industry will be trapped in a stagnant growth feedback loop when the majority of oil palm plantation becomes ageing area and poses a negative impact on CPO production (Wahid & Simeh, 2010). This pressures Malaysia's palm oil industry to ensure the supply in the future can meet the growing world demand including the demand from biodiesel industry.

These three issues are currently at the alarming rate and without proper action will disrupt the track record performance of the industry on the nation economy. Fortunately, the Economic Transformation Programme (ETP) under the Malaysian Tenth Plan has been announced by the government in September 2010 as the potential resolving action for these issues.

1.1.2 Future Direction of Palm Oil Industry in Malaysia

The arising issues highlighted need urgent actions by government to avoid unfavourable outcome in the future. Hence, under the Tenth Malaysia Plan (RMK10), the government has announced the ETP on 25 September 2010 which was formulated as part of Malaysia National Transformation Programme. ETP supports the government effort to move Malaysia to developed nation status by 2020 with Gross National Income (GNI) per capita of US$15,000 (PEMANDU, 2010). This target will be realized through the implementation of twelve National Key Economic Areas (NKEAs) representing economic sectors which accredit for significant contributions to GNI. These NKEAs will receive prioritized government support including funding, top talent and prime ministerial attention (PEMANDU, 2010).

Palm oil is indexed at number three (alongside rubber) as one of NKEAs and is targeted to generate RM 178 billion in GNI by year 2020. To achieve the target, ETP has outlined eight entry point projects (EPP) every year to measure the palm oil industry performance as highlighted in the Table 1.1. EPPs explore new growth area and business opportunities that will enable palm oil sector to move further (PEMANDU, 2010).

Table 1.1

Entry Point Projects Under Palm Oil National Key Economic Areas in 2014 (Source: PEMANDU, 2015).

EPP number	**Key Performance Indicator**
EPP 1	Area of replanting and new planting by independent smallholders (ha) - land preparation completed
EPP 2	Number of new smallholders cooperatives (launched)
	New area of plantation/smallholders complying with COP/NSAP/RSPO/best practice - (ha)
	Increase in national average yield (mt/ha/year)
EPP 3	Number of *Cantas* taken up by plantations and smallholders
EPP 4	Number of new palm oil mills certified by MPOB for Code of Practice and other international certification
	Oil extraction rate
EPP 5	Number of new mills built with biogas facility
	Number of new mills connected to national grid
EPP 6	Take-up rate for the oleo derivatives and bio-based acquisition funds
EPP 7	Commercializing second generation biofuels
EPP 8	Take-up of funds for food and health based products (RM mil)

Among eight EPPs listed in Table 1.1, four of them are the closest possible solutions for the arising issues in Malaysian palm oil industry which has been highlighted in previous section. EPP 1 emphasized on accelerating the replanting and new planting of oil palm. It aims to replace 449,415 hectares of low yield old trees with high yielding seedlings. This is one potential solution to increase palm oil production with the scarcity of available land for oil palm plantation expansion. Next, EPP 2 stressed the target to achieve the increment of national average yield to 5 percent. This is towards the target annual yields of 26.2 tonne per hectare by 2020 for national average across all plantation owners (PEMANDU, 2015). Then, EPP 3 focused on the productivity in terms of plantation workers. It targeted to achieve the usage of 1500 mechanical harvesting tools *Cantas* to increase worker productivity and aimed to resolve the labour shortage issues which currently beleaguering the palm oil industry. Finally, EPP 4 sets the target to increase the oil extraction rate (OER) to 23 per cent by year 2020. This is crucial as OER is the main indicator for palm oil production performance. Note that all four EPPs mentioned are set towards strengthening the production of palm oil in the future to cater the surge of demand including from the alternative energy sector.

Under the latest Malaysia Eleventh Plan (RMK11) announced in 2015, government has continued its commitment in palm oil sector aligned with the previous plan. One main point captured in RMK11 involving palm oil NKEA is under Focus Area E Strategy Number E3 where current biodiesel mandate programme is scheduled to be increased further to B15 in all sectors by 2020 (Economic Planning Unit, 2015). In addition, under Focus Area C Strategy Number C7, government is implementing incentive schemes to encourage the certification of Malaysia Good Agricultural Practices (MyGAP) and Malaysia Sustainable Palm Oil (MSPO) particularly among smallholders which will ultimately help to improve the quality of FFB yield (Economic Planning Unit, 2015).

In conclusion, ETP through palm oil NKEA translates the government commitment to maintain Malaysia's position as the world's leading downstream palm oil player and sustain its status-quo in the world market (PEMANDU, 2010). Successful EPPs execution may help the industry to eliminate the arising issues in Malaysian palm oil industry highlighted before.

1.2 Issues Related to Modeling Approaches in Palm Oil Studies

Previous researches had been adopting various modeling approaches in studying the economic variables in palm oil domain. One of the widely used modeling approach is econometrics that is prevalence in palm oil market studies. Econometrics has its strong attribute in modeling the palm oil market particularly of its statistical properties including unbiasedness, efficiency and consistency. This can be seen in the previous studies (Shamsudin et al., 1988; Mohammad et al., 1999; Talib & Darawi, 2002; Rahman et al., 2011; Arshad & Hameed, 2012; Shri Dewi et al., 2011a, 2011b, 2011c, 2014). However, despite of these advantages, econometrics fail to feature the feedback structure which is prevalent in any complex system like palm oil industry. Generally, econometrics lauds precision but depends heavily on extensive data thus make it less effective for long term policy design process (Meadows, 1980). It is also difficult to incorporate soft elements of a system such as human perception or management biasness into the econometrics model. To overcome this shortcoming, simulation method which is functioning to imitate real world situation mathematically then to study its properties, and finally to draw conclusion and make decision based on the result is needed for the effective modeling ability (Render, Stair, & Hanna, 2011).

As alternatives to econometrics, simulation modeling methods like discrete event simulation (DES), system dynamics (SD) and agent-based modeling (ABM) become a preference for modeling a complex system. However, DES is more suitable for modeling the process in the system, while ABM looks at a system at the micro-level of its constituent units which may involve extremely computer intensive and time consuming modeling process for a huge system (Bonabeau, 2001). On the other hand, SD is effective for modeling a system at a strategic level issue. Studies that applied SD method are prevalence in the palm oil studies such as in Yahaya et al. (2006), Shri Dewi, Arshad, Shamsudin, and Yusop (2010); Abdulla, Arshad, Bala, Noh, and Tasrif (2014); and Mohammadi, Arshad, and Abdulla (2016). However, although these studies were able to incorporate feedback processes and found effective for long term policy analysis, their contribution was limited to only highlighting the findings that exist in the system and less emphasizing on finding optimal solutions to improve the model. To supplement this need, in the operation research field, various optimization methods are available from the simplest linear programming to the complex metaheuristics such as simulated annealing and genetic algorithm. Given the complexity of palm oil industry, the high order approximation method may be needed as offered by metaheuristics family.

1.3 Problem Statement

Palm oil industry in Malaysia is one of the nation’s economy backbone for several decades. It also has a huge social contribution by offering abundance of jobs in its upstream, downstream, and affiliating sector.

However, the major arising issues in palm oil industry including the labour shortage, plantation land scarcity and uncertain production to cater for future palm oil demand especially from emerging palm-based biodiesel industry may obstruct the industry to maintain its status quo and hinder the prospect of its growth. As mentioned earlier, Malaysia has been lagging behind Indonesia in terms of its CPO production growth and the aforementioned issues may be the source of this problem. The government embarked on ETP and identified the key economic area involving eight EPPs to improve the performance of palm oil industry. Four out of the eight EPPs may potentially be the solution to the arising issues mentioned. EPP 3 is targeted to decrease the dependability on human labour by focusing on mechanization whereas EPP 1, EPP 2, and EPP 4 are targeted to increase the national yield and palm oil production with effective replanting scheme and improved oil extraction rate. The EPPs under ETP translate the government commitment to preserve and improvise the palm oil industry for long term future especially the CPO production.

However, what is the optimal mix of policy implementation capable to increase CPO production? To answer these questions, an appropriate modeling approach is needed to facilitate the analysis of variable relationships in palm oil industry and gather all the key players in a holistic system rather than looking at separate model at a time. Furthermore, the method also must be able to offer a platform to evaluate and experiment existing and new policy scenarios to improve the future CPO production strategies in Malaysia. This is highly important in order to reduce the post-policy-implementation financial as well as social cost (Ghaffarzadegan, Lyneis, & Richardson, 2011).

In the current practice, modeler's intuition and expert opinion has always been used as the base test and recommendation to improve a model as adapted in studies by Yahaya et al. (2006), Shri Dewi et al. (2010), Abdulla et al. (2014), Mohammadi et al. (2016). In these studies, none of the analytical method was found to help the existing method to find sufficiently good solutions for model improvement except experts' recommendation. Albeit expert recommendations are reliable in certain context, human intuitions are found to be limited, bias and may be misleading (Duggan, 2008). To resolve this, method from metaheuristics family offer ways to analytically self-recommend a good policy based on the system constraints and desired target. In addition, combination of search method and simulation modeling allow the experimentation of policy interventions under various scenarios while helping to find best policy option to improve the system.

Taking into consideration the limitation of the discussed method, this research proposed a hybrid of SD-GA model to search for sufficiently good solutions in policy design process towards increasing CPO production in Malaysia. By integrating methods, the appropriate changes of policy variables to improve CPO production can be possibly obtained. The proposed SD-GA model in this research provide the leverage to set control variables and objective function at any point of timeline, which has not been featured in existing model such as in Grossman (2002), Duggan (2008), Alborzi (2008), Chen, Tu, and Jeng (2011). This feature allows the finding of optimal policy option being done in phases for better policy design process.

1.4 Research Questions

1) What are the factors that influence the CPO production in Malaysia?

2) What are the appropriate value of parameters in order to assess CPO production in a dynamic environment?

3) How will the proposed hybrid model be evaluated?

1.5 Research Objectives

The general objective of the research is to determine the optimal policy options to increase CPO production in Malaysia. To answer the related research questions, specific objectives are:

1) to determine the factors that influence CPO production in Malaysian palm oil industry;

2) to optimize parameters for assessing CPO production in a dynamic environment; and

3) to evaluate the proposed hybrid model for assessing CPO production in Malaysia.

1.6 Scope of Research

The scope of the research is described to declare any limitation that may exist in the course of the research. The scope of the research includes:

1) Malaysian palm oil industry is used as a base case where the proposed methodology is applied to demonstrate its capability in policy design process.

2) The past studies focused in optimizing chemical formulations related to palm oil are not covered in the literature review in Chapter 2 due to its irrelevancy with our research objective.

3) In terms of the model components, three main factors have been chosen for its impact assessment towards the industry. The variables are plantation area,

labour availability and biodiesel demand referring to the arising issues as been highlighted in the previous section. Plantation area and labour availability are chosen based on their important role in the performance target aligned under EPP. Further, biodiesel demand is chosen due to the foreseen impact on the demand of the future palm oil where strong palm oil production is important as targeted under EPPs.

4) The historical data used in this research were taken in the period of 15 years which is from 2000 to 2015. This is mainly due to the availability of data. Moreover, the chosen period is deemed appropriate because the analysis can be done for pre- and post-biodiesel policy implementation in year 2011. This permeates the behavioural study of the economic variables in different policy implementations scenario.

5) The research did not incorporate the cost analysis in the model. Even though considering the cost element is of important when trying to improve CPO production, this research puts the main focus on the factors that affect CPO production and how the changes of these factors can help improving CPO production. Furthermore, the incorporation of cost element requires the expansion of the model to a whole new level of complexity.

1.7 Significance of the Research

The research will contribute in terms of managerial aspect through the application of the proposed method. More importantly, this research may contribute to the body of knowledge with the proposed hybrid of SD-GA model which is considered new where the simulation and search method has been combined. Conclusively, this research is expected to contribute in methodological and managerial aspect as highlighted below.

1.7.1 Methodological Contribution

The proposed hybrid SD-GA model in this research offers added flexibility in finding sufficiently good solution for policy design process which has not been featured in the hybrid SD-GA model in the study by Grossman (2002); Duggan (2008); Alborzi (2008); and Cheng, Tu, and Jeng (2011). The integration of GA with SD in this research allows an optimization capability to set a time-sensitive objective function. That is, the objective function in the proposed hybrid SD-GA model can be set to be achieved at any point of the model time line. Whereas in contrary with previous hybrid SD-GA model, objective function is set to only improve the overall behaviour SD model at the end of the simulation. Further, this integration also permeate the setting of policy variables in a time sensitive manners, which mean the policy variables' value required to achieve objective function can be set to be searched at any point of time in the model time line. If successfully done this will greatly help in policy designing process where certain policy target may be subjected to be achieved at specific time with policy changes set to happen at a specific time in the time line. In conjunction with this, the search for optimal policy can be done in phases for more effective policy design process. This is demonstrated in Chapter 4.

Finally, this study proposed an alternative method of solving time-dependant dynamic optimization (DO) problem using the combination of traditional GA and SD. In time dependant DO problem, time is one of the dynamic element where the movement of time in each change occurs in other element is considered in solving the problem (Branke, 2000). In evolutionary computing field, solving DO problem requires the exploitation of GA code to adapt the dynamic nature of a system (Branke, 1999). However in the proposed hybrid of SD-GA model, the dynamic part of the system will be handled by SD modeling thus only traditional static-based GA is sufficient for resolving a time-dependant DO problem.

1.7.2 Managerial Contribution

This research introduces a structured policy design framework applicable in palm oil industry context. This framework offers a platform to evaluate, to experiment and to design new policies related to palm oil industry. To the best of our knowledge, no previous study has been found proposing a structured policy design framework for palm oil industry. Thus this research will contribute in the growing literature on palm oil industry studies. Furthermore, with appropriate parameter and minor modification this framework can be generalized for assisting the policy design process in other commodity industries such as rice, cocoa and coconut.

Although there are many studies adopted modeling approaches in the past, none of them has employed optimization method to assist in policy design process. Thus, this research can shed a light of possible changes to be implemented for improving CPO production. Specifically, this research will help:

1) The government to assess the effectiveness of ETP toward strengthening palm oil industry in Malaysia.

2) Malaysian Palm Oil Board (MPOB) in evaluating the current policy impact on Malaysia palm oil industry. As the authority in the industry, MPOB can test new

policy options before its implementation to avoid costly consequences in the long term.

3) Industry members to evaluate their current strategy and design new strategy to stay competitive in palm oil industry. This includes the planters, palm oil producers and palm oil traders.

1.8 Organization of Thesis

The thesis has been organized into five chapters. Chapter one described the background of the problem and presented the significance of the research. Furthermore, this chapter discussed the contribution of the research towards the body of knowledge, especially in the palm oil market modeling problem domain.

Chapter two provides the theoretical reviews on modeling approaches used in palm oil industry studies and the empirical reviews of previous Malaysian palm oil industry studies that adopt modeling approaches. These reviews lead to the identification of research gaps.

Chapter three describes the methodology used in this research and the research processes to achieve the objectives as described in chapter one. This chapter explains the process involves in the development of dynamic simulation model, followed by the development of search algorithm, and the integration mechanism of these two methods.

Chapter four present the results obtained in this research. These include the result of several validation tests on the SD model, parameter searching for GA operators, and the experimentations performed to search for optimal policy options using hybrid SD-

GA model towards improving CPO production. The experimentation results are discussed in detail.

Finally, in chapter five a conclusion of the thesis is presented. This is followed by the summary of the proposed methodology and the successful accomplishment of research objectives. This chapter ended with the declaration of research limitations and some recommendations for the future work.

CHAPTER TWO
LITERATURE REVIEW

In this chapter, the characteristics of key components in palm oil industry are described. This is followed by the review of approaches used in modeling palm oil industry which include econometrics and simulation model. Further, optimization method used in palm oil as well as agriculture related researches are reviewed. Then, the review of several potential metaheuristic methods are presented. Research gaps identified through the literature review process that result to a contribution to the knowledge in the relevant field is also highlighted.

2.1 Key Components of Palm Oil Industry

Modeling acts as a tool to assemble variables to assist the analysis of their inter-relationship in the studied system. In the earlier stage of modeling process, it is important to identify the components especially the key variables that influence performance of the system. Hence, this section proceeds with the explanation of key variables and main factors that influence the palm oil industry in this research context.

Generally, palm oil industry is comprised of three core components, which are supply (consist of its production, import and end-stock), demand and price. This is aligned with the generic commodity model as proposed by Meadows (1970). As mentioned earlier, Malaysia has been surpassed by Indonesia of its CPO production since 2004. The reason for this stagnant growth may come from several factors within the vast system of interrelated network in palm oil industry. By looking at the palm oil industry in a systematic view, the factors that influence CPO production comes from the supply and demand sector. Furthermore, CPO supply and demand relation has been found to have a strong connection with its price as suggested by traditional economic supply and demand theory. On the other hand, the price also is found to be affected by CPO production which illustrates the existence of feedback processes in the palm oil industry (Asari, Rahman, Razak, Ahmad, Harun, & Jusoff, 2011). The strong interdependency and non-linear relationship of these three main components exhibit the complexity of the industry (Shri Dewi, 2010; Abdulla et al., 2014; Mohammadi et al. 2016). Hence, the model of the industry has to be done holistically considering all the feedback process among variables for effective analysis.

2.1.1 Supply

Palm oil stock consists of CPO and processed palm oil (PPO) that includes all amount in the mills, refineries, bulking installations and oleo chemical plants (Nordin & Simeh, 2009). CPO is palm oil in its raw form whereas PPO is a product after further processing of CPO. At the end of each year, the net palm oil stock is called end-stock and it is highly depending on production and export, while import and local consumption play minor role (Shamsudin et al., 1995). However, recently the amount of imported CPO is increasing and has becoming important element in palm oil supply sector. Thus, incorporating it in market analysis is essential in the current state of industry (Nordin & Simeh, 2009).

2.1.2 Demand

Similarly, palm oil demand constitutes various sources of demand. In the pre-biodiesel mandate implementation period, the variables that constitute total CPO demand include the CPO demand for export, PPO demand for export, PPO demand for local consumption, and PPO demand for further processing (Nordin & Simeh, 2009).

However starting from 2011, incorporation of the demand from biodiesel industry is important as significant demand from this industry has been recorded due to the implementation of B5 mandate programme (Yusoff et al., 2013).

2.1.3 Price

Palm oil price is heavily dependent on its supply and demand factor (Shamsudin et al., 1988; Rahman, Balu, & Shariff, 2013). A study by Nordin and Simeh (2009) stated that palm oil stock is a strong indicator of its price. The negative relationship between palm oil price and its stock actually has long been endorsed by Shamsudin et al. (1988). The study concluded that palm oil prices is highly sensitive to change in stock levels. It has also stated that changes in prices determined by the stock disequilibrium, and the speed of price adjustment towards equilibrium is generally faster for agriculture commodities. Arshad and Hameed (2012) further the study by incorporating crude oil price as determinant of the stock level and palm oil price. In their analysis, they concluded that crude oil price plays significant role in determining the stock equilibrium and subsequently affects palm oil price. The palm oil price also is influenced by its closest substitute's price, the soybean oil. Studies by Senteri (1988), Shri Dewi, Arshad, Shamsudin, and Hameed (2011a), and Arshad and Hameed (2012) supported this fact where high positive correlation between soybean oil prices with palm oil prices was shown in their analysis.

2.2 Factors Influencing the Supply and Demand of Crude Palm Oil

Palm oil supply and demand are the core components of palm oil industry model where the interplays determine the price. Next, we elaborate the factors that have been identified bringing huge influence on palm oil supply and demand namely the plantation area, labour and palm-based biodiesel demand.

2.2.1 Plantation Area

Plantation area is considered as the variable that directly influences the palm oil supply particularly the CPO production. Plantation area refers to an area in which the oil palm trees are being cultivated. It is one of the important components because wider plantation area result to physically higher fresh fruit bunch (FFB) yield rate. Plantation area can be categorized into three main areas called premature, mature and ageing area (Wahid & Simeh, 2010; Abdullah, 2012). By definition, pre-mature area consist of young tree with the age range of zero to three years. Turning to four years, the trees will start to produce its first yield and continue its productivity up to the age of 25 years old. A mature area reaches at this age and it is considered as the most productive period for an oil palm tree. However, ageing more than 25 years makes the tree less productive and this can be categorised as ageing area (Abdullah, 2012). Malaysia has recorded approximately 5.6 million hectares of plantation area with 18.48 tonne per hectare of FFB yield in year 2015 (MPOB, 2016). Roughly, there are only approximately 1 million hectare potential land suitable to be converted into oil palm plantation which signal a significantly low domestic expansion opportunity[2].

When the plantation area reached more than 25 years old, replanting should take place to replace the old oil palm trees. Replanting will then make the area lagged 3 years before the area can become productive again. This leads to the cyclical pattern in the palm oil production (Abdullah, 2012). Thus a well-planned replanting program by

[2] Anonymous informational interview with Malaysia palm oil research body

narrowing the yield gap of the low productive trees and using new higher yielding planting materials are essentials to avoid unwanted sudden palm oil supply interruption (Wahid & Simeh, 2010).

Developing new oil palm plantation area is difficult not only because of the scarcity of the potential area and rising in cost of input, but also to meet the sustainable issue raised by the environmentalist group which need to be considered (Yean & Zhidong, 2014; Shri Dewi et al., 2011a). As such, some companies in Malaysia has opted to expand their plantation area offshore, in Indonesia and certain African country where all the mentioned hindrance at its lowest level (Shri Dewi et al., 2011a).

With limited land for plantation area, the way forward is to make full use of the existing palm oil plantation by boosting the productivity measured by FFB yield per hectare (Wahid & Simeh, 2010).

2.2.2 Labour

Labour is another important factor to be considered in having influence on CPO production. This is because labour can be assumed as the ‘main’ mover in every work sector in palm oil industry, from the oil palm planting, nurturing, harvesting and transporting to the palm oil processing mills. Palm oil industry can thus be considered as labour intensive industry, especially in the oil palm plantation sector (Abdullah et al., 2011; Ismail, Ahmad, & Sharudin, 2015; MPOB, 2016).

In Malaysia, 70 percent of the workforce in plantation area specifically are foreign workers and most of them are Indonesians (Ismail et al., 2015; MPOB, 2016). This is due to the lack of interest of locals to do the critical and labour intensive plantation jobs like harvesting, collecting fruits and weeding (Wahid & Simeh, 2010). Another reason that makes this kind of job not locally popular is the increasing level of education among local young generations (Abdullah et al., 2011; Ismail, 2013). With increasing education level, the job at plantation which they termed as “3D” or “Dirty, Dangerous, and Difficult” become the lesser choice as a career among local youth.

However, high dependability on foreign workers has resulted into major crisis in recent years as workers have low interest to work in Malaysian oil palm plantation. Apart from rigid Malaysian foreign labour policy which hardened the hiring process of foreign labour (Hai, 2000; Abdullah et al., 2011), much of the labour crisis sources come from the rapid growth of Indonesia palm oil industry as our counterpart guarantee better working environment at home country with competitive salary as compared to Malaysia (Hai, 2000). Even though the average wages in Indonesia oil palm plantation is reported at three times lower than that in Malaysia, it is relatively higher compared to Malaysia considering the living cost and working environment in their own home-country (Cramb & McCarthy, 2016). However, with higher agriculture sector growth at 3.4 percent as compared to Malaysia at 0.8 percent, it is anticipated that the wages as well as working environment will improve overtime which increase the attractiveness for immigrant Indonesia workers in Malaysia to go back to their home country (Cramb & McCarthy, 2016).

Labour shortages is critical to the industry in the long term. The low interest of Indonesian to work in Malaysian palm oil industry is inevitable due to Indonesian palm oil industry growth. The way forward is thus by increasing the labour productivity (measure by labour per plantation area) through the adoption of mechanization in the industry. As mechanization adoption is capable to boost up to double of the productivity of labour, this can be the direct resolution for the worrying labour crisis (Jelani, Hitam, Jamak, Noor, Gono, & Ariffin, 2008). MPOB has initiated the international competition on palm oil mechanization organized every year with astounding price up to RM 1 million for the winner (MPOB, 2016). This is done to entice interest from all parties including academicians and private sector to develop new technology to facilitate oil palm activities.

2.2.3 Palm-based Biodiesel Demand

Increasing demand from the palm oil-based biodiesel sector has become a contributing factor that determines CPO stock. To produce it, CPO or PPO is processed to obtain Palm Methyl Esther (PME), a substance capable to be used as vehicle engine fuel and categorized as biodiesel. In 2006, government has launched the National Biofuel Policy (NBP), affirming the government effort towards the development of greener fuel and lower dependency on fossil fuel (MPIC, 2006). Not limited to that, palm biodiesel industry also is aimed to utilize the excess palm oil stock and help to mitigate the palm oil price. This is relevant on the account of study by Shamsudin et al. (1988) which stated that palm oil stock have negative relationship with its price, that the lower the stock level will boost the price up.

Malaysia has launched the first biodiesel blend mandate in 2011 in an effort to stimulate biodiesel industry growth. However, it has also put the industry as the mandate driven industry, where at the current state the industry is sustained with the support of government. The biodiesel blend mandate denotes the blending of certain percentage of PME with certain percentage of petrol diesel. For instance, B5 mandate programme indicates the blending of 5 percent of PME with 95 percent of petrol diesel. With the introduction of B5 mandate programme for transportation sector in 2011, Malaysia has boosted its domestic biodiesel consumption to approximately 0.5 million tonne per year (Adnan, 2016). Further, in 2014 the government increased the mandate to B7 for transportation sector and the consumption of biodiesel rose to approximately 0.7 million tonne year (Adnan, 2016). As the trend of diesel consumption is increasing, the demand on palm oil for palm biodiesel production will also increase in the future. Furthermore, the further increase of biodiesel blend mandate is capable to increase the palm oil demand (Wahid, Abdullah, & Shariff, 2010; Yusoff et al., 2013). This is true where experts had anticipated the local consumption of approximately 1 million tonne of biodiesel with the latest launching of B10 and B7 for transportation and industrial sector respectively (Adnan, 2016). There is a high hope that the launch of new mandate of B10 for transportation sector and the introduction of B7 for industrial sector will lift the national biofuel industry to a new high level[3]. Moreover, the successful implementation of the new blend mandates will put Malaysia at par with other biofuel producing countries like the U.S. with B10 and Indonesia with B20 (Adnan, 2016).

Nevertheless, palm-based biodiesel industry has become increasingly important in influencing the dynamicity of palm oil industry especially its price. Particularly, the biodiesel programme is a long term commitment aligned under NBP and the commitment has been strengthen under Eleventh Malaysia Plan (RMK11) announced in 2015. This highlight the possibility of further increase in biodiesel blend mandate in the future, thus incorporating biodiesel sector in the analysis is evidently crucial.

[3] The new B10 and B7 mandate has been officially launched in March 2016. However, after few month of postponement due to several issues, it is targeted to be implemented somewhere in 2017 (Adnan, 2016).

2.3 Review of Modeling Approaches in Palm Oil Studies

A modeling process can be described as a tool for approximating real life behaviour and testing scenarios (Maidstone, 2012). When it comes to modeling a system, there are plethora of modeling methods available from various disciplines designed to achieve their own distinctive objective. In palm oil industry domain, econometrics and simulation model have been widely used to study the economic variables and their relationships.

2.3.1 Econometrics

Researchers in economics have extensively used econometrics method for analysing economics model. By definition, econometrics is the application of mathematics and statistical methods to analyse economics variables (Geweke, Horowitz, & Pesaran, 2008). In theory, econometricians are searching for estimators that have desirable statistical properties including unbiasedness, efficiency and consistency. In application, econometrics uses theoretical econometrics and actual data for testing economics theories, developing models, analysing economic trend, and for the forecast purpose (Granger, 2008). Generally, econometricians adopt various statistical methods in their analysis which include Two Stage Least Squares (2SLS) (Shamsudin et al., 1988), Non-linear Two Stage Least Squares (N2SLS) (Mohammad et al., 1999), Autoregressive Distributed Lag (ARDL) (Arshad & Hameed, 2012), and Ordinary Least Squares (OLS) (Rahman, Abdullah, Simeh, Shariff, & Jaafar, 2011).

Modern econometrics also include simulation process called counter-factual analysis. Pesaran and Smith (2012) termed counterfactual in econometrics as “what would have occurred if some observed characteristics or aspects of the processes under consideration were different from those prevailing at the time”. In econometrics counterfactuals analysis are used in policy evaluations (Heckman, 2008, 2010; Shri Dewi et al., 2009).

Several studies have been found in the literature using econometrics approach in the context of Malaysian palm oil industry. For instance, Shamsudin et al. (1988) found a negative relationship between palm oil price and palm oil stock level using 2SLS technique. This is among the earliest economics studies that empirically confirm the effect of stock level on palm oil price, where one percent increase in stock is expected to decrease palm oil price by 1.41 percent. However, the equations in the econometrics model has not included the actual causal of variables' inter-relationship, in which feedback process was absent. This practice is common in econometrics where the relationship between variables are established based on the coefficient value (Geweke et al. 2008). This on the other hand may not reflect the true relationship between variables as compared to relationship constructed using feedback-based modeling as argued by Olaya (2015). In the study by Shamsudin et al. (1988) for instance, CPO production relationship with its prices was constructed by multiplying CPO prices with its coefficient. This was straight forward relationship which may also suggest a correlation instead of causal relationship. There was certainly one missing variable in the equation (that is demand) because in reality, the demand response based on the price, which in turn affect CPO production. This kind of process constitute feedback loops in the model and econometrics method fails to incorporate it.

In another study, Mohammad et al. (1999) uses N2SLS method to examine the impact of liberalization of palm oil import from Indonesia to examine the excess capacity issues in refining facilities in Malaysia. In this study, CPO price has been found to decrease by 1.7 percent with the increase of CPO import. In addition, this study has incorporated labour factor in the form of wage rate in the model and highlighted the negative impact of labour shortage on palm oil production. The equations used in this study also posed similar problems with causal and correlation relationship. For instance, the study related the mature oil palm plantation area with CPO prices and natural rubber prices. These were correlation rather than causality, because both CPO and natural rubber prices are supposed to indirectly affect mature area. There were clearly some missing variables, for example CPO prices supposed to influence the 'motivation of planting' among planters, and this motivation on the other hand will influence the planting works in premature area before it effects the mature area. Again, this kind of feedback processes cannot be captured effectively using econometrics method. Further, econometrics method also cannot incorporate soft-variable (the variable which involve human judgment or biasness) like 'motivation of planting' given in the previous example.

Econometrics analysis by Talib and Darawi (2002) applied 2SLS suggested that palm oil price also being influenced by plantation area but with low price-elasticity of 0.055 and 0.291 in short and long run respectively. These show that the change in total planting area is not a strong factor to determine palm oil price due to the existence of land constraint. In addition, palm oil price also has been found to have effect the palm oil export along with world population, soybean price and exchange rate. This means that when palm oil prices are lower relatively compared to soybean oil prices, palm oil export is expected to increase. Similar with Mohammad et al. (1999), this study assume the direct relationship between oil palm plantation area with palm oil and natural rubber prices in equation, which was arguably missing some variables critical to establish the actual feedback process in palm oil industry.

In June 2006, the palm-based biodiesel industry has been introduced in Malaysia. Since then, researcher has been incorporating the demand from this emerging industry into their model development. The impact of biodiesel demand on palm oil price was further investigated by Ramli, Abas, and Rahman (2007) using Auto-Regressive Moving Average (ARIMA) and they had projected the increment of CPO price between seven and 28 percent in 2008 from 2007 due to the increase CPO demand for biodiesel. The assumption of relationship between biodiesel demand and CPO prices were made using the trend from historical data. This assumption may be accepted considering there is no shock or uncertainties in the future trend for example like sudden increase in biodiesel demand or deep plunging of palm oil export. There is a serious shortcoming on econometrics method which is over-reliant on historical data when it comes to uncertainties as highlighted by Giraldo et al. (2008). Econometrics tend to forecast the future trend based on past trend using coefficients value rather than representing the actual system based on actual feedback process that caused the change in the system (Giraldo et al., 2008; Olaya, 2015). Thus, misleading analysis may occur without anticipation of uncertainties in the future market scenario.

Furthermore, the studies on the impact of rising biodiesel demand on Malaysia palm oil industry was extended by Shri Dewi et al. (2009). In this study, the counter-factual analysis was conducted with 70 percent sustained increased of biodiesel demand scenario. The simulation resulted in CPO stock expected to decrease by 142.6 percent while CPO supply and CPO price expected to increase by 21.86 percent and 109.74 percent respectively. The simulation done through counterfactual analysis managed to simulate the sudden shock in the biodiesel demand. However, the equation relating biodiesel demand and CPO prices posed the typical econometrics method shortcoming, which is failing to capture the feedback processes in the system. For instance, in connecting CPO production and its prices, the equation divest demand which play critical role in affecting CPO production and determining CPO prices. This feedback loop is important in depicting the dynamicity of palm oil industry, but failed to be captured by econometrics method.

Biodiesel blending mandate was launched in 2011 in the federal administration capital of Putrajaya. The mandate requires the blending of 95 percent of petrodiesel and 5 percent of palm oil. In their econometrics model, Rahman et al. (2011) used OLS to examine the impact of the biodiesel mandate program on CPO prices. The result shows that the implementation of biodiesel mandate has contributed to the total palm oil demand, where one percent increase of the mandate will lead to 0.14 percent increase of CPO price. In addition, crude oil price also is found to affect CPO price where one percent increase will lead to 0.14 percent increase of CPO price. The equation denoting CPO prices in this study did incorporate the supply and demand, including the demand from biodiesel sector. However, the equations of econometrics model in this study still lack of feedback process, for instance, CPO prices did influenced by supply and demand but the price on the hand should also influence demand, which constitute a feedback loop.

Arshad and Hameed (2012) has incorporated crude oil in their econometrics model to investigate its influence on Malaysia palm oil market especially palm oil price and stock using ARDL. The study found that in the short run, price-elasticity for crude oil is inelastic (value of 0.0378) compared to long run (value of 1.456). This suggest the high sensitivity of palm oil price to the movement of crude oil price over time. Palm oil price is also found to be highly sensitive with the level of palm oil stock with the price-elasticity of 1.4284 in the long run compared to the short run (-0.0584). A typical econometrics shortcoming was shown by the econometrics model in this study. The CPO prices equation was constructed by multiplying the coefficients with crude oil price and palm oil ending stock, denoting the direct correlation between these variables. Important variables were missing from the equation to effectively explain how the crude oil prices and palm oil ending stock actually effect CPO prices. The missing variables may include, for example, the biodiesel demand (where high crude oil prices will increase biodiesel demand thus reducing the palm oil stock and subsequently increase CPO prices). This kind of feedback process cannot be captured by econometrics model.

Rahman et al. (2013) incorporated all the supply and demand factors as well as market sentiment factor in palm oil econometrics model using multiple regression technique to examine its impact on the CPO prices. The factors include palm oil demand, soybean price and crude oil price. The results had shown that with one percent increase in palm oil demand, soybean price and crude oil price, CPO price is expected to increase by 0.15 percent, 0.55 percent and 0.04 percent respectively. The equations of econometrics model in this study have similar shortcoming as in Rahman et al. (2011). There was lack of feedback processes incorporated in the equation. For instance, CPO prices was modelled by equating it with CPO production, CPO export and soybean oil prices. This equation supposed to construct a feedback loop, where the demand (CPO export) should be influencing the CPO stock, which disrupt the supply and demand ratio, and subsequently impose an impact to CPO price. Again, econometrics method failed to capture this.

The implementation of B5 mandate program has been found to create additional demand for palm oil which further increase the palm oil price. This study has been done by Shri Dewi et al. (2014) where they have specifically investigated the effect of B5 mandate program on Malaysian palm oil market using 2SLS in econometrics. The study has proven that the implementation of B5 mandate program is expected to increase domestic palm oil demand by 1.0771 percent. Similar with Shamsudin et al. (1988), the equations of econometrics model in this study assume the direct relationship between CPO prices and palm oil stock multiplied with the coefficient. Variables like supply and demand were missing, which are considered critical to establish the actual feedback process in the palm oil industry.

Conclusively, despite its widely use in palm oil industry domain, the econometrics modeling has its downturn as follows:

1) Econometrics is not effective in capturing the actual feedback process in a system. Thus, an econometrics model may not representing the real situation of a system in the real world (Olaya, 2015). Furthermore, econometrics also is not capable to incorporate soft variables (e.g. human judgement, decision biasness) in their modeling process, which is important to depict real system based on its feedback processes (Meadows, 1980; Olaya, 2015).

2) Econometrics is heavily reliant on huge historical dataset to construct the model. According to the review by Meadows (1980), each element in an econometric model must be observable and sufficient historic observation is essential to permit precise estimation of its quantitative relationship to other variables. Thus, the problem with less data is not appropriate to apply econometrics approach.

3) With the sufficient data available, econometrics can provide very precise information about a system. On that account, econometric models are mostly short term prediction of aggregate economic variables, thus are least applicable to policy question that range over long time horizon, or into circumstances that has not been historically observed (Meadows, 1980).

4) It can be concluded that econometric models are developed when the changes to the system has been made. That is, the modeler focus on enhancing the ability of the model to reproduce the real behaviour of the system in the past rather than the representation of the actual structure of the system (Giraldo et al., 2008).

Conclusively, econometrics approach is effective when the problem is enriched with data and mostly appropriate for short term analysis. Moreover, the analysis process using econometrics may be limited within the person that profess with the method itself. Non-expert may find it difficult to conduct and comprehend econometrics analysis process.

2.3.2 Simulation Model

In Operation Research (OR) field, a model can be defined as a collection of logical and mathematical relationships that represents aspects of the situation under study (Jensen, 2004). Simulation model is one of the preferable methods for complex system analysis where they can mimic the behaviour of a system in real life. There are three main methods categorized under simulation, which are Discrete Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM). If econometrics method required extensive data and profound mathematical skills, simulation model offers a more user-friendly platform. One characteristic that these three methods share in common is they offer a user-friendly visual interface rather than plain mathematical formulas. This facilitate the experimentation process for non-expert personnel.

2.3.2.1 Discrete Event Simulation

In general, DES works by modeling a process as a series of discrete events. This method has been widely used in operation research field for over forty years (Siebers, Macal, Garnett, Buxton, & Pidd, 2010). The first work on DES was introduced in 1962 by Lackner (1962). By definition, DES highlights the sequences of each event in a discrete time at a certain point of changes where entities enter the system and visit some of the states before leaving the system (Majid, Aickelin, & Siebers, 2009). Typically, DES is thought of as network of servers and queues (Maidstone, 2012). The method has been widely used in an area of operational or tactical level focusing on the process in an organization such as production of products. However, the major downturn of DES is that it is not suitable to model the complex system behaviour at strategic level, as the core strength of DES focuses on the process in the system (Siebers et al., 2010).

There are few studies being conducted using DES in the palm oil modeling literature. This includes study by Lestari, Ismail, Hamid, Supriyanto, Yanti, and Sutupo (2014) which developed a combination of DES with supply chain operational reference (SCOR) model to measure the value added of CPO processed by palm oil downstream industry. In this study, the palm oil mills production process was simulated using DES where simulation is built on relationships between suppliers, manufacturing and customer. This study found that the highest value added will be obtained when the downstream sector produce finished products for end-customer. On another account, Fazeeda and Razman (2012) had evaluated the current capacity of the palm oil processing mill using DES. In this study, DES is used to simulate the effect of underutilized capacity on the production cost of a mill. The study found that with 60 percent increase in machine utilization will result into 10 hours of effective working time instead of 16 hours per day. This may lower the production cost due to increase efficiency. In addition, study by Lair, Chan, Chua, and Liew (2012) had demonstrated the use of DES to find the way to improve palm oil mill performance. This study compared the simulation outcome of existing and improved palm oil mill and found that 19.54 percent improvement can be made in palm oil mill performance in terms of its throughput.

2.3.2.2 System Dynamics

SD rooted from the invention of industrial dynamics by Forrester in 1950s to analyse complex behaviours in social sciences through computer simulations (Forrester, 1961). As one of the prominent methods in system thinking approach, SD has evolved over time and termed as interdisciplinary approach. The need for developing the concept was due to the situation in which decisions made to tackle a problem resulted in unexpected outcomes (Sterman, 2000). In practice, SD is a powerful dynamic simulation modeling tools which able to mimic behaviour characteristics of complex real problem and incorporating the feedback processes within. Furthermore, SD also grounded in the theory of non-linear dynamics and feedback control which can be found in mathematics, physics and engineering (Sterman, 2000). This compelling traits make SD an effective approach for policy design process.

The word "system" as defined by Maani and Cavana (2000) is a collection of parts which act together and function as a whole. Therefore, the system will always be bigger than its part. Furthermore, the word "dynamic" in SD indicates the continuous change of state overtime or corresponds to the changes of the part of the system. Thus, SD can be defined as the combination of system components to solve equations in a dynamic environment and correspond to the changes of the part of the system (Doebelin, 1972).

Presently, SD as defined by the International System Dynamics Society "… is a computer-aided approach to policy analysis and design. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems – literally any dynamic systems characterized by interdependence, mutual interaction, information feedback, and circular causality".

SD is different from DES as it focuses more on flows around network compared to the individual behaviour of entities (Maidstone, 2012). Generally, SD highlight the feedback structure within which permit a holistic analysis of the system. Hence, SD is best in facilitating the process of understanding the complex system in order to find opportunity to improve weaknesses. Another ability of SD is that it helps the modeler to identify and to understand the key factors that influence the system behaviour. The identified key factors will then assist the modeler in experimenting different type of interaction against the system. Due to this reason, it has been extensively used by the policy designer to develop or to improve the public policy by identifying the common question that might appears in an organization (Ghaffarzadegan et al., 2011).

In palm oil studies, several researchers have adopted SD as modeling approach. For instance, Yahaya et al. (2006) adopted SD method to investigate the impact of biodiesel demand on Malaysian palm oil industry. In their simulation of crude oil price shock scenarios, the increase of crude oil price has been found to increase the biodiesel demand thus encouraging plantation expansion. On the other hand, the decrease of crude oil price will lower the biodiesel demand and resulted in the decrement of CPO price due to high stock level and subsequently discourage plantation expansion. The SD model in this study used the simulation time interval of one month which is useful in the study context in building up the CPO price setting mechanism. However, using one month as simulation time interval is rather short for effectively incorporating the planting phases in palm oil industry. Furthermore, the model did not incorporate labour as one of the factor that influence CPO production.

Shri Dewi et al. (2010) then used the combination of econometrics and SD to simulate the impact of increase in biodiesel demand on this industry. The reason of using SD is to capture the feedback process which is lacking in econometrics method. The simulation of 30 percent increase in biodiesel demand has resulted to small increment of CPO price by 0.0004 percent and decrease of CPO stock by 0.7728 percent. The findings were contradict with the previous study by Shri Dewi et al. (2009) that was conducted without SD where the impact of increasing biodiesel demand on CPO price was only modest. These illustrate that by adopting SD, the analysis has captured the feedback process in palm oil industry which may discount the effect of biodiesel demand on CPO price and stock as compared to previous study.

Shri Dewi, Abidin, Sapiri, and Zabid (2015) also conducted a scenario simulation to examine the rationality of increasing blending mandates using SD. With B10 mandate being implemented, the CPO demand for biodiesel is expected to increase up to 100 percent, followed by the increase of CPO price by 0.075 percent. The study conclude that increasing the blending mandate is a counter-intuitive policy because the increase of CPO demand for biodiesel will further increase CPO price as main feedstock which is a huge disadvantage for biodiesel producer. However technically, the scope of the model was limited to the perspective of cost-profit of biodiesel production only which resulted into unfair analysis. The element of labour also has not been included as one of the critical factor influencing the CPO production. On the contrary, the model should expand its scope by considering the impact wide-economic perspective that will allow a multi-perspective analysis to avoid bias conclusion on Malaysia biodiesel industry.

Latest study by Mohammadi et al. (2016) simulated the scenario of increasing the palm oil-based biodiesel blend mandate in their study. It is found that by increasing the mandate to B10 and B15, CPO demand is expected to increase by 49 percent and 66 percent respectively. The authors suggested that the increase CPO demand has to be supported by steady production which can be achieved through mechanization and high quality crops. The SD model in this study assumes that replanting is based on the percentage of decay rate of ageing trees. However, this does not reflect the real life dynamic of oil palm plantation. It is more appropriate to include the replanting rate to depict the changing phase between ageing tree and young tree to effectively observe the fluctuation of FFB yield. Moreover, the model also did not include the labour element as the critical factor influencing CPO production, even though the author admitted the important of increasing labour productivity through mechanization. Finally, the study did not conclude the practicability of increasing blend mandate even though the analysis shows the need of improving the industry related policy.

Although SD is effective to be used for modeling complex systems, concerns arise where the modeler has to clearly define the problem to avoid over-simplification and misleading analysis. Another limitation of SD is that the modeling process may become over complicated when trying to model huge system with too many complex scenarios (Sterman, 2000).

2.3.2.3 Agent-Based Modeling

The first ABM concept was introduced in 1971 by Thomas Schelling through his segregation model, in which agent-based models as autonomous agents interacting in a shared environment with an observed aggregate, emergent outcome (Schelling, 1971). Compared to DES and SD, ABM is the most recent simulation method, particularly useful in modeling the system behaviour with autonomous and interactive abilities (Bonabeau, 2001; Macal & North, 2008). In ABM, the model is being made up of autonomous agents which follow a series of predefined rules to achieve their objectives whilst interacting with each other and their environment (Maidstone, 2012). Agents could represents anything relevant to the system, from people in an organization to cells in a body. ABM has been used in various field of studies including agriculture (Cheng, Lim, & Liu, 2009; Acosta, Rounsevell, Bakker, Doorn, Gómez-Delgado, & Delgado, 2014), business (Xie & Peng, 2012; Baptista, Martinho, Lima, Santos, & Predinger, 2014) and healthcare (Barnes, Golden, & Price, 2013; Das & Hanaoka, 2014). Likewise, ABM also facing one major practical issue where it looks at a system at the micro-level of its constituent units. Thus, when the process involve modeling a huge system, simulating all units can be extremely computer intensive and time consuming (Bonabeau, 2001).

Review of literature found only one study that specifically employed ABM in palm oil industry studies. A study by Choong and McKay (2014) focuses on the sustainability issues in Malaysian palm oil industry where a priority of eco-labelling was highlighted. The study concluded that in order to deliver eco-labelling, pertinent information from different tiers of the supply chain has to be gathered. Thus, ABM was found to be effective to capture the interaction between all supply networks in order to find the area of improvement.

In a wider scope, an application of ABM in other agriculture sector has been demonstrated by Balmann, Happe, Kellerman, and Kleingarn (2002). In this study, the authors used ABM to investigate the impact of financial support on agriculture policy in Hohenlohe region of Germany. Result shows that monetary support bring about production efficiency and increase average farm size as well as farmers' income. Moreover, Schreinemachers, Berger, Sirijinda, and Praneetvatakul (2009) used ABM to study the diffusion of greenhouse agriculture in a watershed in the northern uplands of Thailand. The simulation results found that limited access to credit has become a major constraint for the farm household from adopting the new innovation of greater irrigation water system.

General comparison of the three methods reveal the suitability of SD method to be used for macro-level policy evaluation and experimentation due to its characteristic. This includes homogenous entities and feedback process offered in SD which allowed the analysis of a system to be done at strategic level. On the contrary, DES and ABM are more suitable to be used for micro-level policy analysis where there is a need of distinct treatment on each entities. The summary of the characteristics of the three methods are listed in Table 2.1 below.

Table 2.1

The Characteristics of the Three Simulation Methods

System dynamics	**Discrete event simulation**	**Agent-based modeling**
System-oriented; Focus on the flow of the network.	Process oriented; Shows on the sequences on each event in a discrete time.	Individual oriented; Focus is on modeling the entities and interactions between them.

Homogeneous entities where each entities are similar at all level.	Heterogeneous entities where each entities has its own distinctive attributes.	Heterogeneous entities where each entities has its own distinctive attributes.
Representation of entities at macro level.	Representation of entities at micro level (passive entities).	Representation of entities at micro level (active entities).
Driver for dynamic behaviour of system us "feedback loops".	Driver for dynamic behaviour of system is "event occurrence".	Driver for dynamic behaviour of systems is "agent's decisions and interactions".
	LIMITATIONS	
Modeler has to clearly define the problem to avoid over-simplification and misleading analysis of the model.	Not suitable to model the complex system behaviour in a wider perspective, as the core strength of DES focuses on the process in the system.	When attempts to model a huge system, simulating all units can be extremely computer-intensive and time-consuming.

2.3.3 Summary of Modeling Approaches in Palm Oil Studies

The summary of studies using various modeling approaches in Malaysian palm oil industry is provided in Table 2.2. It can be concluded that majority of studies has been using econometrics method that exclude the feedback process in the model. This explains a huge difference in the results obtained from the same variables using econometrics and SD, exemplified in the study by Shri Dewi et al. (2009) and Shri Dewi et al. (2010). Thus, for effective modeling of palm oil industry, a method with holistic and feedback enriched process like SD is essential. Furthermore, most studies adopt single modeling approach, with the exception to Shri Dewi et al. (2009), Lestari et al. (2014) and Choong and McKay (2014). Using single modeling approach may be effective for the study's context, however further analysis of the model may require the combination with other method. Finally, based on the review of modeling approaches, all studies only highlighted the relationship between variables that exist in the system but less emphasizing on finding sufficiently good solution to improve the system. On that account, there is a need of complementary structured analytical tools to assist the search for optimal solution as policy option to improve the model.

Table 2.2

The Compilation of Reviewed Literature on Modeling Approaches Adopted in Malaysian Palm Oil Industry

Reference		Shamsuddin et al.	Mohammad et al.	Talib & Darawi	Yahaya et al.	Ramli et al.	Shri Dewi et al.	Shri Dewi et al.	Rahman et al.	Shamsudin et al.	Fazeeda & Razman	Lair et al.	Rahman et al.	Shri Dewi et al.	Lestari et al.	Choong & McKay	Shri Dewi et al.	Mohammad et al.
Year		1988	1999	2002	2006	2007	2009	2010	2011	2012	2012	2012	2013	2014	2014	2014	2015	2016
Methods	Econometrics	✓	✓	✓		✓	✓	✓	✓	✓			✓	✓				
	System dynamics				✓			✓								✓	✓	✓
	Discrete event simulation										✓	✓			✓			
	Agent-based modeling															✓		
	Others														✓			
Key Variables Highlighted in Findings	Biodiesel blend mandate								✓				✓	✓			✓	✓
	Biodiesel production																✓	
	Biodiesel profitability				✓												✓	
	Crude oil price				✓			✓	✓	✓			✓					
	Crude palm oil demand for biodiesel				✓	✓	✓	✓					✓	✓			✓	✓
	Crude palm oil import		✓															
	Crude palm oil price		✓		✓	✓	✓		✓	✓			✓	✓			✓	
	Crude palm oil production							✓	✓		✓	✓	✓		✓	✓		✓
	Crude palm oil stock						✓			✓			✓				✓	
	Currency exchange rate			✓														
	Domestic economic activity			✓										✓				
	Fresh fruit bunch yield																	✓
	Labour		✓															
	Palm oil* consumption	✓																
	Palm oil demand								✓				✓					
	Palm oil domestic demand						✓											
	Palm oil export			✓				✓					✓					
	Palm oil price	✓		✓									✓					
	Palm oil stock	✓						✓										
	Plantation area			✓														
	Refining capacity								✓		✓	✓			✓	✓		
	Soybean price			✓					✓				✓	✓				
	World economic activity	✓																
	World population			✓														

* Palm oil refers to crude and processed palm oil

2.4 Review of the Optimal Solution Search Method in Palm Oil Domain

Modeling approaches has been proven of its effectiveness in evaluating policy options. However, there is a time when the search for optimal policy parameter is essential to make an appropriate decision within certain constraints. Optimization can be used to search for optimal solution. It can be defined as the process of attempting to find the best possible solution amongst all those available as stated by Burke and Kendall (2005). Further, optimization also can be defined as the process of finding the right design parameters (Beyer & Sendhoff, 2007). However, Sterman (1996) referred optimization as a model that does not tell what will happen in certain situation, but instead telling what to do in order to make the best out of situation. Nevertheless, it can be concluded that optimization is a method that search for best solutions within given set of constraints.

Traditionally, optimization can be done manually through testing on different parameter values or broadly termed as "trial-and-error". However, suitability of this approach is limited only when it involves a small model. As the model becomes more complex, the search for global optimal values can be difficult (Grossman, 2002). Hence, the need for appropriate optimization method is crucial to help the finding of optimal values in a complex problem.

In operation research field, there are several optimization technique like linear programming, non-linear programming, integer programming, mixed-integer programming, stochastic programming, and heuristics (INFORMS Computing Society, 2013). This section highlights past studies that have been done for optimal solution search which focus in palm oil industry domain. The review classifies the research context based on the technique used for searching the optimal solutions and the level of analysis.

Based on the review, this research categorizes the literature into three type of level of analysis namely operation level, supply chain level, and broad-economic level.

Operation level analysis refers to the optimization process that was carried out in particular process of an operation, for instance the production in a palm oil mill or crops cultivation at plantation. On the other hand, supply chain level involves optimization works in a supply chain network. Compared to operation level, supply chain level has a broader scope. Finally, broad-economic level consider inter-relationship of variables in a bigger perspective as being focused in this research. This mainly involve optimization of economic variables such as export, import, total production and world demand. In a nutshell, it can be concluded that the analysis at operation level is conducted at the smallest scope whereas broad-economic level is done at the biggest scope, while supply chain level is in the middle of the two level.

2.4.1 Linear programming

Linear Programming (LP) was first proposed by Leonid Kantorovich, a Russian economist in 1939 (Schrijver, 1998). It is a mathematical technique used for optimization (Taylor, 2007). Theoretically, LP consists of objective function, decision variables and constraints. As its name suggest, LP assumes the relationship between variables as linear. The standard form of LP is shown by Equation 2.1 as adapted from Luenberger and Yinyu (2008), where b_i, c_i, and a_{ij} are fixed real constants, and the x_i are real numbers to be determined.

$$
\begin{aligned}
&\textit{minimize } c_1x_1 + c_2x_2 + \cdots + c_nx_n \\
&\textit{subject to } a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n = b_1 \\
&\qquad\qquad a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n = b_2 \\
&\qquad\qquad \vdots \qquad\qquad\qquad\qquad \vdots \\
&\qquad\qquad a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n = b_m \\
&\quad \textit{and } x_1 \geq 0, x_2 \geq 0, \ldots, x_n \geq 0,
\end{aligned}
\tag{2.1}
$$

In general, LP has been used to solve the management and operation problem in palm oil industry. In 1998, Tan and Fong (1998) employed LP programming to model strategic decision in Malaysia palm oil plantation. The objective of the model is to maximize the revenue in a risky condition done by penalizing negative returns. In this model, under a certain price condition an optimum crop production combination for a perennial plantation is identified. Another study by Murugan, Choo, and Sihombing (2013) designed LP model for palm oil mill processing to optimize the production planning and minimize production cost. Simplex method was used to solve the linear equations. The research has thought to be successfully replicating the real palm oil mill processing system. However, the author admitted that the inclusion of stochastic element from the actual oil and kernel extraction rate are important but cannot be captured using LP. In another case, Valizadeh et al. (2014) uses LP for optimal planning of biofuel supply chain in order to minimize the total operational cost for the production of biodiesel from palm oil and jatropha in Malaysia. Although the optimal cost has been successfully found, one of the limitation of the study is that the model did not incorporate uncertainties from feedstock, demand and price which may result into better analysis.

LP has also specifically been used to maximize the profit by holding onto set of limited resources in palm oil plantation. For instance, Nwawe et al. (2008) used LP to find optimum planning for palm oil and its combination inputs including capital and labour in regions of Nigeria. This is to guide farmers in Nigeria with economic rationale for the choice of food crops and oil palm. In similar fashion, Suksaard and Raweewan (2013a) used LP to maximize profit of entire palm oil supply chain. However, they optimize the demand size of CPO and crude palm kernel as well as palm oil product for achieving maximum profit. Another research with profit maximization is by Silvia et al. (2016) that applied LP on Output Unit Price Cobb-Douglass Profit Function to maximize profits with limited resources available in smallholder palm oil farm in Aceh province Indonesia. The resources include the availability of plantation area although they had excluded the importance of incorporating old plantation area as one of the constraint.

Apart of maximizing profit, LP also has been used for minimizing total cost associated with transportation in palm oil industry. As an example, Nwauwa (2012) found an optimal transportation scheme that can satisfy regional demands in Nigeria while minimizing total cost of transportation. The author states the usefulness of LP for analysing economics related problem in palm oil industry. Further, in 2016 the author complement their method with Ravallion model and spatial equilibrium model for finding the market integration of palm oil market and determine values for price, quantities and trade flows between spatially separated regions and markets in Nigeria (Nwauwa, Adenegan, Rahji, & Awoyemi, 2016a; Nwauwa, Adenegan, Rahji, & Olaniyi, 2016b). In another study, Suksaard and Raweewan (2013b) uses LP to find optimal land allocation for plantation in each region and to specify distribution route moving FFB to mills. The objective of the model in this study is to minimize cost of management in CPO and crude palm kernel production.

Based on the review made, it is found that one of the major limitation of LP is that the assumption of linearity among variables in the problem domain. Real world application however prove that most of the time the relationship involves non-linear and stochastic elements.

2.4.2 Non-linear Programming

To cater the nonlinearity problem, nonlinear programming (NLP) was introduced in 1951 by Kuhn and Tucker (1951). Unlike LP, NLP is the process of solving an optimization problem where some of the constraints or objective function are nonlinear (Bertsekas, 1999). In the palm oil study, not many research has been found adopting NLP. For instance, Banitalebi et al. (2016) employed NLP to minimize the total operational cost in palm oil plantation management. In this study, the author has considered two state variables as the density of the young palm oil trees and the part of biomass that can produce oil. Furthermore, the author has also demonstrated a numerical simulations with two situation where optimal control being applied and not being applied. The application of NLP is technically appropriate due to the presence of nonlinearity element of the mathematical model. However, one of the challenges in dealing with nonlinear problems even with the used of NLP is the high probability of getting stuck in local optimum (Chinneck, 2006).

2.4.3 Stochastic Programming

Stochastic programming (SP) is a method of solving optimization problem involving uncertainties. SP is the extension of LP and NLP to decision models where coefficients (parameters) are not known with certainty and have been given a probabilistic representation. In limited palm oil research adopting SP, Azadeh, et al. (2014) applied SP to optimize tactical decision in the biofuel supply chain network. In this study, biofuel demand and price are the main sources of uncertainties that affect the operations of the biofuel supply chain and modeled using scenario-based approach. In addition, Geometric Brownian motion was used for dependent price formulation.

As SP is the extension of LP and NLP with probabilistic representation, the common problem with local optima in nonlinear problem is expected with the adoption of SP (Hannah, 2015).

2.4.4 Dynamic Programming

Dynamic programming (DP) was first introduced by Richard Ernest Bellman in 1953. The main attribute of DP is that it divides a problem into a number of sub-problems where a stage wise solutions starts with the smallest sub-problem (Bhowmik, 2010). For instance, in finding optimal replanting policy that has minimum carbon dioxide emission, Diban et al. (2016) employed DP over a finite time horizon for commercial agriculture plantations in Malaysia. The advantages of using DP is that it consider all possibilities in reaching optimal value including non-economical solution of replanting the trees at early ages. However, in this study some modification are required for DP in order to exclude unfavourable alternatives. Bhowmik (2010) highlight that among limitation of DP is that it is only highly effective on object which are linearly ordered and cannot be rearranged such as characters in string. Furthermore, it is difficult to write code that evaluates sub-problems in the most efficient order (Wagner, 1995).

2.4.5 Metaheuristics

Metaheuristics is a technique applied to find the best-so-far solution in a feasible region. To the best of our knowledge, only one research has been found applying metaheuristic method for finding optimal solution in palm oil studies. Study by Utama, Djatna, Hambali, Marimin, and Kusdiana (2012) had used Ant Colony Optimization (ACO) to search the most optimum path of palm oil based bioenergy supply chain. In this research, ACO has been improved for the usage in multi objectives supply path problem. However, one of the limitation of ACO is that the convergence time is uncertain which makes the use of ACO is experimental and non-practical (Selvi & Umarani, 2010).

2.4.6 Summary of Optimal Solution Search Method in Palm Oil Domain

The whole range of techniques used in palm oil industry domain is listed in Table 2.3. To conclude, optimization technique reviewed in this section has been widely employed for both operation and supply chain level analysis. However, no studies has been found using optimization technique for broad-economic level analysis. Furthermore, most of the optimization study has utilized traditional mathematical optimization method. The major limitation of the traditional optimization method employed is that its effectiveness in static and non-dynamic environment only. Further, as the dimension of the problem increase (complexity arise), the search for optimal solution can be drifted beyond infinite time and becomes impractical in terms of process time. This is true for a non-deterministic polynomial (NP) problem. On that account, an alternative method like metaheuristics offers the capability to find nearly optimal solution in reasonable time frame by streamlining certain process and executing search effort from predefined feasible area. Although the use of metaheuristics are increasingly prevalence in other problem domain, only limited study has been found adopting the method in palm oil industry domain. Next section is a review of several metaheuristic methods which are effective for optimal solution search on palm oil problem domain.

Table 2.3

The Review of Optimization Technique in Palm Oil Related Studies

Type of optimization method	**Analysis level**	**Reference**
Linear programming	Operation	Tan & Fong (1988); Murugan et al. (2013);
	Supply chain	Nwawe et al. (2008); Nwauwa (2012); Suksaard & Raweewan (2013a); Suksaard & Raweewan (2013b); Valizadeh et al. (2014); Nwauwa et al. (2016a); Nwauwa et al. (2016b); Silvia et al. (2016)
	Broad-economic	-
Non-linear programming	Operation	-
	Supply chain	Banitalebi et al. (2016)
	Broad-economic	-
Stochastic programming	Operation	-
	Supply chain	Azadeh et al. (2014)
	Broad-economic	-
Dynamic programming	Operation	-
	Supply chain	Diban et al. (2016)
	Broad-economic	-
Metaheuristics	Operation	-
	Supply chain	Utama et al. (2012)
	Broad-economic	-

2.5 Potential Metaheuristics Methods to Solve Palm Oil Optimal problem

Metaheuristics is a higher level procedure designed to find heuristics that may provide sufficiently good solution to optimization problem (Bianchi, Dorigo, Gambardella, & Gutjahr, 2009). In combinatorial optimization, metaheuristics can often find good solutions with less computational effort by searching over large set of feasible solutions compared to other optimization method. According to Blum & Roli (2003), most metaheuristics shared the similar attributes such as:

1. A form of strategies to guide search process;

2. Objective to efficiently explore the search space in order to find near-optimal solutions;

3. Metaheuristics are approximate method and usually non-deterministic; and

4. Metaheuristics are not problem-specific.

Unfortunately, limited studies have been found applying metaheuristic method in palm oil industry domain. There is a plethora of metaheuristics methods available in the literature. However, this research only focuses on the attributes of three metaheuristics method namely Tabu Search (SA), Simulated Annealing (SA) and Genetic Algorithm (GA), and their limitations. This is towards consideration of suitable metaheuristics method to be applied in this research.

2.5.1 Tabu Search

Tabu search (TS) was introduced by Fred W. Glover in 1989, employing local search methods used for mathematical optimization (Glover, 1989, 1990a). The name Tabu is originated from the word Taboo means something that is non-usual. Conceptually, in TS process the previously visited search spaces are marked as 'tabu' and the search process is forbid to re-visit this space due to the presence of local optima solution (Mayer, 1998). Thus, the search process eventually is expected to obtain a global optimal solution. TS recorded the visited search space in what is called ‘tabu list’. One of the most important controlled element in TS is thus the length and method of maintaining the tabu list (Glover, 1990b). There is an improved TS which employed a number of advanced strategies for dynamically managing the tabu list called the reactive tabu search strategy (Battiti & Tecchiolli, 1994).

TS can be viewed as an iterative technique which explores a set of problem solutions, *X*, by repeatedly making moves from one solution *s* to another solution *s’* located in the neighbourhood *N(s,k)* of s with k as the number of iteration (Glover, 1993). The tabu list is memorized in *N(s,k).* These moves are performed with the aim of efficiently reaching a solution that qualifies as good by the evaluation of some objective function *f(s)* to be minimized. The generic algorithm for TS is shown in Figure 2.1.

```
Set of problem solutions = X
Solution = s
Solution in neighbourhood = s’
Iteration = k
Neighbourhood of s with k = N(s,k)
Sample of solutions = V*

(a) Choose an initial solution s in X
    s*:= s and k:= 1

(b) While the stopping condition is not met do
    k := k + 1
    Generate V*⊆N(s,k)
    Choose the best s’ in V*
    s:= s’
    if f(s’)< f(s*), then s*:= s’
    end while

Stop when an optimal solution is found.
```

Figure 2.1. The generic algorithm for Tabu Search (adapted from Glover, 1993)

Though TS has been employed in various problem domain, researchers has argued of its effectiveness in a larger application (Mayer, 1998). One of the major limitation is the difficulty of Tabu search to maintain an adequate length of the memorised tabu list (Glover, 1990b). Larger list are needed to prevent the process from cycling back to sub-optimal solutions (Glover, Taillard, & Werra, 1993).

2.5.2 Simulated Annealing

Simulated Annealing (SA) is a heuristic method based on the cooling process in metallurgy developed to solve deterministic combinatorial optimization problems (Kirkpatrick et al., 1983). SA was first formulated by Khachaturyan, Semenovskaya, and Vainshtein (1979) using computer simulation to mimic annealing and cooling of such a system to find its global minimum. SA search process involves a slow and thorough search in order to find the global optimum solutions, albeit there is no guarantee that global optimum solutions will be obtained (Ingber, 1993). In SA, the challenging part is to control the rate of cooling, where fast cooling rate prevent the convergence to global optimal solutions whilst slow cooling rate consume longer time. SA has been widely used in various problem domain including groundwater management (Kuo, Michel, & Gray, 1992), forestry (Lockwood & Moore, 1993), and dairy farming (Mayer, Belward, Burrage, & Stuart, 1995).

The generic SA algorithm is shown in Figure 2.2. The basic SA algorithm is known as Boltzman annealing (Du & Swamy, 2016). T is a control parameter which controls the magnitude of the perturbations of the energy function E(x). The cooling schedule for T is critical for efficiency in SA procedure. At high T, the system ignores small changes in the energy and approaches thermal equilibrium rapidly, that is, it performs a coarse search of the space of global states and finds a good minimum (Du & Swamy, 2016).

As T is lowered, the system responds to small changes in the energy, and performs a fine search in the neighbourhood of the already determined minimum and finds a better minimum (Du & Swamy, 2016).

```
(a) Initialize the system configuration.
    Randomize x(0).
(b) Initialize T with a large value.
(c) Repeat:
    a. Repeat:
       i. Apply random perturbations to the state
          x = x + Δx
       ii.Evaluate ΔE(x) = E(x + Δx) - E(x):
          if ΔE(x) < 0, keep the new state;
          otherwise, accept the new state with
          probability P = e^(- ΔE/T)
       until the number of accepted transitions is below
       a threshold level.
    b. Set T = T - ΔT.

    until T is small enough.
```

Figure 2.2. Generic algorithm for Simulated Annealing (adapted from Du & Swamy, 2016)

Even though SA is effective search method in certain problem domain, it mainly has been criticised on its slow process particularly in order to find satisfied global optimum solutions. To overcome this issue, Ingber (1993) demonstrate a modified SA called Simulated Quenching (SQ) which at least in some cases can perform faster than SA with at par accuracy.

2.5.3 Genetic Algorithm

In evolutionary computation (EC) field, optimization problem is often solved using heuristic approach. A heuristic optimization is also known as an approximation method due to the concept of randomness in order to search for the optimal solution (Das, Abraham, & Konar, 2009). One of the popular heuristics approach in EC field is

Evolutionary Algorithm (EA) which falls under the population-based evolutionary computing techniques from the big heuristics method family. EA consist of GA, Evolutionary Programming, Evolution Strategy, Genetic Programming and hybrid of any of EAs technique. Among all EA method, GA is the most commonly used due to its successful achievement when applied to the real world problems (McCall, 2005). GA were first introduced by John Holland in 1975 and was then being further developed by David Goldberg (Goldberg, 1989; Mitchell, 1996).

GA basically depicts the biological evolution process, in which the individual in GA processed undergoing reproduction is named as chromosomes. Each basic unit of a chromosome is named a gene. A chromosomes can be defined as a vector or string where each of its component is a possible form a possible set of values as shown in Figure 2.3. The gene value in a particular chromosome is called as allele. The allele can be in the form of binary coded, real (decimal) coded or string.

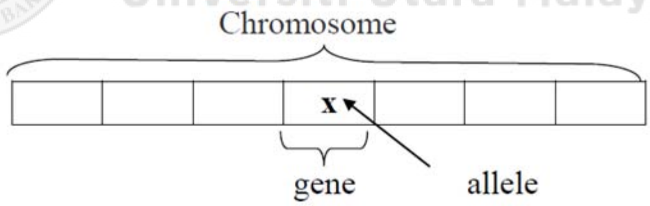

Figure 2.3. Gene in a chromosome

A group of this vectors combined make up the population. Number of population (denoted as N) is generated as an initial population for the GA operation. Small population size may decrease the effectiveness of exploring the search space, whereas population that is too large may substantially increase the time to obtain good solutions. There was research that relates the population size to the string length (Reeves & Rowe, 2003). However in many cases, the population size of 50 is sufficient as suggested by

Reeves and Rowe (2003). A pseudo-code for a common version of the algorithm is as shown in Figure 2.4 below.

```
choose initial population
evaluate each individual's fitness
repeat
Scale every individual according to their fitness
        select individuals based on their scaled fitness values
        mate pairs at random
                 apply crossover operator with a certain probability
                 apply mutation operator with a certain probability
         evaluate each individual's fitness
until terminating condition (e.g. until at least one individual has
          the desired fitness or enough generations have passed)
```

Figure 2.4. Genetic algorithm pseudo-code (Source: Rahman, 2014)

Each of the steps as implied by the pseudo-code can be done with different operators, functions, or values. There are many elements in GA that provide flexibility in coming up with an appropriate algorithm for the search space, which makes GA more complicated compare to neighbourhood search method. The general GA process is shown in Figure 2.5.

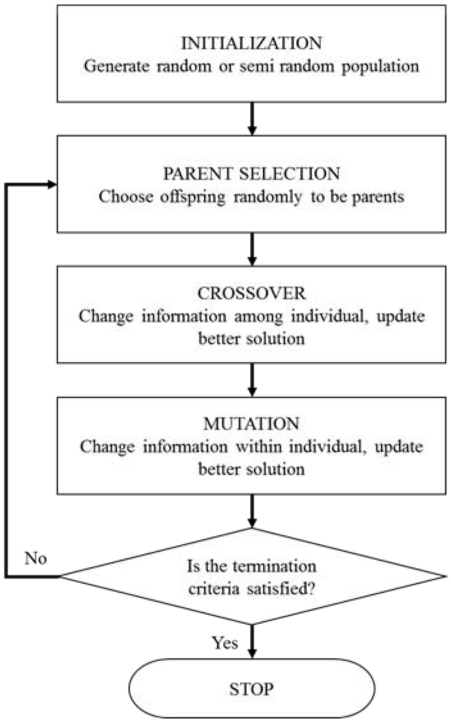

Figure 2.5. The generic structure of genetic algorithm (Source: Rahman, 2014)

GA function by reproducing the population to gain a better chromosomes. A common GA that produces good results in many practical problems is composed of three operators namely selection, crossover and mutation (Goldberg, 1989).

Selection operators: Selection plays a very important role in GA process. The widely used method of selection is roulette-wheel where individuals are given a part of the wheel proportional to their probabilities obtained by scaling. Then, the wheel is spun n times where n denotes the number of individuals or parents needed for reproduction. The fittest individual will have higher probability to be chosen. More effective way to choose individuals from the wheels is to create one random number and the increment of equal size (1/n) is continued. Another method of selection is tournament, where τ chromosomes are selected randomly and the fittest is chosen among the τ. This procedure will be repeated n times. Sometimes there will be variations of this tournament where the best string does not always win but wins with a chance of $p < 1$. These are called soft tournaments whereas the former type is called strict tournament (Reeves & Rowe, 2003).

Crossover operator: Process of combination or 'mating' is the next process to produce an offspring in GA process and is called crossover. The most basic crossover type is single point crossover as shown in Figure 2.6. In the chromosomes, the position of gene that will undergo crossover is fixed or determined randomly. Then, the new offspring are created by swapping all genes after that point (Booker et al., 2000).

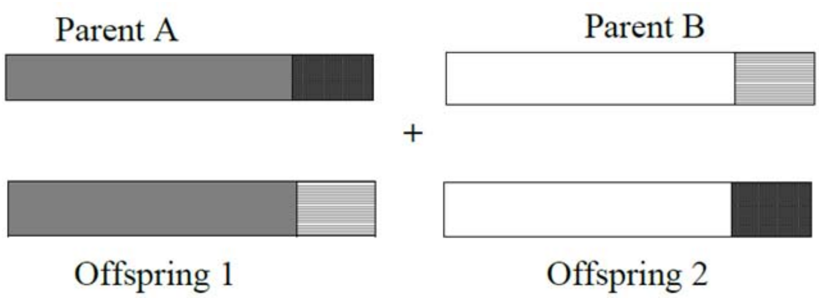

Figure 2.6. Example of single point crossover

Another type of crossover is multipoint crossover which is the extension of the single point crossover. In this crossover type, two or more points are randomly chosen from two parents and swapping the corresponding segments as illustrated in Figure 2.7. However, multi-point crossover is not suitable for problems with short structure as the population may become homogenous after many generations (Spears & De Jong, 1990).

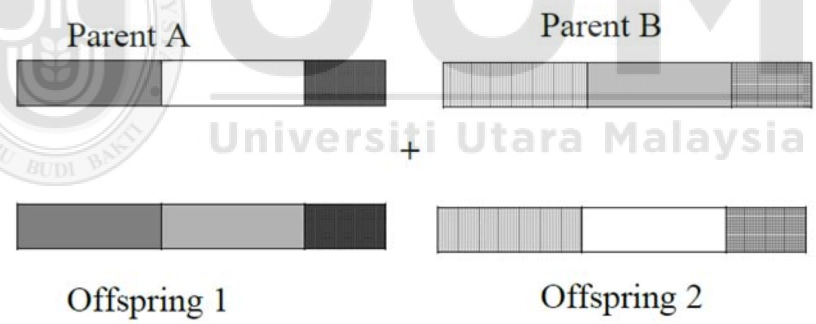

Figure 2.7. Example of multi-point crossover

Mutation operator: Mutation is also a process where the gene in a chromosome is changed or altered. But unlike crossover, the mutation operator is simply changing the value of gene randomly in one chosen chromosome. Mutation process prevents the population from becoming too identical each other to avoid local minima in the evolution process (Eshelman, 2000). There are two widely used type of mutations which are Uniform Mutation (Michalewicz, 1994) and Power Mutation (Deep &

Thakur, 2007). Uniform mutation replace gene with a random value between the constraints' lower and upper bounds. On the other hand, power mutation is the enhancement of uniform mutation that is controlled by its index, where a small index value produces less perturbance in the solution whilst large index values achieve large diversity (Rahman, 2014).

In GA process, the crossover and mutation can both or either one being applied (Reeves & Rowe, 2003). The selection of probabilities of implementing crossover and mutation is a strategy in the GA process. In this case, both crossover and mutation can be applied to obtain offspring for next generation, or neither of them is used where parent's gene is copied to become the offspring of next generation without any alteration. Strategy to apply either of them could be chosen where at least one of the two is applied. This would mean a certain part of the population is created by using crossover and the rest using mutation (Reeves & Rowe, 2003).

Elitism: To retain the high quality chromosome, elitism concept is featured, where the fittest chromosome is forwarded to next generation without undergoing crossover and mutation process. In GA process, reproduction of population may result to the next generation contain or not contain the best individual from the previous generation. Losing the best individual cannot be tolerate in the works of optimization. Thus, to deter this problem, born the idea of elites (De Jong, 1975). Elites or elitism, is the concept where the best individuals from previous population are allowed to pass on to the next generation to avoid losing best solution (López-Pujalte, Bote, & Anegon, 2002; Sharief, Eldho, & Rastogi, 2008). Elitism helps in obtaining near optimal solution by avoiding unnecessary gene modification (through crossover and mutation) which 'kill' the fittest chromosome during mid-optimization process.

A complex problem in real world often involve dynamic elements thus in this case the algorithm in GA is manipulated to expand its ability in dynamic environment (Branke, 1999). Basically, there are several GA-based optimization method designed to solve dynamic optimization (DO) problem in EC fields (Branke, 1999). There are method like hypermutation (Cobb, 1990), variable local search (Vavak, Jukes, & Fogarty, 1997), thermodynamical GA (Mori, Kita, & Nishikawa, 1996), multinational evolutionary algorithm (Ursem, 1999), forking GA (Tsutsui, Fujimoto, & Ghosh, 1997) and shifting balance GA (Oppacher & Wineberg, 1999). These variance method of GA were designed to deal with DO problems by exploiting the search population or instilling the memory in the search population.

In general, solving a DO problem in evolutionary computation field using GA requires the modification of its algorithm to cater the need of the dynamic environment. Compare to hybrid method, altering the algorithm in GA is much more difficult and it requires profound programming skill.

2.5.4 Comparison of Tabu Search, Simulated Annealing and Genetic Algorithm

As all the aforementioned metaheuristic methods have their distinctive traits, researchers had been comparing the effectiveness of TS, SA, and GA in solving a combinatorial optimization problem. For instance, Mayer compared the performance of SA and GA in a complex dairy farms problem (Mayer et al., 1995). The authors had concluded that SA is more reliable method for optimising simulation models especially via its more efficient modification of QS but with critical control of the temperature decline rate. GA on the other hand had shown a good rate of convergence but not as effective as SA in terms of final solutions. However, the authors argued that GA may overcome SA in higher dimensional problems because SA may be facing inefficiencies issues in terms of having the right cooling schedule to produce optimum solution.

In further research, Mayer, Belward, & Burrage (1998) had used the same dairy farm model to include TS in the previous comparison test between SA and GA. The results found TS may be effective for discrete allocation-type problems but not as effective for optimizing models with continuous variables and higher dimensionality. The authors conclude that in a typical agricultural models, both SA and GA appear to be efficient and effective in identifying the global optimal solutions as compared to TS.

There is also an attempt to integrate the main features of TS, SA and GA as being done by Thamilselvan and Balasubramanie (2012). Based mainly on GA, TS method is used to generate new members in GA population while SA helps in accelerating the convergence by GA. The integrated method was applied to the job shop scheduling problem and has been found to increase the speed of the convergence of the optimal solutions. The effectiveness of the integrated method however has not being tested in highly complex problem such as agricultural system.

2.5.5 Summary of the Potential Metaheuristics Method

Nevertheless, individually TS is not suitable to solve high dimension optimization problem as compared to SA and GA. The integration of the three methods may also be possible to increase the effectiveness of the method in solving optimization problem but the effectiveness has not being tested in typical agricultural system. Direct comparison between SA and GA in agricultural system has also been tested and generally both method are effective at least at some extent to be used in high dimension optimization problem like in palm oil industry. However, as highlighted in the previous studies, GA may perform better than SA in highly complex model. Furthermore, as compared to GA, obtaining sufficiently good solution using SA is more difficult because the need of having right scheduling of T, or else there will be inefficiency issues in term of acceptable length of time versus good enough solution (Mayer et al., 1995). On that account, GA has been deemed to be more suitable to be hybrid with SD in achieving the research objective in this study.

In next section we explore the integration of SD and optimization method done in previous researches. This is followed by the review of the research development on SD and GA integration throughout the time gathered from past researches.

2.6 System Dynamics and Optimization

Generally, improvement of the system behaviour is the paramount goal need to be achieved in any of SD study. SD has been striving to be effective on the use of optimization tools even though it provide efficiency and improvements during the model building and policy design process. With the growing of quantitative data and trend towards the aspiration for quantified results, abundant use of optimization tools in SD methodology is inevitable (Graham & Ariza, 2003). Figure 2.8 illustrate the time line of SD and optimization works for the past 40 years.

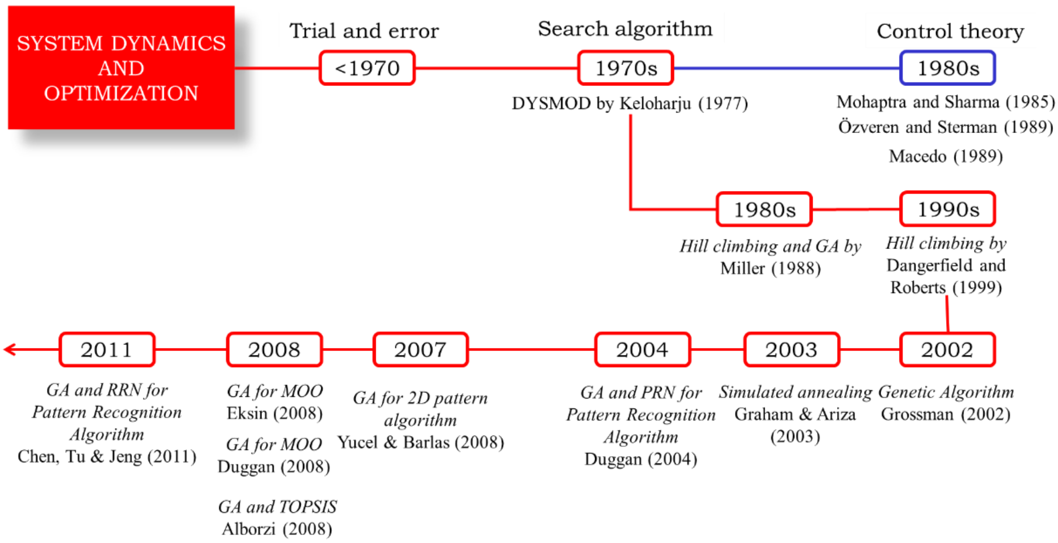

Figure 2.8. Time line of system dynamics and optimization works

Initially, traditional approach of trial-and-error was used for policy design process, the informal process where the modeller applies parametric or structural changes to the model on a trial-and-error basis (Coyle, 1977). However, intuitive ability of modeller to produce an acceptable policy options bound the traditional approach. Hence, more analytic and structured approach to replace the traditional trial-and-error approach should be developed (Porter, 1969).

2.6.1 System Dynamics with Search Methods

Structured approach of policy design process in SD has utilized two main optimization tools from control theory (optimal control) and search algorithms. In the early edition of "System Dynamics Review" journal, there has been a lot of interest to apply control theory methods to policy design process. The used of control theory in SD was mainly due to the reason to understand and to provide policies that manage the system according to certain goal. Some of the pioneer studies of modal control theory method in SD are done by Mohapatra and Sharma (1985) and Özveren and Sterman (1989).

There was also combination of optimal control and modal control method as proposed by Macedo (1989). However, these methods were criticized because they were difficult to be employed and the modeler should have a good mathematical background.

The incompatibility of control theory and SD can be explained from the type of problem that they are focused in. In SD, model development is very critical and it creates a critical thinking environment based on the feedback received from the other variables in the model. In comparison, control theory basically assumes model as black box or set of dynamic equations that creates outputs based on given inputs. As such, unlike control theory, SD offers more flexibility for policy design process. Furthermore, SD has the ability to deal with uncertain behaviour because the model parameters and structures can be changed according to the modeling purpose. There were few studies like Wolstenholme (1986) and Yasarcan (2003) that proposed a generic structural changes leveraging the flexibility in SD method.

There is also other wing of optimization in SD by using heuristic proposed by past studies. Pioneer of this method, Keloharju (1977) used heuristic to optimize parameter values according to a certain objective function and has introduced the optimization package called Dynamic System Model Optimizer and Developer (DYSMOD). As stated by Keloharju, the optimization process should be seen as simulation through repeated optimization instead of optimization via repeated simulation. Then, he combined control theory rules of thumb with Keloharju’s method (Coyle, 1985). Other researchers have followed in employing simulation-based algorithmic search. For instance, Wolstenholem and Al-Alusi (1987) has used DYSMOD package in an army defence model to optimize the army strategy. Furthermore, Dangerfield and Roberts (1999) has used hill-climbing method to fit model to AIDS data to obtain the distribution incubation period. Graham and Ariza (2003) on the other hand used SA to present the application of policy design by parameter optimization.

SD optimization has evolved from the traditional trial-and-error practice to the more structured optimization with the application of control theory and search algorithm like heuristics method. Due to the complexity and non-compatibility of control theory with SD, heuristic method is deemed to more suitable to complement SD for optimization purpose. This is due to its flexibility and compatibility of heuristic method to be used as third-party method.

2.6.2 System Dynamics Integration with Genetic Algorithm

GA has been potentially an effective algorithm for highly non-linear solution spaces due to its ability of avoiding being trapped in local optima. Thus, various studies has been found in literature experimenting the possible integration between SD and GA. Grossman (2002) employed GA optimization in SD on the Information Society Integrated System (ISIS) model for policy optimization purpose. Interestingly, the author used the matrix tool to compare the distance of optimized parameters between several objective functions to facilitate the process of choosing the best policy. There are five distinct objective functions which are aimed to be optimized individually. Then, the correlation among objective functions were calculated to find the best combination of policy variables in order to equally satisfy all objectives function. These study demonstrate the use of hybrid SD-GA model to solve multi-objective optimization problem. However, the process was complicated in terms of SD and GA integration. That is, SD model which was developed using Stella has to be converted into C++ programming code before integrating with GA. These hectic process will be a major hindrance for highly complex SD model with countless variables and feedback loops.

Similar with Grossman, Duggan (2008) introduce Multiple Objective Optimization (MOO) framework which employed SD and GA that is promising in solving multiple objective function in two agent beer game model. In this study, there are two objective functions which are to minimize retailer cost and wholesaler cost. The author used the 'dominate and non-dominate' concept to obtain the best solution among two conflicting objective function. He also expressed the importance of human intervention or known as 'higher order information' approach in the final stage of decision making process. Although the use of SD-GA is effective, the change in policy variables were only done at the beginning of the simulation where optimal parameter was searched and fixed in the model to be used for the rest of the simulation. In certain problem domain like palm oil industry for instance, the policy variables may be needed to be changed in specific point in the model time line.

Similarly, Alborzi (2008) employed SD and GA integration with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranking system to solve the multiple objective function in production and inventory model. The optimization process starts with GA generating all the possible solution and TOPSIS helps in ranking the solution. Then, the best ranked solutions were used in SD model for simulation. The integration of SD and GA in this study however was difficult as the model need to be run manually for each chromosomes produced by GA. The limitation of this study is similar as in previous studies, where the changes of policies were fixed into the model at the beginning of the simulation.

In another study, Eksin (2008) had used SD and GA to meet multiple goals in the behaviour of dynamic parameters. The author demonstrated the hybrid model on electric circuit model and the generic stock management model. In each of the problem, the multiple objective functions were set by using different weight. This study emphasize the important role of time horizon for a simulation based optimization. However, the limitation of this study is similar with previous studies, where the change of policy variables were fixed into the model at the beginning of the simulation.

On the other hand, study by Chen and Jeng (2004) transformed SD model into a specially designed neural network. Next, they used GA to generate policies by fitting the desired system behaviour to patterns established in the neural network. The author claim that this approach is flexible where it is capable of finding policies for a variety of behaviour patterns including stable trajectories. However the modeler have to convert SD to partial recurrent network (PRN) before integrating the model with GA, which may become difficult when the SD model increase in complexity . This approach has been further explored by Yucel and Barlas (2007) which also introduce a pattern recognition algorithm together with SD and GA in the pattern-based system optimization. However, the pattern recognition algorithm are lacking of numeric features of the desired pattern in the objective function in the search algorithm. Instead, this approach only focus on pattern seeking rather than numerical values where some policies may require a numerical-oriented policy target and changes.

Finally, instead of using PRN, Chen, Tu, and Jeng (2011) extended their study by using recurrent neural network (RNN) to be integrated with SD and GA. Contrary with PRN, RNN has state units added to the input layer and are connected by the outputs units directly. RNN is closely equivalent to a traditional stock and flow diagram in SD. Nevertheless, there is still the need of converting SD model to RNN model.

The key studies related to the experimentation of integration between SD and GA published in journals and conference proceedings is summarized in Table 2.4 below.

Table 2.4

Published Literature on the Integration of System Dynamics and Genetic Algorithm

Reference	Type of model	Description	Main limitations
Grossman (2002)	System dynamics and genetic algorithm	Demonstrate the use of genetic algorithm with system dynamics models.	The process of transforming STELLA models to C++ code is hard and tedious. Need an expert in programming.
Chen & Jeng (2004)	System dynamics and genetic algorithm with partial recurrent network	Proposes a policy design method for system dynamics based on neural network and genetic algorithm approaches.	The SD model has to be converted to neural network model before integrating with genetic algorithm.
Yucel & Barlas (2007)	System dynamics and genetic algorithm with 2D pattern algorithm	Develop support tool that can be used for pattern-based parameter search, which may be utilized in model identification, validation and policy analysis stages.	Lack of numeric features of the desired pattern in the objective function of the search algorithm. Only focus on pattern seeking rather than numerical values.
Eksin (2008)	System dynamics and genetic algorithm	Demonstrate the use of parameter search to meet multiple goals in the behaviour of dynamic system.	The search for optimal policy variables were meant to be fixed in the model in the beginning of the simulation.
Duggan (2008)	System dynamics and genetic algorithm	Propose the synthesis of two analytical approaches to support decision making in complex systems.	The search for optimal policy variables were meant to be fixed in the model in the beginning of the simulation.
Alborzi (2008)	System dynamics and genetic algorithm with TOPSIS	Propose the integration of system dynamics and genetic algorithm with the help of multi criteria objective function evaluator.	The integration of system dynamics and genetic algorithm is difficult, where some process has to be done manually
Chen, Tu, & Jeng (2011)	System dynamics and genetic algorithm with neural network.	Propose a policy design method for SD models based on recurrent neural networks.	The SD model has to be converted to recurrent neural network model before integrating with genetic algorithm

The integration between SD and GA shows a huge potential to be used in decision making process. Hence, there are several studies found employing the hybrid model of SD and GA in a real case from various problem domains.

Satsangi, Mishra, Gaur, Singh, & Jain (2003) had developed a SD model to analyse dynamics of system behaviour in urban management model. This study trained ANN with SD model for fast feature extraction of the dynamics of the integrated urban model. Then, GA was used to optimise simulation trajectories for alternative policy scenario of input variables. The author conclude that the hybrid model of SD and GA has been effective in providing quick response in solving the city problem in a dynamic integrated urban system.

Pereira and Saraiva (2011) had used hybrid model of SD and GA with two module to solve the generation expansion planning problem in electrical sector. The first module uses SD to capture the electricity demand and market price of the different generation technologies while the second module used GA to solve the individual investment problem for each generation. In the optimization process, first the information regarding the behaviour of electricity prices and demand were captured using SD. Then, GA used this information to produce the individual expansion plans for each generation agents. These become the input for simulating SD model again to update the evolution of price, demand and the capacity factors. The author conclude the hybrid model has been a great help in assisting the investment plans due to its capability in getting more insight on the problem and taking more robust solutions.

Akopov (2012) on the other hand integrate SD and GA in order to obtain solution that can maximize shareholder value in an oil company. This study uses GA optimization algorithm with fading selection due to the complex procedures in the problem is stipulated by non-linear dependence which is classed as NP-complete problems of high dimensionality. The author claimed that the proposed SD-GA model has helped in providing an efficient search procedure of suboptimal investment decisions as compared to the traditional economic model.

In another study, Yu and Wei (2012) proposed a hybrid model based on GA and SD for coal production environmental pollution control in China. The used of GA with SD in this study was an attempt by the author to reduce the subjectivity derives from human-sketched lookup function as in previous study using SD in energy problem domain. From the results, it was shown that GA performs well in optimizing the desired parameters of SD model, as well as in simulating the historical data with high degree of accuracy through model calibration. GA has been found to successfully solve the subjectivity of artificial parameters setting and lookup function extensive used in SD modeling.

In another problem domain, Hussein and El-Nasr (2013) applied SD and GA to optimize budget distribution in the quality education assessment model. In this study, the hybrid model was used to give an idea to the quality management planers on the impact of possible policy by optimizing the solution to achieve maximum education quality. SD model was developed to capture the complex relations that effect behaviour of the education quality model while GA helps in finding the best possible budget distribution while be able to provide the best quality of education. In addition, the author highlighted the importance of having robust SD model by involving all the related experts before the process of policy designing using GA optimization to achieve advance level of prediction.

On the other hand, Jahanpour, Afshar, and Alimohammadi (2013) uses SD and GA to solve conjunctive water use problem of a cyclic storage system in Kineh Vars Reservoir in Iran. The objective function of the study was to minimize the present value of costs of the conjunction water management at the reservoir. The author highlight the novel combination of SD methodology (as the simulation module) with GA (as the optimization module) to form a hybrid model. The developed hybrid model is capable of minimizing the total system cost while fulfilling the predefined water demands and satisfying all of the system constraints. The author stated that previous studies using SD in water management domain were limited to running a few simulation scenarios to find a setting of model parameter to achieve a better solutions. By using hybrid SD-GA model, this limitation has been removed by helping SD model to find the optimal solution to solve optimization problem.

Finally, latest study by Skraba, Stanovov, Semenkin, and Kofjac (2016) uses SD and GA to search for appropriate transition strategies in the human resources management model. The structure of the organizational human resource system was developed using SD with GA developed to optimize the larger number of transitions, fluctuations, and recruitment coefficients in the SD model. In this study, the developed hybrid model was able to obtain optimal transition and recruitment coefficients without the undesired oscillations in the transitions between classes and in the shortest possible time. However, one of the challenge highlighted in this study is the possibility to provide two equally good strategies with different control vectors.

Summary of the application of the hybrid model of SD and GA in various problem domains are shown in Table 2.5 below.

Table 2.5

Published Literature on the Application of Hybrid Model of System Dynamics and Genetic Algorithm in Various Field of Studies

Reference	**Problem domain**	**Research objective**
Satsangi et al. (2003)	Urban management	To analyse dynamics of system behaviour in terms of various performance indicators representing city problems.
Pereira & Saraiva (2011)	Electrical sector	To solve the generation expansion planning problem in competitive electricity markets.
Yu & Wei (2012)	Environmental control	Proposes a hybrid model based on GA and SD for coal production–environmental pollution load in China.
Akopov (2012)	Business and investment	To maximize the shareholder value of an oil company
Hussein & El-Nasr (2013)	Education	To optimize the budget distribution in the education quality model.
Jahanpour et al. (2013)	Water management	To solve conjunctive water use problem of a cyclic storage system in a water reservoir.
Skraba et al. (2016)	Human resource management	To search for appropriate transition strategies in the human resources model

2.6.3 Summary of System Dynamics and Genetic Optimization Integration

Past studies that combined SD and GA has become the subject of researches and shows promising outcome in returning the optimal solutions thus make it suitable for decision making process. However, some shortcomings have been spotted from their studies as follows:

1) There is a need of converting the SD model into other programming code like C++ programming or neural network model to integrate the model with GA. This can be complicated and time consuming process especially for huge and complex problem.

2) The combination of SD-GA model were used for searching the optimal policy variables in which will be fixed into the model at the beginning of the simulation. However in a real case, policy maker may want to design a policy which is set to be implemented at specific point of time while achieving the desired target at another specific point of time. To address this issue, optimization model that capable of changing policy variable value at varying point of time while achieving the objective function is required.

There are huge potential of SD and GA integration as the approach capable to solve dynamic optimization problem. This is possible because the dynamic nature of SD modeling when combined with the optimization ability of GA, may produce an effective dynamic optimization tool. However, the published of SD and GA studies reveals some shortcomings. Therefore, new variant of SD and GA integration model has to be further explored that can improve the capability and technical aspect of the methods.

2.7 The Advantages of Integrating SD and GA in this Research Context

This chapter has presented the prevalence used of econometrics and simulation modeling in the studies related to Malaysian palm oil industry. The review of literatures has accentuated the appropriateness of modeling approaches to facilitate the analysis related to the context of their study. However, there are very limited studies that put emphasis on finding optimal solutions to improve the model especially as long term policy option.

In general, the need of capable method to capture the dynamic nature and underlying feedback process among the variables in the model is required in order to achieve our research objectives. Furthermore, the method also has to acquire an effective optimization mechanism which needed to search for appropriate policy option. Hence, based on the review of literature, one of the suitable approach to be applied in this research is the combination of SD and GA optimization approach. Table 2.6 compiled the reason of integrating both methods towards achieving the research objectives.

Table 2.6

The Functionality of System Dynamics and Genetic Algorithm Towards Achieving the Research Objectives

Requirement of research	**Methods**	
	System dynamics	**Genetic algorithm**
Process of identifying and evaluating the factor that influence palm oil industry behavior.	SD model focus on feedback process in the system which covers related variables depending on the model context.	-
Policy design process by looking from the wide perspective of the industry.	SD offers analysis at macro-level.	-
Treat palm oil as the entities which moves around the system network.	SD model a system with homogenous entities (similar at all level).	-
Optimal solution needed in designing policies in complex system.	-	GA optimization return sufficiently good solution and less likely to be stuck in local optima.
Inter-operability between model and optimization tools.	-	GA is compatible for integration with third party method.
Optimal policy search in palm oil industry which is a dynamic complex system.	SD is a dynamic-based modeling method.	GA is a meta-heuristic optimization method.

The need of policy scenario evaluation and experimentation to improve the model.	SD offers a platform to test several scenarios on key variables.	GA optimization helps in optimizing the parameters within given constraints to achieve desired target.

In principle, SD and GA seems to be a mutual-complementary method due to their individual criteria. As compared to econometrics method, SD is notable for incorporating the feedback process in a complex system. Besides, SD is suitable for modeling from macro perspective at strategic level where policy option is assumed to have comprehensive effects on the system behaviour. In addition, unlike ABM and DES where each entity or agent in a model is treat distinctively, SD model a system with homogenous entities as being deemed for palm oil in the industry model.

In addition to the reason put forward above, other reason that makes SD suitable to be adopted in this study is discussed with regards to its capability as follows:

(i) During intervention process, SD provides control on the studied system by maintaining other factors unmodified while modifying one factor, which allow the observation of the effect of the modification on the system (Sterman, 2000). In this study, variety of factors that influenced CPO production are incorporated. By controlling these factors, the policy maker can observe the impact on the whole system before any real world implementation.

(ii) SD model have an advantage in dealing with a system where continuous change occurred over time (Ossimitz & Mrotzek, 2008). In this study, variables like CPO production, demand and prices are changing over time thus its impact on palm oil industry can be effectively captured using SD.

(iii) SD has the ability to represent non-linear relationship between variables using lookup table function. In this study, there are numbers of situations with non-linear relationship and feedback process appears in the palm oil industry model. For instance, the function relating CPO price influence on CPO demand which is better represented with s-shape relationship. Lookup table function is found to be effective in realizing this kind of relationship.

(iv) It is widely accepted that SD offers an approach where it is possible to look at the system as a whole and not isolation. On that account, in this study SD allows the consideration of factors from oil palm plantation, labour and palm-based biodiesel sector in one model.

On the other hand, GA is needed in helping to find sufficiently good solution in the complex palm oil model mainly because the problem itself is a NP-hard problem considering the nature of interdependencies between small sub-systems in the industry. The model consist of many inter-connected variables, where changes in each variable will influence change in other variables. These dynamicity makes finding optimal policy to increase CPO production in palm oil industry as a complex or NP-hard problem.

Furthermore, GA is selected over other aforementioned optimization methods mainly because of its capability in returning sufficiently good solution with less likely to be stuck in local optima. Furthermore, GA is a highly flexible optimization algorithm with compatibility of integration with third party method.

In theory, the integration of SD and GA is seen to be capable of solving a dynamic optimization problem in a complex system like palm oil industry. This is because, SD is a dynamic-based modeling method, whereas GA is a metaheuristic optimization method. Thus the combination of these two methods are expected to complement each other. Moreover, this research involves policy scenario evaluation and experimentation in dynamic environment. While SD offers the platform to evaluate and test policy options, integration with GA will facilitate the process of searching sufficiently good solutions in order to achieve desired policy target.

2.8 Key Papers in Modeling Palm Oil Industry

This section lists a few studies that used SD to model palm oil industry. The differences of each model are discussed to help in explaining the contribution of our research model. The summary of each paper are listed in Table 2.7.

In conclusion, none of the studies have the objective similar with this study. All of the studies focus on CPO prices and biodiesel sector. In terms of modeling scope, our research incorporate more variables in several sub-models combined into a holistic model. The four models (as in Yahaya et al., 2006; Shri Dewi et al., 2010; and Shri Dewi et al., 2015; Mohammadi et al., 2016) on the other hand limit their scope by not incorporating the labour factor. Furthermore, all four models were ended with analysis on the behaviour of the model after policy intervention. In comparison, our research extent the policy designing capability of SD by using embedded GA in order to find optimal policy.

For methodological comparison, the study by Grossman (2002) and Duggan (2008) are referred. The main limitations of these studies are the optimization capability of GA when combining with SD model, where the change applied on the policy variables is done at the beginning of the simulation and were fixed for overall model improvement.

For policy design process that required policy changes and target in varying point of time, these SD-GA model may be a major shortcoming. On the contrary, we propose improved SD-GA model with the capability of setting the objective function and policy variables at specific point of time, for further effective optimal policy search.

Finally, to the best of our knowledge no study in palm oil industry has been found that integrate SD and GA in the Malaysia context. On that account, this study is expected to be the reference for further exploration on the potential of SD and GA in facilitating the policy design process particularly in palm oil industry.

Table 2.7

Key Papers in This Study

Criteria	**Palm Oil Problem Domain**				**Methodological**	
	Yahaya et al. (2006)	**Shri-Dewi et al. (2010)**	**Shri-Dewi et al. (2015)**	**Mohammadi et al. (2016)**	**Grossman (2002)**	**Duggan (2008)**
Objective	To investigate the impact of biodiesel demand on Malaysian palm oil industry.	To simulate the impact of increase in biodiesel demand on this industry.	To investigate the rationality of increasing blending mandates.	To investigate the impact of increasing blending mandates.	Demonstrate the use of genetic algorithm with system dynamics models.	The search for optimal policy variables were meant to be fixed in the model in the beginning of the simulation.
Method	SD	SD and econometrics	SD	SD	SD and GA	SD and GA

2.9 Summary

Palm oil industry is certainly a complex system consisting many interrelated components that regulate the industry behaviour. Issues in palm oil industry required urgent response of improvement as delay in action will result to disastrous consequences on CPO production. The issues include the scarcity of plantation area, labour shortage and the demand surge from palm-based biodiesel industry. Modeling methods like econometrics and simulation model has been empirically proven of its application in facilitating the understanding of a complex system. These methods were also being combined with the other method to achieve the objective setting in solving a complex problem. One of the combinatorial method with huge potential is optimization method which has been widely used in solving static and dynamic optimization problem. Furthermore, optimization has been empirically reported of its potential in assisting SD for finding optimal solution in policy design process. This includes the usage of metaheuristics optimization method like ANN, SA, and GA.

Further exploration on the integration of SD and GA have to be done to overcome the shortcoming found in the past studies. This include the need of having the intermediate platform between SD and GA as found in previous studies employing SD-GA model. The new integration of SD and GA should be able to set the objective function and control variables at specific point of time for effective policy design process. Finally, the GA-based dynamic optimization method offered in EC field required altering of the algorithm which is difficult in order to solve a dynamic optimization problem. Alternatively, a more straightforward method by integrating SD and traditional static GA have the potential to solve the dynamic optimization problem which is prevalent in palm oil industry. Next chapter will elaborate in details about the concept of SD and GA as our research methodology.

CHAPTER THREE
RESEARCH METHODOLOGY

In this chapter, the explanations on the concepts of the methodologies used in this research are presented. It begins with the explanation on the principles of system dynamics (SD) followed by the concept of genetic algorithm (GA). Next, the explanations on research design research process are presented. Then, in-depth explanation of the research process is presented. Finally, summary of the content close this chapter.

3.1 Research Design

The aim of this research is to develop a hybrid of SD-GA model towards improving the CPO production in Malaysia. This research will be conducted through two phases. The first phase is about SD model development whereas the second phase is about the development of hybrid of SD-GA.

Malaysian palm oil industry has been chosen as the domain where the hybrid model is adopted to search for the policy option towards improving CPO production. Primary data were collected from the interview with palm oil industry members and secondary data were collected from review of literature and palm oil statistic reports. Then, the hybrid model of SD-GA is developed with the incorporation of policy variables namely plantation area, labours, and biodiesel demand. Following through, the optimal result of CPO production obtained from the optimization process will be interpreted for policy recommendation. The final stage of the research is to evaluate the model by comparing its results from all optimization in terms of their suitability to be implemented in the real world.

3.2 Research Process

The process for this research is presented in Figure 3.1. This process is adapted and modified based on the four modeling stages presented by Randers (1980).

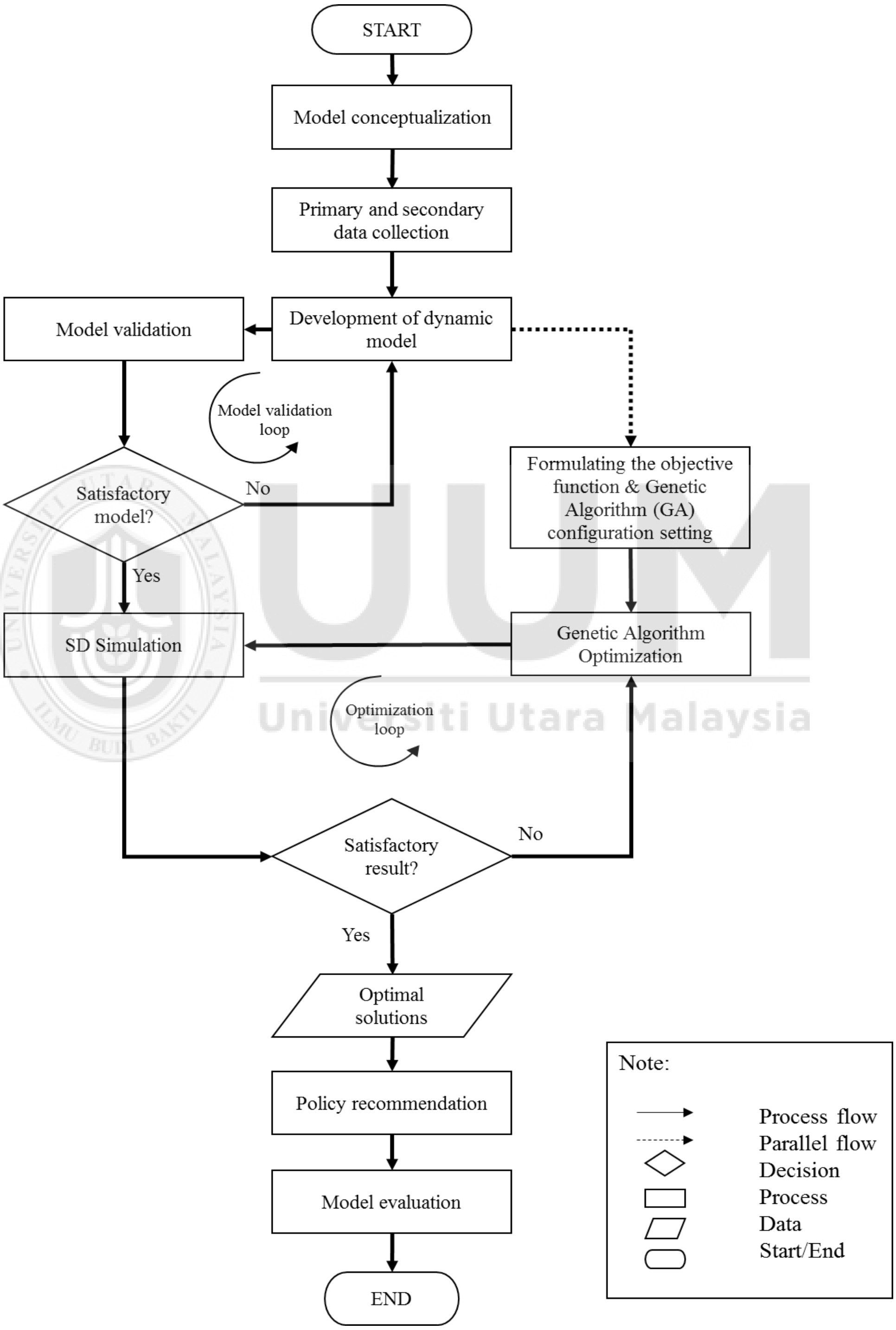

Figure 3.1. Structure of the research

Each stage of the research process was designed to achieve the research objectives as illustrated in Figure 3.2. Generally, the research process is divided into two main phases. The first phase consists of four stages which involves the development of the dynamic model. Following through, second phase consist of four stages, including the GA optimization setup, the hybridization of SD and GA model, policy recommendation, and model evaluation. The figure also highlights the linkage of each phases in achieving the research objectives. The following section focuses on the elaboration of the SD model formulation stages and the development of GA codes.

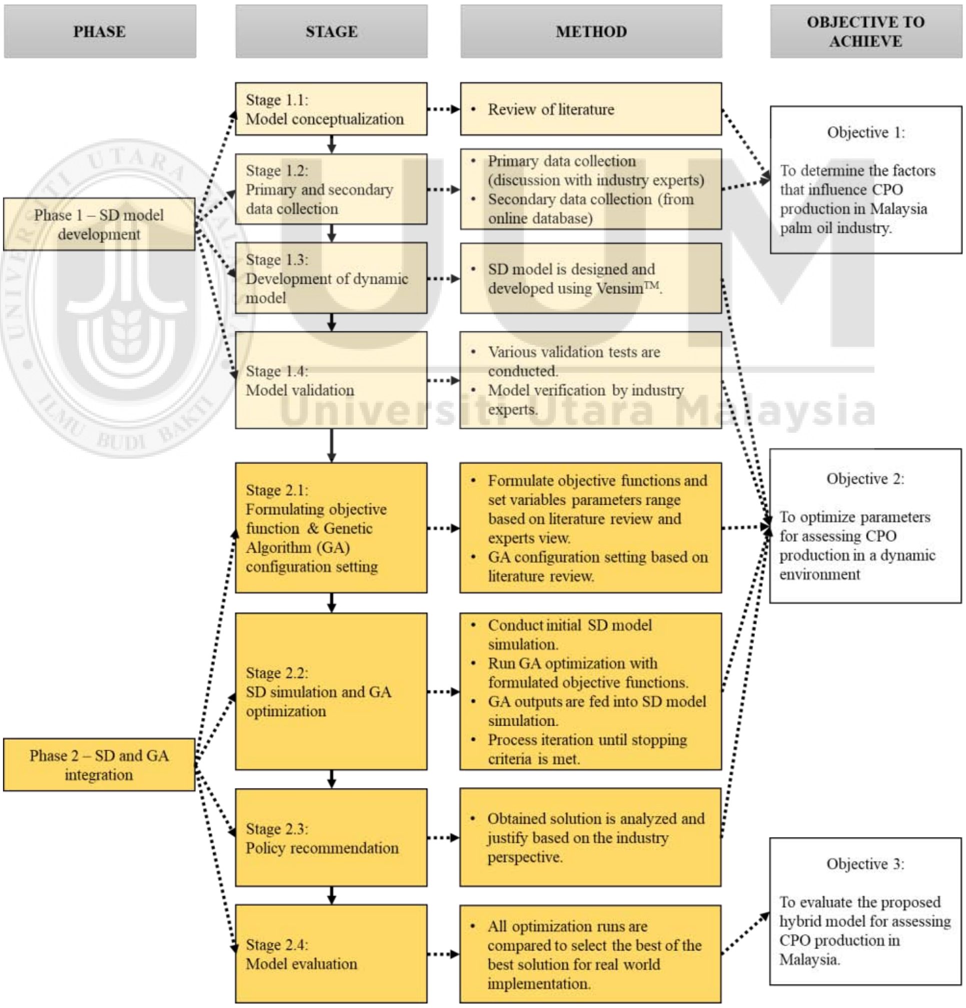

Figure 3.2. Research activities

3.3 System Dynamics Modeling Process

In SD, the modeling process emphasizes on: (i) putting a boundary around the studied system; (ii) identifying feedbacks among different variables of the studied system; and (iii) exploring and analysing the dynamics exhibited by the studied system to various structural and parametric changes. The SD model is developed to achieve the second research objective which is to optimize parameters for assessing CPO production in a dynamic environment. Next, the discussions on the step based on research process in Figure 3.2 are presented in detail.

3.3.1 Model Conceptualization

In SD model development, the process starts with model conceptualization. Model conceptualization is the initial stage where modeler must determine the purpose of the model, the model boundary, the shape of the reference modes and the basics mechanism of the studied system through a casual network or a cognitive map (Albin, 1997; Eden, 1994; Groesser & Schaffernicht, 2012). The four important steps in model conceptualization stage are shown in Figure 3.3.

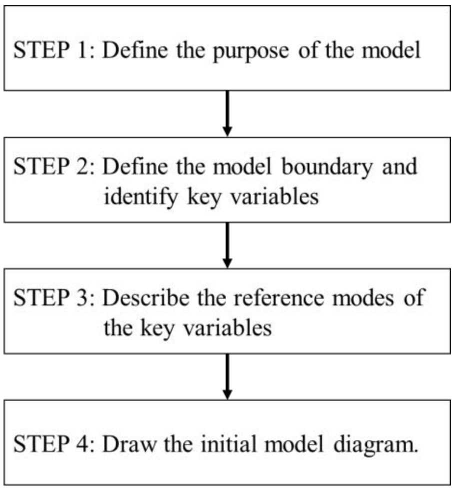

Figure 3.3. Four steps in model conceptualization process

3.3.1.1 Define the purpose of the model

The first step is to focus on the problem in the studied system and stating the purpose of the model. The general objective of this research is to develop a hybrid model of SD and GA towards improving CPO production in Malaysia. To answer the related research questions, specific objectives are developed as described in Chapter 1 Section 1.5.

To summarize, plantation area, labours and biodiesel demand are used as the input whereas CPO production will be measured as the output of the research as illustrated in Figure 3.4. The plantation area, labours, and biodiesel demand were all features as the main factors affecting CPO production, as explained in Chapter 2. As such, these factors were explicitly modeled as a sub-model. Variables in these sub-models will be optimized simultaneously in order to achieve maximum CPO production.

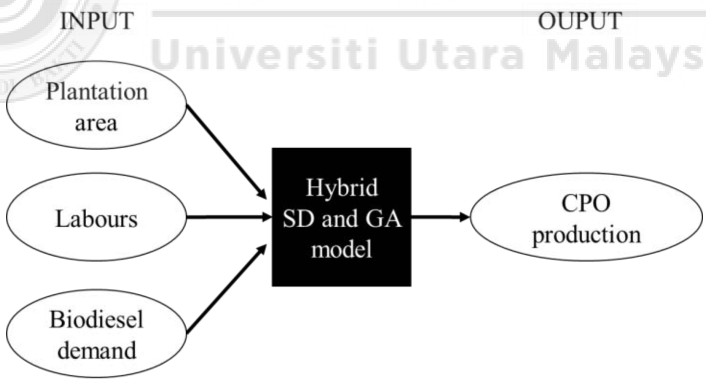

Figure 3.4. The input and output of the research

3.3.1.2 Determination of model boundaries and key variables

Model boundaries can be defined as a closed boundary where the behaviour of interest is generated in a feedback system (Albin, 1997). In creating a SD model, the model boundary has to be clearly defined which include determining all components deem necessary for creating a model. Then, the initial component list has to be generated. The rule of thumb is that nothing excluded from the model is necessary to generate and properly represent the behaviour of interest as set by the model purpose (Forrester, 1980). The variables in a system are categorized based on its type namely endogenous and exogenous. Endogenous variables involve in feedback loops of the system while exogenous variables are components whose values are not directly affected by the system (Morecroft, 2007).

Based on the review of published literature and the Malaysian palm oil statistics annual report, it has led to the initial list of variables categorized by endogenous and exogenous as shown in Table 3.1. CPO stock, CPO price and all the demand are the main components that constitute the supply and demand of palm oil industry. Then, plantation area and labour availability variables are representing the related EPPs under ETP to improve the palm oil industry performance. We also include biodiesel demand in the list to represent the biodiesel sector. On the other hand, exogenous variable which are modeled as constant value or taken from the historical data are functioning to determine the rules function of the endogenous variables. Finally, the initial component list also contains the excluded variable. Note that we decided to include adverse weather effect due to its huge effect on oil palm plantation[4] (Rahman et al., 2012; 2013). However, the incorporation of the adverse weather is done exogenously with pre-set parameter. The reason of such simplistic assumption is that the level of intricacy needed in incorporating meteorological influence will result in a highly complex model. In addition, studying the effect of adverse weather on oil palm plantation is beyond the scope of this research.

[4] Adverse weather include the excessive rainfall caused by La-Niña and dryness caused by El-Niño.

Table 3.1

Initial Component List of Malaysian Palm Oil Industry

Endogenous	**Exogenous**
CPO stock	Oil extraction rate
CPO price	Soybean oil price
CPO local demand	Crude oil price
CPO export demand	Export tax
PPO local demand	Currency rate
PPO export demand	Biodiesel mandate
Plantation area	CPO import
Labours availability	Adverse weather
Biodiesel demand	

There are other possible factors that may influence the industry. However, setting the boundaries of the model is to ensure the modeler is on track subsequently avoiding the overly complex model and futile analysis. As such, the initial components as listed were chosen based on its high relativity in resolving the research question. However, the final SD model may differ as compared to the initial list. The addition and deletion of components may be realized in the later stage of model development. Hence the list acts only as a guideline to facilitate the model development process.

3.3.1.3 Reference mode of the key variables

Reference mode is a graph plot of the key variables in a system over time. This graph helps to capture the mental models and give guidance to appropriate model structure (Albin, 1997; Sterman, 2000). Generally, the common practice is using the historical reference mode. For this research, Figure 3.5 shows the CPO production projection made for Malaysia and Indonesia until 2020. Indonesia CPO production is assumed to retain its growth and achieve the production at approximately 40 million tonne in year

2020. Making this as benchmark, this research will address the question on what, why and how Malaysia can catch up the same CPO production growth pace as Indonesia by year 2020. Depending on the policy option made, there are three possible projections for Malaysia towards year 2020, whether it will be able to expedite its CPO production growth, become stagnant, or decline.

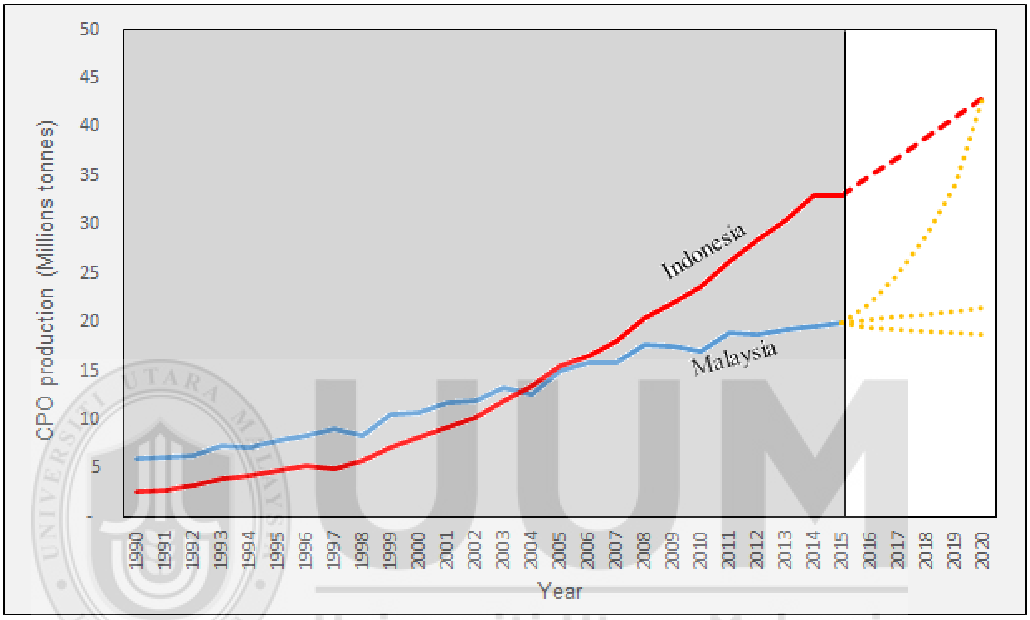

Figure 3.5. Malaysia and Indonesia CPO production projection until 2020

Apart from the determination of reference mode, the selection of an appropriate time horizon is also crucial. In this research, the selected time horizon for the model development is 15 years which is between 2000 until 2015. The availability of data is the main reason for the selection. In addition, the selected period is appropriate for this analysis as the model will be able to show the transitional phase in the Malaysian palm oil industry from pre-biodiesel mandate (before year 2011) and post-biodiesel mandate implementation (after year 2011). As for the simulation purpose, the model will be simulated until year 2050. The reason of choosing long simulation period is because the delay involves in oil palm plantation sub-model are more than 25 years for the planting phases. Choosing long simulation period will allow the observation of the model behaviour stem from the changes in oil palm plantation sub-model.

3.3.1.4 Initial model diagram

The final step in model conceptualization stage is deciding on the basic mechanism of the studied system. Particularly, a system's basic mechanism is the feedback loops in the model drawn in an initial diagram using causal loop diagram (CLD). CLD is a visual model which graphically represents a working mechanism of the system. It is drawn to capture the qualitative model at the beginning of the process and helps in projecting the cause and effect relationship and feedback processes among variables. The CLD also represents the model in a way that emphasizes feedback loops and delays (Sterman, 2000; Lane, 2008). In CLD, the variables are linked by arrows based on their relationship and show the direction of influence. The arrow also accompanied by polarity depicting the effect of influence either positive for direct and negative for inverse influence. These polarities helps in capturing the feedback process in the system. On the other hand, delays are represented by a double line orthogonal to a causal link.

Feedback is one of the important traits of SD where the systems stock and flow are part of feedback loops. Feedback loops enable a model system to endogenously represent dynamic aspects of a system (Richardson, 1999). It also known as cause-and-effect chain which act as a closed-loop structure that return result from previous action back to control next action in the system. Positive feedback, also called self-reinforcing loop function to initiate growth in reinforcing pattern. On the other hand, negative feedback, also called self-correcting loop, on the other hand function to control a loop by introducing a balancing mode. In other words, the negative loop balance or adjust the system to a certain level to ensure the stability of the system (Sterman, 2000). Conclusively, to represent significant delays, feedback loops, and feedback loop polarity, a CLD has advantages, since it explicitly address all three components in an aggregated form to improve comprehensibility (Groesser & Schaffernicht, 2012).

The initial diagram modeled using CLD shows the basic mechanism of Malaysia palm oil industry as illustrated in Figure 3.6. Overall, there are four balancing loops (labelled with ‘B’) and one reinforcing loop (labelled with ‘R’) that representing the main feedback loops in Malaysia palm oil industry.

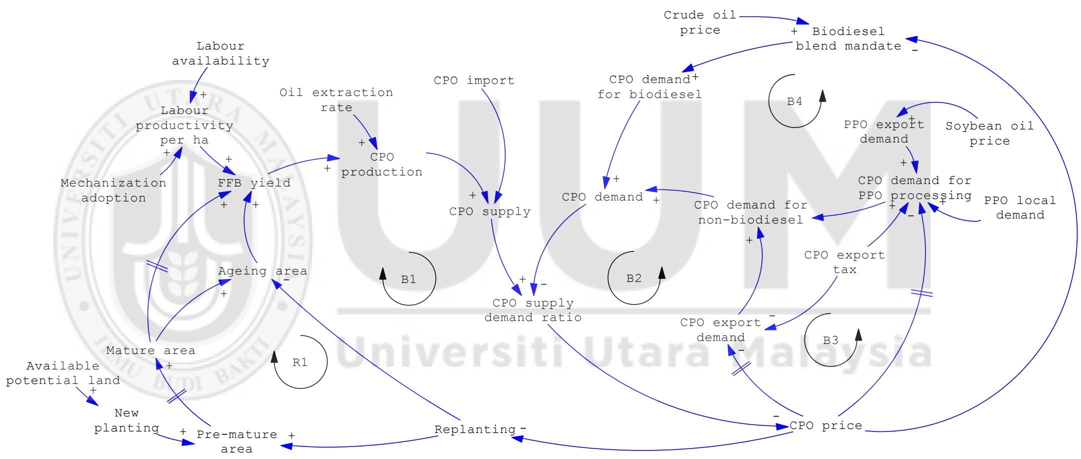

Figure 3.6. Initial causal loop diagram of Malaysia crude palm oil production

In loop R1, it depicts the plantation sector with non-effective replanting scheme. In this loop, due to the absence of effective replanting scheme the ageing area will be accumulated. Due to lower productivity as compared to mature area, FFB yield per hectare will be affected thus lowering the CPO production. On the contrary, with effective replanting scheme in loop B1, old trees are systematically replaced and lead to smaller ageing area but wider mature area, subsequently ensure the nearly consistent optimal FFB yield per hectare. This loop also highlights the inverse relationship of CPO price and replanting. When CPO price is high, the planters (particularly smallholders) tend to delay their replanting plan to reap as high profit as they can get. On the other hand, low CPO price will increase the motivation in replanting (Wahid & Simeh, 2010).

Aside of replanting, new planting also contribute to the increase of premature area, which means the increase of total plantation area. However, this is subject to the availability of potential land to be converted into oil palm plantation. In Malaysia context, we are facing a scarcity of plantation land where new domestic plantation expansion can be assumed currently at very low rate[5]. This is also the reason why there is no relationship drawn connecting CPO price (deemed as long-term profit) with oil palm plantation new expansion plan even though it is prevalent in previous study like Yahaya et al. (2006), Abdulla et al. (2014), and Mohammadi et al. (2016).

Note also the influence brought by labour on FFB yield. As plantation is a labour intensive sector, failing to supply adequate labour will affect the labour productivity per hectare. However, sufficient mechanization adoption will help in increasing the labour productivity per hectare thus increasing the FFB yield.

On the demand side, loop B2 represent the negative relationship of CPO price with CPO export demand, whereas loop B3 represent the negative relationship with CPO local demand. It is understandable when CPO price is high that both overseas and local demand becomes low albeit some delay. Note that the role of CPO export tax in influencing both export and local demand are also incorporated in these loops. CPO export tax is known as one of the means for the government to control the CPO export (The Star, 2015; 2016a). In addition, soybean oil has been incorporated as influencing

[5] Anonymous informational interview session with a Malaysia palm oil research body.

factor of PPO export demand. As supported by Senteri (1988), Shri Dewi et al. (2011a), and Arshad and Hameed (2012), soybean oil price has positive relationship with PPO export demand.

Finally, loop B4 representing the effect of biodiesel blend mandate on CPO supply demand ratio thus affecting CPO price. With increase biodiesel blend mandate there will be more CPO demand for biodiesel production, disrupting the CPO supply ratio thus increasing the prices. Note the relationship of crude oil and CPO price on biodiesel blend mandate incorporated in this loop. This relationship is actually the informational relationship rather than physical. The level of crude oil and CPO price hugely affect the decision of increasing the mandate. This is true where the ministry has decided to delay the implementation of B10 from March 2016 to January 2017 by taking into the consideration the difference between CPO and crude oil prices in the current volatile market (The Star, 2016b).

The CLD is a sketch of mental model for the real system and taken as the conceptual model of Malaysia palm oil industry in this study. CLD in Figure 3.6 serve to give initial idea on the relationship between components and how they collectively constitute the underlying feedback processes in the model. However, CLD is not adequate to be taken as a final model diagram because the modeler cannot conduct any policy analysis, locate leverage points, or tell which loop is dominant with just causal loop diagram (Albin, 1997; Sterman, 2000). This leads to the development of stock and flow diagram.

3.3.2 Primary and Secondary Data Collection

Two types of data are needed for this research. The first type is the primary data. Primary data are collected from meetings and discussions with industry players.

Industry players include the oil palm planters, palm oil producer, palm oil related association members like Malaysian Biodiesel Association (MBA), and the research body like Malaysian Palm Oil Board (MPOB). The primary data include the industry player's view and on-the-field experience of the past as well as current situation of Malaysian palm oil industry. This is important to ensure that the model adhere with Baker's criterion which stated that the model should be developed based on the decision maker bounded rationality and avoiding the modeler's cognitive bias (Sterman, 2000; Morecroft, 2007).

The second type is the secondary data. These data are collected from publicly opened source like MPOB websites, Department of Statistics Malaysia, and other published sources from the internet. Keeping up to date with the current situation of Malaysia palm oil industry through updated newsletter and conference also are a crucial part of secondary data collection process. The desired period of data is fifteen years, starting from year 2000 until 2015. The type of data and its source used in this research are compiled in Table 3.2 below. On the other hand, Table 3.3 detail out the informational interview session with industry member.

Table 3.2

Type of Data and Its Source

Data type	Description	Source	Year
Primary data	Overview on the past and current situation of Malaysia palm oil industry.	• Meeting with industry member • Attending palm oil related conference	2000 - 2016
Secondary data	Historical time series data on palm oil market (e.g. production, prices, export, and consumption)	MPOB website	2000 - 2016
	Latest data on palm oil market including palm oil production, prices, export, and consumption.	• MPOB website • Newsletter from MPOB • Annual report from MPOB	2016

* MPOB = Malaysian Palm Oil Board

Table 3.3

Interview Session with Industry Players

Interviewee	Affiliation	Venue	Date and Time
1. Deputy President	Malaysian Biodiesel Association (MBA)	Biodiesel Mills, Pulau Carey, Selangor.	9 September 2016, 10.00am – 12.00pm
2. Director	Malaysian Palm Oil Board (MPOB)	MPOB head office, Menara Sawit, Kelana Jaya, Selangor.	14 September 2016, 10.00am – 12.00pm
3. Manager	Performance Management and Delivery Unit (PEMANDU)	PEMANDU Satellite Office, KL Sentral	7 October 2016, 3.00pm – 5.00pm
4. Director	Ministry of Plantation Industries and Commodities (MPIC)	MPIC Office, Putrajaya	10 October 2016, 3.00pm – 5.00pm

3.3.3 The Development of Stock and Flow Diagram

Stock and flow diagram (SFD) is a representation of a CLD. Constructing the SFD will complement the system interpretation by CLD, as causal loop diagram is not capable of calculating the exact performance of the system with regard to time-dependent variations (Sterman, 2000). Furthermore, the strength of the link polarity is difficult to determine with CLD (Morecroft, 2007). SFD on the other hand, conjure the actual dynamic of the system by quantifying the relationships among variables in the form of stock and flow. Basically, a SFD consist of four basic components: stock, flow, auxiliary, and link as illustrated in Figure 3.7.

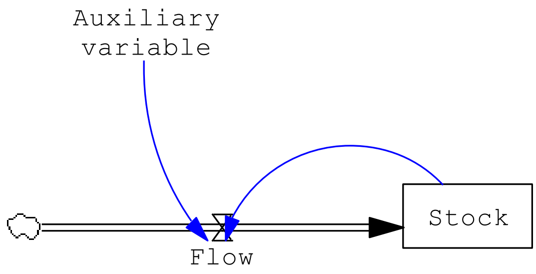

Figure 3.7. Example of stock and flow diagram

A stock is also known as accumulation or state or level. A stock shows the state of the system at one particular time. The value in a stock will accumulate overtime, meaning that the value at any time depend on the value they had previous times. This is shown in equation below.

$$Stock_t = \int_{to}^{t} flow_t \, dt + Stock_{to} \tag{3.1}$$

where $Stock_{to}$ is the initial value of the stock.

Due to their link with flow variables, stocks can change overtime. Stock also can be categorized into tangible and intangible stock. Tangible or physical stock includes natural stocks, capital or goods while intangible stock can be information, psychological or any indexed value (Sterman, 2000). On the other hand, flow variables determine the level of stock. Also known as rates, it can be divided into inflow and outflow. Inflow will increase the stock whereas outflows will deplete the stock. As such, Equation (3.1) can also be written as

$$Stock_t = \int_{to}^{t} (inflow - outflow)\, dt + Stock_{to} \tag{3.2}$$

Auxiliary variables are calculated from other variables within the system and can be divided into endogenous and exogenous. There are equations in an auxiliary variables that specifies the decision rules in which information is carried between the system components. With the auxiliary variables, full logic of causal loop model can be presented. The connections between the variables are established through links. Links act as connector in the form of arrow defining the connection and control between the variables in the system. Table 3.4 summarize the building blocks of an SD model.

Table 3.4

Basic Building Blocks Used in System Dynamics

Building block	**Symbol**	**Description**
Stock (level)	□	Shows an accumulation of any quantity.
Flow (rate)	⧖	Alters stock level by an inflow or an outflow. Attached to a stock.
Connector	→	Link different building blocks and showing causality.

The conceptual model built using CLD in the previous sub-section is converted into SFD to allow more thorough analysis of Malaysia palm oil industry behaviour. The development of SFD is closely referred to the conceptual model built with CLD in Figure 3.6. Vensim DSS version 6.2c software is used for the modeling process. In this research, the final model is comprised the combination of four sub-models namely palm oil supply and demand, oil palm plantation, palm-based biodiesel, and labour. In each of sub-model, there are control variables and non-control variables. Control variables are the policy variables which will be manipulated during the simulation and optimization process at the later stage. On the other hand, non-control variables are the exogenous variable in which the parameter value are either set and assumed based on the credible sources, or determined through parameter assessment process elaborate in sub-chapter 4.1.6.

3.3.3.1 Palm Oil Supply and Demand Sub-model

Palm oil supply and demand sub-model is modeled referring to the generic commodity market model as proposed by Meadows (1970). Some modification has been done however to suit the modeling objectives in this research. The sub-model consist the representation of several segments namely (i) CPO supply and demand; (ii) PPO supply and demand; and (iii) CPO and PPO price setting mechanism. Figure 3.8 shows the CPO supply demand segment of the sub-model.

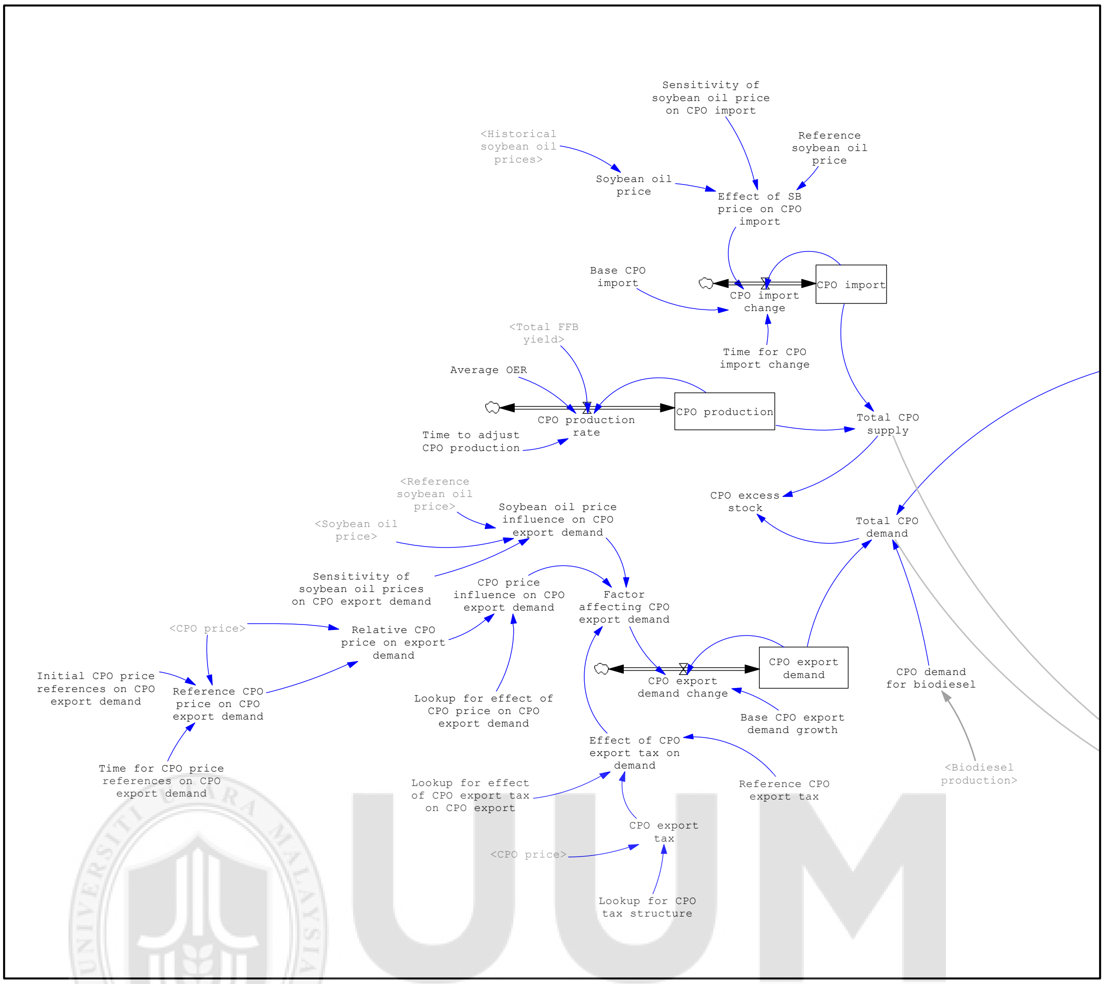

Figure 3.8. The CPO supply demand segment from palm oil supply demand sub-model

In this segment, there are two stocks representing CPO supply side namely CPO production and CPO import. CPO production (*CPO_p*, in tonne) represents production of CPO from FFB. The size of CPO production is determined by the net CPO production rate (r_{CPOp}, in tonne/year). The CPO production rate is depending on CPO production which calculated by multiplying average oil extraction rate (*OER*, dimensionless) with total FFB yield (*$FFBY_T$*, in tonne) divided by the time to adjust CPO production (t_{CPOp}, in year). All equations in the model will be simulated from t = 0 to t = 50 years. Equation 3.3 and 3.4 show the mathematical equation in CPO supply and demand segment.

$$CPO_{p(t)} = \int_{to}^{t} r_{CPOp}\, dt + CPO_{p(to)} \tag{3.3}$$

$$r_{CPOp} = (OER \times FFBY_T)/t_{CPOp} \tag{3.4}$$

Another stock is CPO import (CPO_i, in tonne). The net input of CPO import is the CPO import change (r_{CPOi}, in tonne/year). CPO import change is derived from base CPO import (*Base CPOi*, in tonne) influenced by the soybean oil price. Base CPO import is modeled using RAMP function to depict the historical data of CPO import. The influence of soybean oil price is formulated using power function as suggested by Sterman (2000) to portray exogenous influence on a variable. Thus the effect of soybean oil price on CPO import ($f_{PSBO,CPOi}$, dimensionless) is obtained by multiplying relative soybean oil price (*Relative* P_{SBO}, dimensionless) with the sensitivity of soybean oil price on CPO imports ($s_{PSBO,CPOi}$, dimensionless) as power function. The usage of power function to determine the effect between variables has been demonstrated by Sterman (2000). Relative soybean oil price is the ratio between soybean historical prices (P_{SBOh}, in USD/tonne) and reference soybean oil price (P_{SBOr}, in USD/tonne). The mathematical formulations relating to CPO import are shown in Equation 3.5 – 3.8.

$$CPO_{i(t)} = \int_{to}^{t} r_{CPOi}\, dt + CPO_{i(to)} \tag{3.5}$$

$$r_{CPOi} = Base\ CPOi \times f_{PSBO,CPOi} \tag{3.6}$$

$$f_{PSBO,CPOi} = (Relative\ P_{SBO})^{s_{PSBO,CPOi}} \tag{3.7}$$

$$Relative\ P_{SBO} = P_{SBOh}/P_{SBOr} \tag{3.8}$$

On the demand side, a stock of CPO export demand (S_{CPOx}, in tonne) is included in this segment. This stock level is determined by the net CPO export demand change (r_{CPOx}, in tonne). The CPO export demand change is determined by CPO export demand growth (g_{CPOx}, dimensionless) influenced by CPO price, soybean oil price and CPO export tax. CPO price influence on CPO export demand ($f_{PCPO,CPOx}$, dimensionless) is formulated using lookup function with relative CPO price (*Relative* P_{CPO}, dimensionless) as the input. Relative CPO price is the ratio between CPO price (P_{CPO}, in RM) and reference CPO price (P_{CPOr}, in RM). Lookup function depict the non-linear relationship between CPO price and CPO export demand as illustrated in Figure 3.9. As the CPO price increase relative to the reference CPO price, the CPO export demand tend to reduce. On the other hand, with decrease CPO price, CPO export demand is prone to increase.

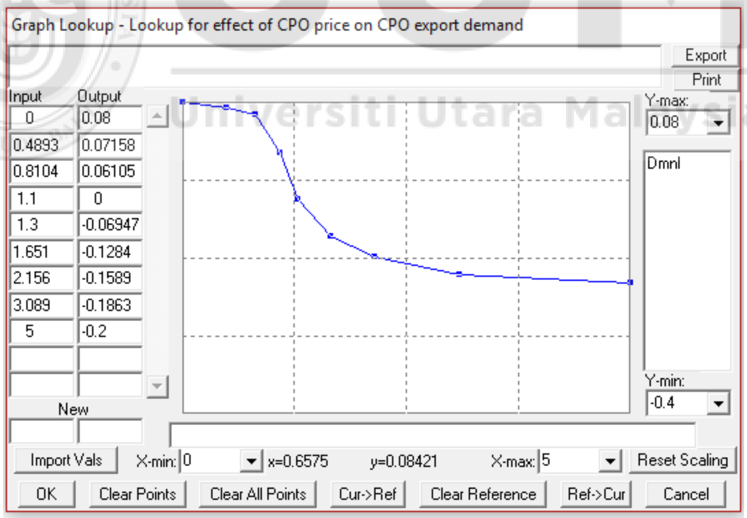

Figure 3.9. Lookup function for effect of CPO price on CPO export demand

The soybean oil price influence on CPO export demand ($f_{PSBO,\ CPOx}$, in USD) is also formulated using power function. Further, CPO export also being influenced by CPO export tax ($f_{CPOtax,\ CPOx}$, dmnl). Similarly, the effect of CPO tax on demand is modeled using lookup function with the basic CPO export tax structure based on the current structure provided by MPOB (MPOB, 2016) as illustrated in Figure 3.10. The CPO export taxes are imposed based on the current CPO prices.

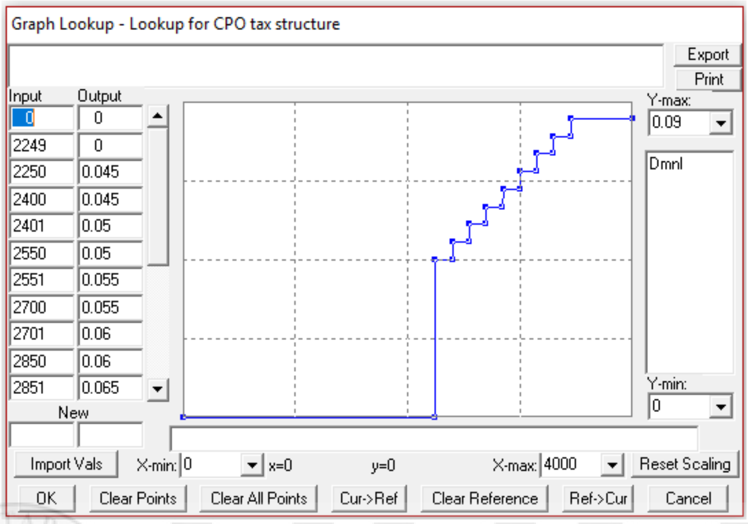

Figure 3.10. Lookup function for CPO tax structure

The mathematical equations in CPO export demand segment are shown in Equation 3.9 – 3.15.

$$CPO_{x(t)} = \int_{to}^{t} r_{CPOx}\, dt + CPO_{x(to)} \tag{3.9}$$

$$r_{CPOx} = g_{CPOx} \tag{3.10}$$

$$g_{CPOx} = f_{PCPO,CPOx} \times f_{PSBO,CPOx} \times f_{CPOtax,CPOx} \tag{3.11}$$

$$f_{PCPO,CPOx} = Lookup_{PCPO,CPOx}(Relative\ P_{CPO}) \tag{3.12}$$

$$Relative\ P_{CPO} = P_{CPO}/P_{CPOr} \tag{3.13}$$

$$f_{PSBO,CPOx} = (Relative\ P_{SBO})^{s_{PSBO,CPOx}} \tag{3.14}$$

$$f_{CPOtax,CPOx} = Lookup_{CPOtax,CPOx}(CPO_{tax}/CPO_{taxr}) \tag{3.15}$$

Aside from CPO export demand, there are demand for CPO for PPO (CPO_{PPO}, in tonne) and palm-based biodiesel sector (CPO_B, in tonne) but both are modeled with high detail in separate sub-model to affectively depict their role on the dynamic of the model. These demand made up the total CPO demand (TD_{CPO}, in tonne) while total CPO supply (TS_{CPO}, in tonne) is consist of CPO production and CPO import as shown by Equation 3.16 and 3.17.

$$TD_{CPO} = CPO_x + CPO_B + CPO_{PPO} \tag{3.16}$$

$$TS_{CPO} = CPO_p + CPO_i \tag{3.17}$$

Next segment in palm oil supply demand sub-model is PPO demand segment as shown in Figure 3.11.

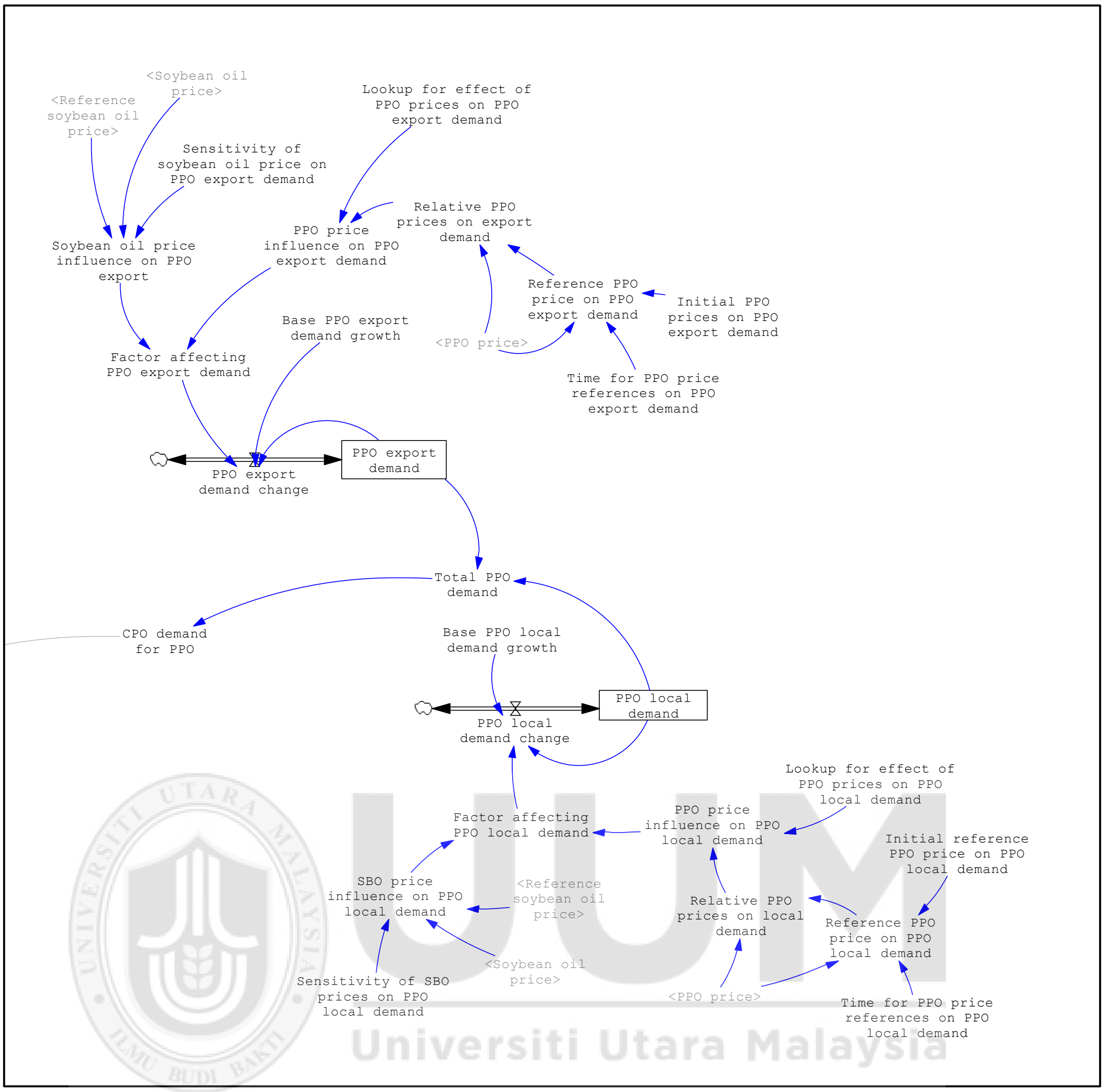

Figure 3.11. The PPO demand segment from palm oil supply demand sub-model

There are two stocks namely PPO export demand and PPO local demand. Soybean price play its role in influencing the level of PPO demand because of its reputation as the closest substitutes to palm oil. The first demand is PPO local demand (*PPO_l*, tonne) which represents domestic consumption of PPO. The net input is PPO local demand change (r_{PPOl}, in tonne/year) and determined by its growth (g_{PPOl}, dimensionless) and influenced by factor affecting PPO local demand (f_{PPOl}, dimensionless). Factor affecting PPO local demand constitute from soybean price and PPO price. The influence of soybean price on PPO local demand ($f_{PSBO,PPOl}$, dimensionless) is modeled as power function with sensitivity parameter ($s_{PSBO,PPOl}$, dimensionless) while the influence of PPO price on PPO local demand ($f_{PPPO,PPOl}$, dimensionless) is modeled using lookup function as illustrated in Figure 3.12. As the PPO prices decrease, the PPO local demand will increase sharply, whereas high PPO price will lower the PPO local demand.

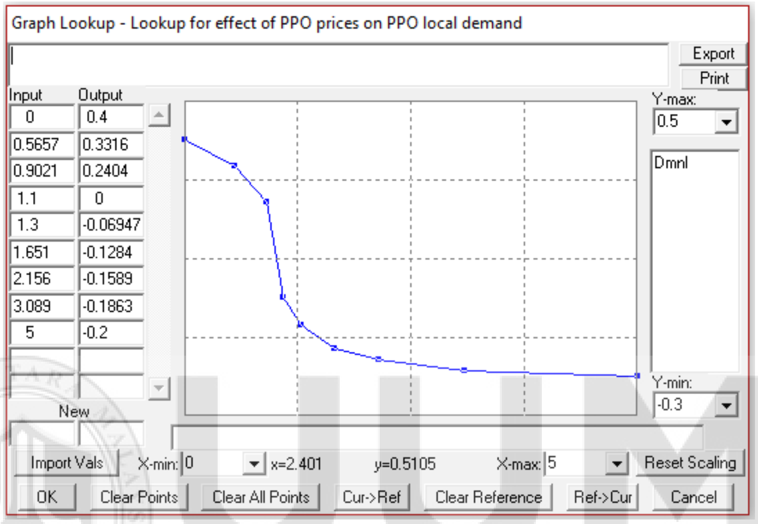

Figure 3.12. Lookup function for effect of PPO prices on PPO local demand

The lists of equations related to PPO local demand are shown in Equation 3.18 – 3.22.

$$PPO_{l(t)} = \int_{to}^{t} r_{PPOl}\, dt + PPO_{l(to)} \tag{3.18}$$

$$r_{PPOl} = g_{PPOl} \times PPO_l \times f_{PPOl} \tag{3.19}$$

$$f_{PPOl} = f_{PSBO,PPOl} \times f_{PPPO,PPOl} \tag{3.20}$$

$$f_{PSBO,PPOl} = (Relative\ P_{SBO})^{s_{PSBO,PPOl}} \tag{3.21}$$

$$f_{PPPO,PPOl} = LOOKUP_{PPPO,PPOl}(Relative\ P_{PPO}) \tag{3.22}$$

The final stock in PPO demand segment is PPO export demand (S_{PPOx}, in tonne). The modeling structure of PPO export demand is similar with PPO local demand. The net input of PPO export demand is PPO export demand change (r_{PPOx}, in tonne/year) which is determined by its growth (g_{PPOx}, dimensionless) with influence from factor affecting PPO export demand (f_{PPOx}, dimensionless). Factor affecting PPO export demand is constitute from soybean oil price and PPO price. Likewise, the influence of soybean oil price on PPO export demand ($f_{PSBO,PPOx}$, dimensionless) is modeled using power function with sensitivity parameter ($s_{PSBO,PPOx}$, dimensionless) while the influence of PPO price on PPO export demand ($f_{PPPO,PPOx}$, dimensionless) is modeled using lookup function as illustrated in Figure 3.13. The non-linear relationship between PPO prices and PPO export demand shows that high PPO prices will lower PPO export demand whereas low PPO prices boosted PPO export demand sharply.

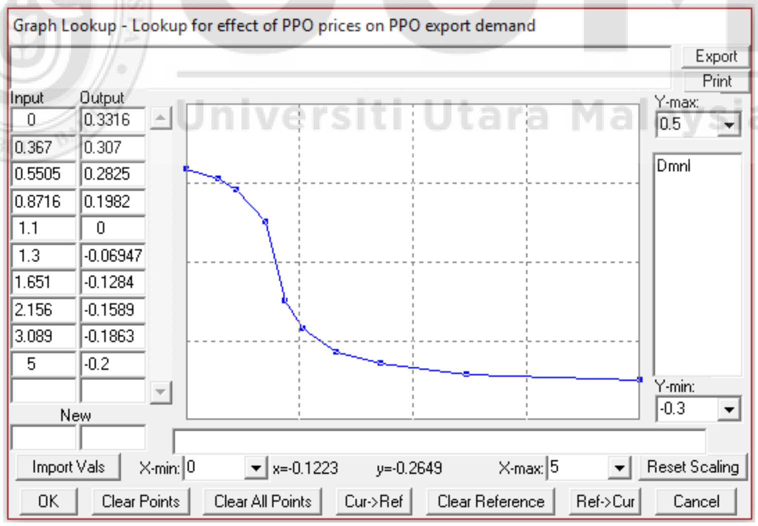

Figure 3.13. Lookup function for effect of PPO prices on PPO export demand

Equation 3.23 – 3.27 listed the equation related to PPO export demand.

$$PPO_{x(t)} = \int_{to}^{t} r_{PPOx}\, dt + PPO_{x(to)} \tag{3.23}$$

$$r_{PPOx} = g_{PPOx} \times PPO_x \times f_{PPOx} \tag{3.24}$$

$$f_{PPOx} = f_{PSBO,PPOx} \times f_{PPPO,PPOx} \tag{3.25}$$

$$f_{PSBO,PPOx} = (Relative\ P_{SBO})^{s_{PSBO,PPOx}} \tag{3.26}$$

$$f_{PPPO,PPOx} = LOOKUP_{PPPO,PPOx}(Relative\ P_{PPO}) \tag{3.27}$$

Both PPO export demand and local demand made up the total PPO demand (TD_{PPO}, in tonne). The mathematical equations are shown as in Equation 3.28.

$$TD_{PPO} = PPO_l + PPO_x \tag{3.28}$$

The final segment, CPO price setting mechanism illustrated in Figure 3.14 is constituted from CPO demand ratio derived from the previous two segments.

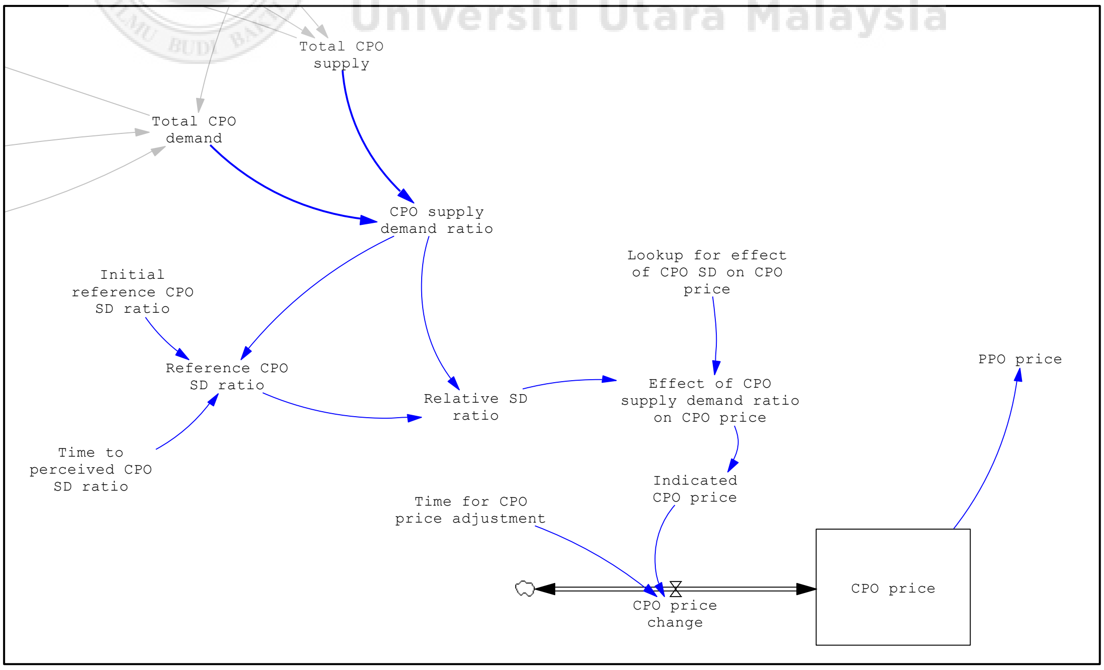

Figure 3.14. CPO and PPO price setting mechanism from the palm oil supply and demand sub-model

CPO price is modeled in a stock form with CPO price change (r_{PCPO}, in RM/year) as its net input. CPO price change is determined by the indicated CPO price (*Indicated* P_{CPO}, in RM) with the time for CPO price adjustment (T_{PCPO}, in year). Indicated CPO price is used to incorporate the effect of CPO supply demand ratio ($f_{ratioSDCPO,PCPO}$, in RM) on CPO price. Influence of CPO supply demand ratio is modeled using lookup function with relative CPO supply demand ratio (*Relative ratio* SD_{CPO}, dimensionless) as its input as illustrated in Figure 3.15. Relative supply demand ratio is equal to CPO supply demand ratio (*Ratio* SD_{CPO}, dimensionless) divided by reference CPO supply demand ratio (*Ratio* SD_{CPOr}, dimensionless). CPO supply demand ratio as the name suggest is computed by dividing total CPO supply over total CPO demand. The lookup function shows that sudden decrease in CPO supply demand ratio will abruptly increase CPO price and vice-versa. A decrease in CPO supply-demand ratio signals the low supply of CPO relative to its demand whereas an increase CPO supply-demand ratio signals the excess CPO supply.

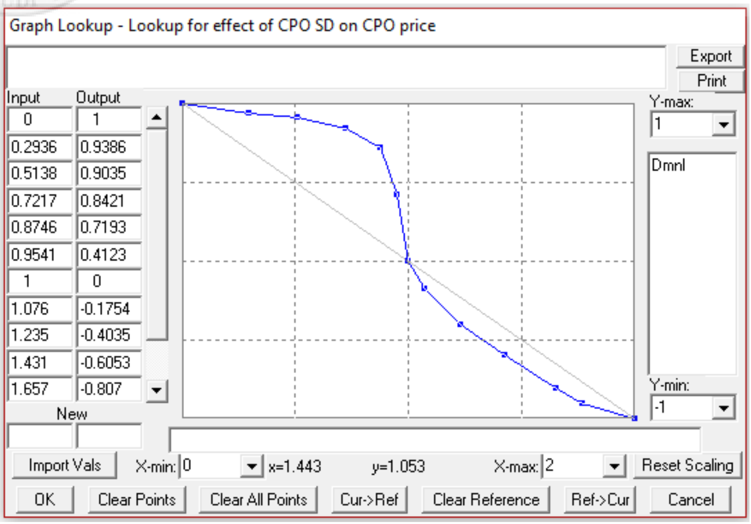

Figure 3.15. Lookup function for effect of CPO supply demand ratio on CPO price

As for PPO price, according to the statistic by MPOB (2016), PPO price in average is 3 percent higher than CPO price, thus PPO price (PPPO, in RM) is computed by simply multiplying CPO prices with 1.03. Equation 3.29 – 3.35 shows the equation relating to CPO and PPO price setting mechanism segment.

$$P_{CPO(t)} = \int_{to}^{t} r_{PCPO}\, dt + P_{CPO(to)} \tag{3.29}$$

$$r_{PCPO} = Indicated\ P_{CPO}/T_{PCPO} \tag{3.30}$$

$$Indicated\ P_{CPO} = f_{ratio\ SDCPO,PCPO} \tag{3.31}$$

$$f_{ratio\ SDCPO,PCPO} = LOOKUP_{ratio\ SDCPO,PCPO}(Relative\ ratio\ SD_{CPO}) \tag{3.32}$$

$$Relative\ ratio\ SD_{CPO} = Ratio\ SD_{CPO}/Ratio\ SD_{CPOr} \tag{3.33}$$

$$Ratio\ SD_{CPO} = TS_{CPO}/TD_{CPO} \tag{3.34}$$

$$P_{PPO} = 1.03 \times P_{CPO} \tag{3.35}$$

The parameters and assumption used in palm oil supply demand sub-model are presented in Table 3.5. One of important assumption made in this sub-model is that soybean oil price is constant at approximately 670 USD per tonne. In this sub-model, there is no policy variable. The parameter estimation process in the model is explained in detail in sub-chapter 4.16. All the equations for this sub-model are available in APPENDIX A.

Table 3.5

Parameters and Assumptions Used in Palm Oil Supply Demand Sub-Model

Parameters	Value/Assumptions	Unit	Sources
Average OER	0.22	dmnl	MPOB, 2016
Sensitivity of soybean oil price on CPO import	0.1	dmnl	Parameter estimation
Base CPO import	50,000	tonne/year	MPOB, 2016
Base CPO export demand growth	2.586	1/year	Parameter estimation
Base PPO export demand growth	0.201	1/year	Parameter estimation
Sensitivity of soybean oil price on PPO export demand	0.004	dmnl	Parameter estimation
Base PPO local demand growth	0.155	1/year	Parameter estimation
Sensitivity of soybean oil price on PPO local demand	0.479	dmnl	Parameter estimation
Time for CPO price adjustment	2	year	Parameter estimation
Soybean oil price	Smoothed historical data from year 2000 – 2015, then constant at $670	USD/tonne	World bank (2016)

3.3.3.2 Oil Palm Plantation Sub-model

Oil palm plantation sub-model depicts the underlying dynamic in the plantation sector as shown in Figure 3.16.

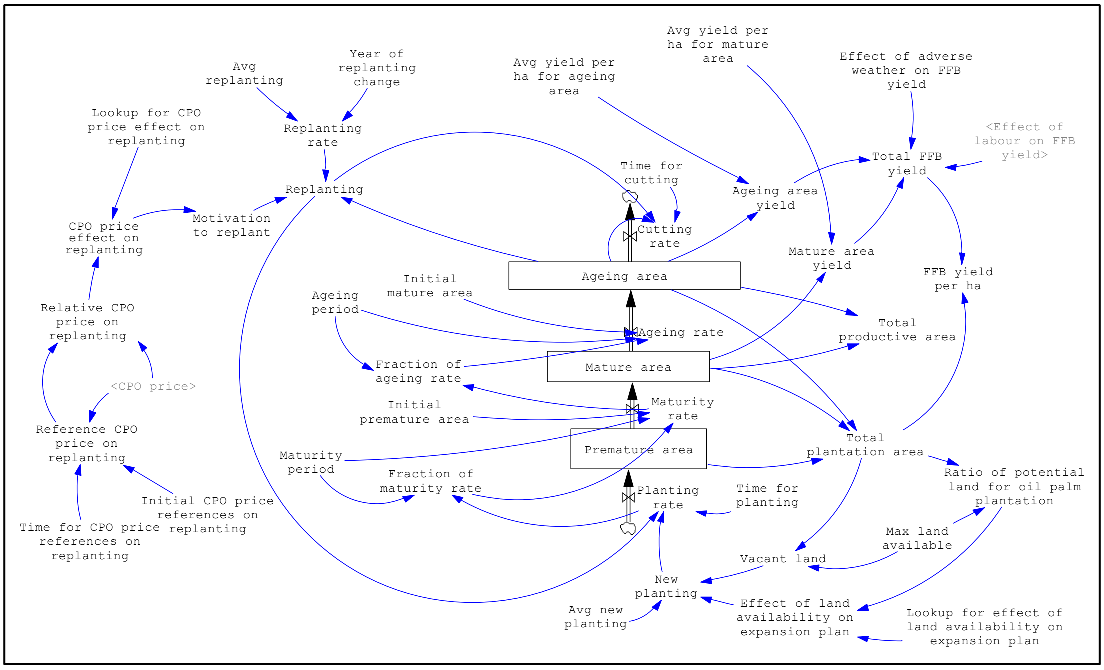

Figure 3.16. The oil palm plantation sub-model

The centre of the sub-model is the various phases involved in plantation area namely premature, mature and ageing area which are modeled in stock form. The rate of each phases are modeled using DELAY FIXED function to closely depict the dynamic of oil palm planting. Starting with premature area (A_{pre}, in hectare), the input is the planting rate (r_{plant}, in hectare/year) with maturity rate as its output (r_{mat}, in hectare/year). Planting rate is equal to the sum of new planting (*NP*, in hectare/year) and replanting (*RP*, in hectare/year). New planting is dependant to the vacant land (*VL*, in hectare) available for oil palm planting and average new planting (NP_{avg}, in hectare/year) influenced by the effect of land availability on expansion plan ($f_{VL,exp}$, dimensionless) modeled using LOOKUP function. The purpose is to depict the expansion plan behaviour in real life where the degree of expansion is high when a lot of land available and become low as the land is scarcely available as illustrated in Figure 3.17.

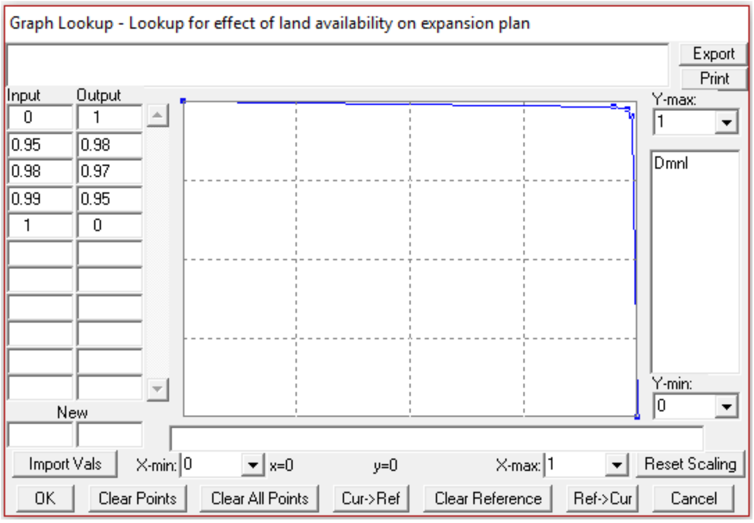

Figure 3.17. Lookup function for effect of land availability on expansion plan

Replanting on the other hand is determined by the motivation to replant (*MTR*, dimensionless) and replanting rate (r_{RP}, in hectare/year). Motivation to replant depict the role of CPO prices in influencing planters to replant ($f_{PCPO,RP}$, dmnl) which comes from the CPO price effect on replanting and is modeled using LOOKUP function as illustrated in Figure 3.18. The lookup function shows that CPO price decrease will increase the replanting rate while higher CPO price will give less incentive for planter to replant.

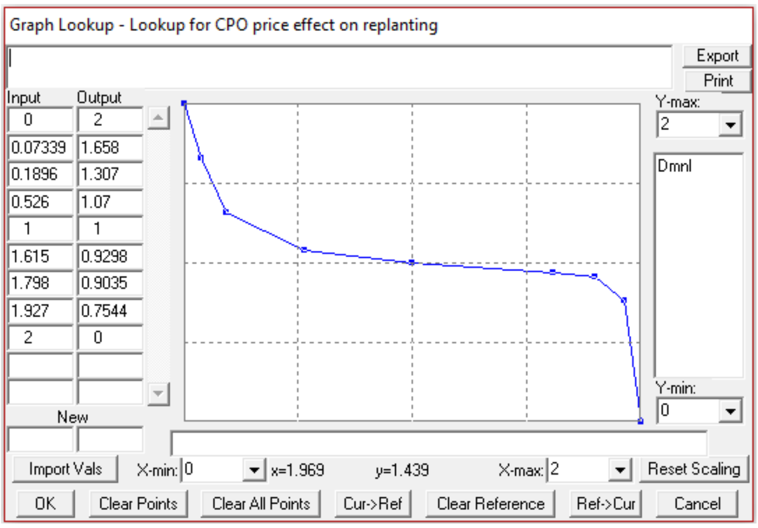

Figure 3.18. Lookup function for CPO price effect on replanting

Replanting rate is determined by the average replanting (r_{RPavg}, in hectare). Maturity rate is equal to the fraction of maturity rate (f_{rmat}, in hectare/year) formulated using DELAY FIXED function with mature period (T_{mat}, in year) as its time delay. The time for premature area becoming mature area is named as mature period, which is equal to 3 years (Wahid & Simeh, 2010). Equation 3.36 – 3.45 shows the Vensim equation relating to premature area.

$$A_{pre(t)} = \int_{to}^{t} r_{plant} - r_{mat}\, dt + A_{pre(to)} \tag{3.36}$$

$$r_{plant} = RP + NP \tag{3.37}$$

$$NP = MIN(NP_{avg} \times f_{VL,exp}, VL) \tag{3.38}$$

$$f_{VL,exp} = LOOKUP_{VL,exp}(Ratio_{VL}) \tag{3.39}$$

$$RP = MTR \times r_{RPavg} \tag{3.40}$$

$$MTR = f_{PCPO,RP} \tag{3.41}$$

$$f_{PCPO,RP} = LOOKUP_{PCPO,RP}(Relative\ P_{CPO}) \tag{3.42}$$

$$r_{RPavg} = r_{RPavg} \tag{3.43}$$

$$r_{mat} = f_{rmat} \tag{3.44}$$

$$f_{rmat} = DELAY\ FIXED\left(r_{plant}, T_{mat}, 0\right) \tag{3.45}$$

Maturity rate, output from premature area become the input for mature area (A_{mat}, in hectare) with ageing rate (r_{age}, in hectare/year) as its output. Likewise, ageing rate is formulated using DELAY FIXED function with ageing period (T_{age}, year) as its time delay. Equation 3.46 – 3.48 shows the Vensim equation relating to mature area.

$$A_{mat(t)} = \int_{to}^{t} r_{mat} - r_{age}\, dt + A_{mat(to)} \tag{3.46}$$

$$r_{age} = f_{rage} \tag{3.47}$$

$$f_{rage} = DELAY\ FIXED\left(r_{mat}, T_{age}, 0\right) \tag{3.48}$$

In ageing area (A_{age}, in hectar), ageing rate become the input while cutting rate (r_{cut}, in hectare/year) is the output of the stock. Cutting rate is determined by the frequency of replanting work. To avoid stock negativity, cutting rate is modeled using MIN function with ageing area as the minimum area available to be cut. The ageing period is equal to 25 years, denoting the time taken for mature area becoming ageing area (Wahid & Simeh, 2010). Equation 3.49 and 3.50 shows the mathematical equation related to ageing area.

$$A_{age(t)} = \int_{to}^{t} r_{age} - r_{cut}\, dt + A_{age(to)} \tag{3.49}$$

$$r_{cut} = MIN\left(RP, A_{age}\right) \tag{3.50}$$

Total FFB yield (T_{FFBY}, in tonne) is the sum of FFB yield in mature area ($FFBY_{mat}$, in tonne) and ageing area ($FFBY_{age}$, in tonne), influenced by two factors namely the effect of adverse weather ($f_{weather,FFBY}$, dimensionless) and effect of labour ($f_{L,FFBY}$, dimensionless). FFB yield in mature area is calculated by multiplying the mature area with average yield per hectare in mature area ($FFBY_{avg,mat}$, in tonne/hectare). Average yield per hectare in mature area is equal to 25 tonne per hectare (Wahid & Simeh, 2010). Likewise, FFB yield in ageing area is calculated by multiplying the ageing area with average yield per ha in ageing area ($FFBY_{avg,age}$, in tonne/hectare). Average yield per hectare is equal to 19 tonne per hectare (Wahid & Simeh, 2010). The effect of adverse weather on FFB yield is modeled exogenously with the assumption that the CPO production will be reduced to 10% annually when the year is hit with excessive rain and dryness (Chidambar, 2016). On the other hand, effect of labour on FFB yield will be elaborated in labour sub-model. Equation 3.51 – 3.53 shows the Vensim equation relating to FFB yield.

$$T_{FFBY} = \left(FFBY_{mat} + FFBY_{age}\right) \times f_{weather,FFBY} \times f_{L,FFBY} \tag{3.51}$$

$$FFBY_{mat} = FFBY_{avg,mat} \times A_{mat} \tag{3.52}$$

$$FFBY_{age} = FFBY_{avg,age} \times A_{age} \tag{3.53}$$

The parameters and assumption used in oil palm plantation sub-model are presented in Table 3.6. In this sub-model, there is one control variable namely average replanting. One important assumptions made in this sub-model is regarding adverse weather effect on FFB yield. It is assumed that the adverse weather hit every 4 years interval based on historical data, with the reduction of 15 percent output in corresponding year. All equations for this sub-model are available in APPENDIX B.

Table 3.6

Parameters and Assumptions Used in Oil Palm Plantation Sub-Model

Parameters	Value/Assumptions	Unit	Sources
Average yield per hectare for ageing area	25	tonne/ha	Wahid & Simeh (2010)
Average yield per hectare for mature area	19	tonne/ha	Wahid & Simeh (2010)
Average new planting	150,000	ha	MPOB (2016)
Max land available	6,000,000	ha	Anonymous interview with palm oil research body
Ageing period	25	years	Wahid & Simeh (2010)
Maturity period	3	years	Wahid & Simeh (2010)
Effect of adverse weather on FFB yield	-10% with 4 years interval	dmnl	MPOB (2016)

3.3.3.3 Palm-based Biodiesel Sub-model

Palm-based biodiesel sub-model in Figure 3.19 represents the biodiesel sector in Malaysia palm oil industry.

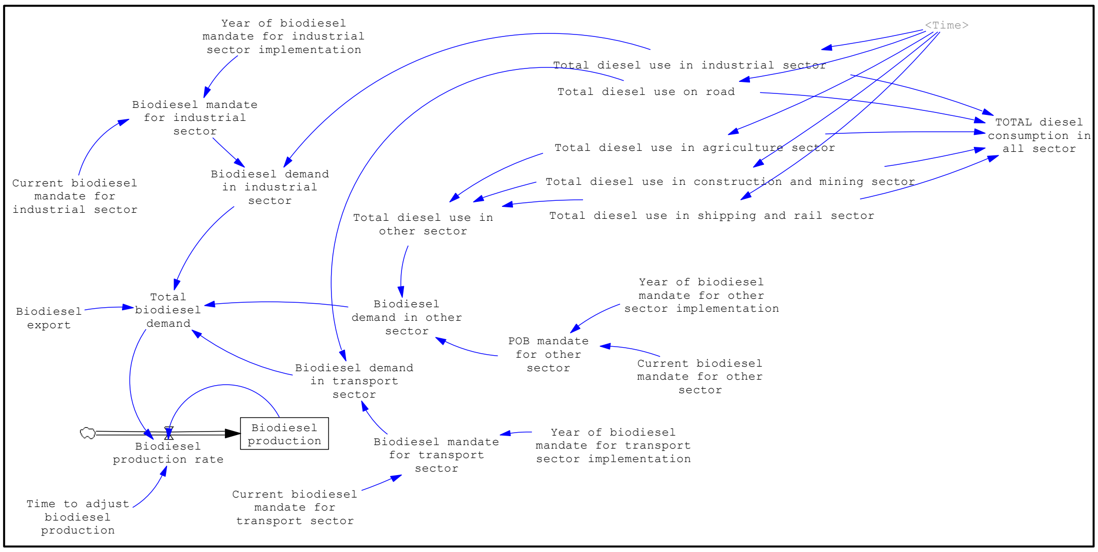

Figure 3.19. The palm-based biodiesel sub-model

The biodiesel production capacity (B_p, in tonne) is modeled in stock form. Its net input, biodiesel production rate (r_{Bp}, in tonne/year) is determined by the total biodiesel demand (TD_B, in tonne) from local as well as abroad. Equation 3.54 and 3.55 shows the Vensim equation relating to biodiesel production.

$$B_{p(t)} = \int_{to}^{t} r_{Bp}\, dt + B_{p(to)} \tag{3.54}$$

$$r_{Bp} = TD_B \tag{3.55}$$

Total demand for biodiesel comes from domestic and abroad. There are five sectors identified to be the largest consumption of diesel in Malaysia. The sectors are transportation, industrial, agriculture, construction and mining, and shipping and rail (USDA, 2015). Current mandate is targeted for transportation and industrial sector, thus we group the remaining sector under 'other sector'. Biodiesel demand in transportation (D_{Btrans}, in tonne), industrial (D_{Bind}, in tonne) and other sector (D_{Bother}, in tonne) is calculated by multiplying total diesel consumption in the sector (DC_{trans}, in tonne; DC_{ind}, in tonne; DC_{other}, in tonne) with corresponding biodiesel mandate (M_{trans}, dimensionless; M_{ind}, dimensionless; M_{other}, dimensionless). Equation 3.56 – 3.59 shows Vensim equation relating to biodiesel demand.

$$TD_B = D_{Btrans} + D_{Bind} + D_{Bother} \tag{3.56}$$

$$D_{Btrans} = M_{trans} \times DC_{trans} \tag{3.57}$$

$$D_{Bind} = M_{ind} \times DC_{ind} \tag{3.58}$$

$$D_{Bother} = M_{other} \times DC_{other} \tag{3.59}$$

The parameters and assumption used in the palm-based biodiesel sub-model are presented in Table 3.7. In this sub-model, there are three control variable namely current biodiesel mandate for transportation sector, current biodiesel mandate for industrial sector and current biodiesel mandate for other sector. All the equations for this sub-model are available in APPENDIX C.

Table 3.7

Parameters and Assumptions Used in Palm-Based Biodiesel Sub-Model

Parameters	**Value/Assumptions**	**Unit**	**Sources**
Biodiesel export	100,000	tonne	MPOB (2016)
Total diesel use in transportation sector	Data projection	tonne	USDA (2015)
Total diesel use in industrial sector	Data projection	tonne	USDA (2015)
Total diesel use in agricultural sector	Data projection	tonne	USDA (2015)
Total diesel use in construction and mining sector	Data projection	tonne	USDA (2015)
Total diesel use in shipping and rail sector	Data projection	tonne	USDA (2015)

3.3.3.4 Labour Sub-model

Figure 3.20 shows the labour sub-model.

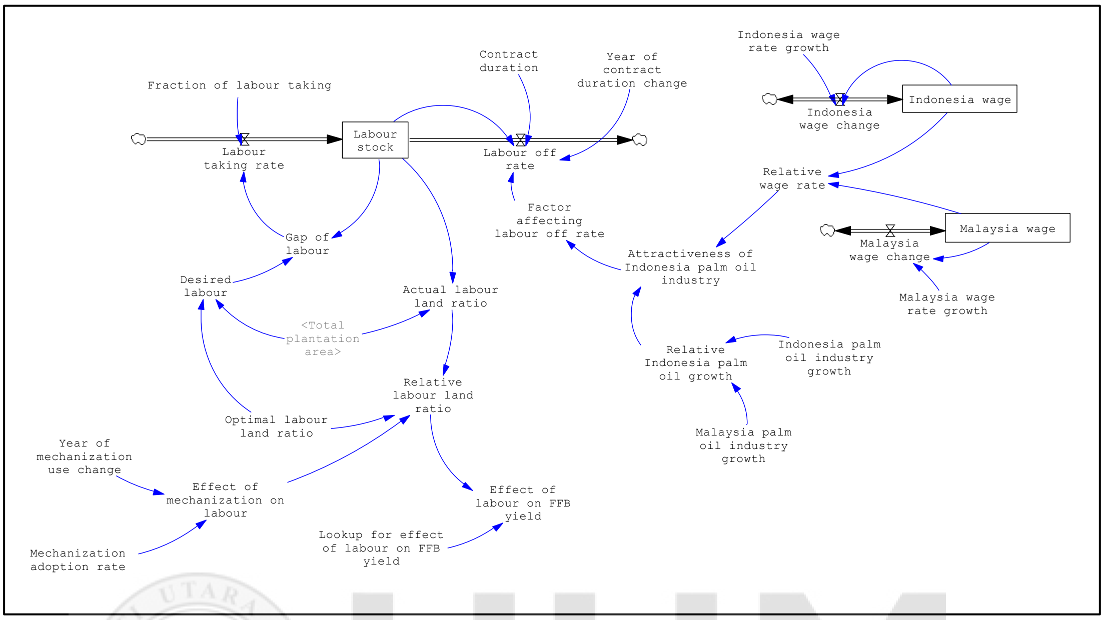

Figure 3.20. The labour sub-model

Labour (L, in labour) is modeled in stock form to depict the labor availability in the industry. The input of labour is the labour taking rate (r_{Lin}, in labour/year) while the output is the labour off rate (r_{Lout}, in labour/year). Labour taking rate is calculated by multiplying the fraction of labour taking rate (f_{rLin}, dimensionless) with the gap of labour (L_{gap}, in labour) between desired labour (L', in labour) and current labour. Desired labour is determined based on the optimal labour land ratio ($Ratio_{LAopti}$, in labour/hectare) times the total plantation area. The labour availability in the industry pose a significance influence to the FFB yield as the work of nurturing, maintaining and harvesting the oil palm is a labour intensive job. The effect of labour on FFB yield is modeled using LOOKUP function with relative labour land ratio ($Relative\ ratio_{LA}$, dimensionless) as its input as illustrated in Figure 3.21. The lookup function shows that as mechanization rate increase and labour improve, the FFB yield will increased until it achieve the equilibrium value at one.

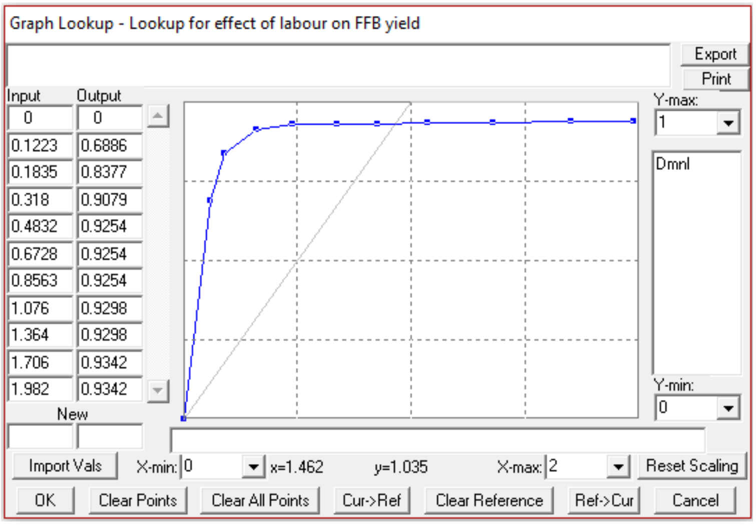

Figure 3.21. Graph lookup function for effect of labour on FFB yield

Relative labour land ratio is equal to actual labour land ratio (*Ratio*$_{LA}$, in labour/hectare) over optimal labour land ratio time the effect of mechanization on labour. Mechanization is incorporated in this sub-model so that it would help in improving relative land and labour ratio. Labour usage can be reduced as low as 50 percent with the adoption of mechanization (Ismail, 2003; Ismail et al., 2015). The effect of mechanization on labour ($f_{Mech,L}$, dimensionless) is modeled as direct function to relative land labour ratio. Equation 3.60 – 3.65 shows the mathematical equation relating to labour and labour taking rate.

$$L_{(t)} = \int_{to}^{t} r_{Lin} - r_{Lout}\, dt + L_{(to)} \tag{3.60}$$

$$r_{Lin} = f_{rLin} \times L_{gap} \tag{3.61}$$

$$L_{gap} = L' - L \tag{3.62}$$

$$L' = Ratio_{LAopti} \times T_A \tag{3.63}$$

$$f_{L,FFBY} = LOOKUP_{L,FFBY}(Relative\ ratio_{LA}) \tag{3.64}$$

$$Relative\ ratio_{LA} = Ratio_{LA}/(Ratio_{LAopti} \cdot (f_{Mech,L})) \tag{3.65}$$

Labour off rate is computed by dividing the stock of labour with the contract duration ($T_{contract}$, in year) influenced by the factor affecting labour off rate (f_{Lout}, dimensionless). While there are various factors attracting labours to work in plantation industry, the main factor would be the wages and the growth of the industry (Ayob et al., 2016). Thus, the main factor affecting labour off rate is the attractiveness of Indonesia palm oil industry ($Attractiveness_{IPO}$, dimensionless) which are measured based on the Indonesia's wage rate (W_{IPO}, in RM) over Malaysia's (W_{MPO}, in RM), and the growth rate of Indonesia palm oil industry (g_{IPO}, dimensionless) over the growth rate of Malaysia palm oil industry (g_{MPO}, dimensionless). The Indonesia wage rate is modeled in stock with the growth rate based on its current inflation rate. This is similar with Malaysia wage rate. The sum of the two factors constitutes the attractiveness of Indonesia palm oil industry. Equation 3.66 – 3.70 shows the mathematical equation relating to labour off rate.

$$r_{Lout} = f_{Lout} \times L/T_{contract} \tag{3.66}$$

$$f_{Lout} = Attractiveness_{Lout} \tag{3.67}$$

$$Attractiveness_{Lout} = Relative\ W_{IPO} + Relative\ g_{IPO} \tag{3.68}$$

$$Relative\ W_{IPO} = W_{IPO}/W_{MPO} \tag{3.69}$$

$$Relative\ g_{IPO} = g_{IPO}/g_{MPO} \tag{3.70}$$

The parameters and assumption used in the labour sub-model are presented in Table 3.8. In this sub-model, there is one control variable namely the mechanization adoption rate. All equations for this sub-model are available in APPENDIX D.

Table 3.8

Parameters and Assumptions Used in Labour Sub-Model

Parameters	Value/Assumptions	Unit	Sources
Contract duration	5	year	MPOB (2016)
Fraction of labour taking	0.25	1/year	Parameter estimation
Indonesia palm oil industry growth	3.4%	dmnl	Cramb & McCarthy (2016)
Malaysia palm oil industry growth	0.8%	dmnl	Cramb & McCarthy (2016)
Indonesia wage growth	4.0%	1/year	Bank Indonesia (2016)
Malaysia wage growth	1.8%	1/year	Department of Statistics Malaysia (2016)

3.3.4 Model Validation

Model validation is the work of approving the worthiness of a model. The purpose of validation in SD model is to uncover flaws and errors so the modeler can understand the model limitations, improve it, and ultimately produce the best available model to assist in important decisions (Sterman, 2000). Past researchers have developed a wide variety of specific tests to validate an SD model. As suggested by Sterman (2000) and Forrester and Senge (1980), validation test must be done to both structure and behaviour of the model. As such, there are two types of validation test in SD modeling which are structural and behavioural test. Structural test is conducted to check the model's internal consistency while behavioural test examine the comparability of the model with real system behaviour. Six tests had been conducted covering the structural and behavioural test critical to an SD model. These tests are structural assessment, dimensional consistency, extreme condition, integration error, sensitivity analysis test, and behavioural validity test.

3.3.4.1 Structural and parameter assessments

Structure assessment is the test to validate the structure of the developed model. It is conducted basically to determine whether the model is consistent with knowledge of the real system relevant to the purpose and focuses on the level of aggregation, the conformance of the model to basic physical realities and the realism of the decision rules for the agent (Sterman, 2000).

In this study, structural assessment test is done by examining the boundary adequacy of the model and check the appropriateness of variables in order to achieve the modeling objective. This is done initially by having a close look on causal loop diagram (CLD). Further, parameter assessment test is done by referring the model parameter from previous studies and published reports on Malaysia palm oil statistics, as well as verification with the industry players through interview session.

3.3.4.2 Dimensional Consistency Test

Dimensional consistency test also known as unit test is conducted to identify any inconsistency in the units of measure for each variables (Sterman, 2000). This test is one of the most basic test and should be done along the process of building the model. This test not only reveal the typographical error, inverted ratio, or missing time constant, it also more often reveals the unit error which is the important flaws in understanding the structure or decision process of the developed model (Sterman, 2000). This test may be the first critical indication of an erroneous model.

In this study, dimensional consistency test is done by checking both hand sides of selected equations in the model. For complete test on all equations, the built-in dimensional consistency test module in Vensim has been performed.

3.3.4.3 Extreme Condition Test

By definition, robustness is the culmination point which is measured in term of quality of a model. Under extreme condition, the model should behave in a realistic fashion and adhered to its physical limits no matter how extreme the inputs or policies that being imposed to the model. As proposed by Sterman (2000), extreme condition test can be conducted through direct inspection of model equations and simulation.

In this study, selected variables from each sub-models were observed while changing the correspondent parameters to extreme value. The variables were selected based on their critical role influencing the behaviour of each sub-model and also their role representing the main factors (scarcity of plantation area, labour shortage and biodiesel demand) that influence CPO production in this research. They are oil extraction rate, average replanting, biodiesel mandate for transportation, industrial and other sector, and mechanization adoption rate. Table 3.9 listed the selected variable for extreme condition test and the expected outcome.

Table 3.9

Selected Variables for Extreme Condition Test and the Expected Outcome

Sub-model	Variables	Extreme test	Expected outcome
Palm oil supply demand	Oil extraction rate	From 0.22 to 0	CPO production become zero
Oil palm plantation	Replanting rate become extremely low at zero.	From 50,000 hectare to 0 hectare	Premature and mature area become zero; Ageing area equal to total planting area.
Palm-based biodiesel	Biodiesel mandate for: (i) transportation (ii) industrial (iii) other sectors	 From 0.10 to 1 From 0.07 to 1 From 0 to 1	Biodiesel demand increase.
Labour	Mechanization adoption rate	From 0.22 to 1	Labour productivity increase.

3.3.4.4 Integration Error Test

To test whether the model is sensitive to the choice of time step or integration method, integration error test is conducted. By definition, a good model will have a time step that yields an approximation of the underlying continuous dynamic with high accuracy to the modeling objective. According to Sterman (2000), integration test can be done by cutting the time step (*dt*) in half and running the model again. It is expected that the stock variables in the model behave in the same manner and project insignificant change regardless the time step. Any changes of result occur in ways that matter indicate that the time step is too large. The process is continued until the results are no longer sensitive to the choice of time step.

In this study, three values of time step namely 0.25, 0.125 and 0.0625 were chosen and the main stock variables from each sub-model are observed.

3.3.4.5 Sensitivity test

Sensitivity analysis is a test used to check whether the conclusions change in ways important to the model purpose when assumptions are varied over the plausible range (Sterman, 2000). This test develops a level of confidence in model structure as model output variations or dynamic behaviour is within acceptable form as parameter value change over some ranges. In this research, our main concern is the behaviour sensitivity. A wider range of parameters will be set to test the sensitivity of the certain variables to the model behaviour. If the result produced is beyond the logical expectation of the system, the model has to be re-checked of its structure validity.

In this study, at least one exogenous variable had to be chosen from each sub-model for its sensitivity test towards CPO production. The average oil extraction rate (OER) has been chosen from palm oil supply and demand sub-model to observe its changes on the CPO production and prices. The rest of the variables chosen from each sub-model are the policy variables which impact on CPO production and prices are expected. The range of parameters are varied between -20% and +20% of the values which are used in base run (Hekimoglu and Barlas, 2010). Further, multi-variate sensitivity analysis is conducted where all variables are simultaneously changed. A total of 50 simulation runs has been performed using sensitivity analysis module embedded in Vensim. The parameter range from corresponded sub-model is listed in Table 3.10.

Table 3.10

Sensitivity Analysis Parameter Setting

Sub-model	Variable	Parameter range	Unit
palm oil supply and demand	Average OER	0.17 – 0.26	dmnl
Oil palm plantation	Average replanting	40,000 – 60,000	hectare
Palm-based biodiesel	Biodiesel mandate for transportation sector	0.08 – 0.12	dmnl
	Biodiesel mandate for industrial sector	0.06 – 0.08	dmnl
	Biodiesel mandate for other sector	0 – 0.02	dmnl
Labour	Mechanization adoption rate	0.16 – 0.24	1/year

3.3.4.6 Behaviour Validity Test

In this test, the simulation output is compared with historical data. The comparison is made by quantifying the mean error between simulation and historical data. The time period for data comparison is subject to data availability. The historical fit test was used to estimate model parameter by minimizing the weighted sum of the squared error between the model and the historical data simultaneously.

In this study, statistical error analysis using Root Mean Square Percent Error (RMSPE) and Theil's inequality coefficient has been conducted for validation purpose on selected variables Sterman (1984). The RMSPE provides a normalized measure of the magnitude of the error. Theil's inequality coefficient on the other hand consist of U^M, U^S, and U^C which reflect the fraction of the mean-square-error due to bias, unequal variance, and unequal covariance respectively (Sterman, 1984; 2000). Equation 3.71 to 3.74 shows the RMSPE and Theil's inequality coefficient formula used in this study.

$$RMSPE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[\frac{(S_t - A_t)}{A_t}\right]^2} \tag{3.71}$$

$$U^M = \frac{(\bar{S} - \bar{A})^2}{\frac{1}{n}\sum(S_t - A_t)^2} \tag{3.72}$$

$$U^S = \frac{(S_S - S_A)^2}{\frac{1}{n}\sum(S_t - A_t)^2} \tag{3.73}$$

$$U^C = \frac{2(1 - r)S_S S_A}{\frac{1}{n}\sum(S_t - A_t)^2} \tag{3.74}$$

Where,

n = Number of observations (t = 1, … n)

S_t = Simulated value at time t

A_t = Actual value at time t

$\bar{S}$= Mean of S

$\bar{A}$ = Mean of A

S_S = Standard deviation of S

S_A = Standard deviation of A

Total plantation area, CPO production, CPO price, CPO export demand, PPO local demand and PPO export demand are the chosen variables for the test. Total plantation area is chosen because any discrepancies produced indicate erroneous behaviour modeling of oil palm planting phases. Whereas CPO production is chosen because it is the main output investigated in this research. On the other hand, CPO prices are selected due to its importance in connecting CPO production and CPO demand. Finally, three source of demands namely CPO export, PPO local and PPO export demand are included in the test as their output influence the CPO prices.

3.3.5 Simulation run

A base run and three scenario setting runs are performed to obtain the idea on the feedback process and mechanism of the model component, particularly the CPO production.

3.3.5.1 Base run

The first simulation run is a base run, which represents the 'business as usual' scenario of Malaysia palm oil industry. In other words, all the policies currently in effect are remained with the assumption of no change take place in the future. Table 3.11 shows the control variable and its corresponding value used in the base run.

Table 3.11

Control Variable Used in the Base Run

Codes	Variables	Value	Unit
a	Mechanization adoption rate	20%	dmnl
b	Average replanting	50,000	hectare
c	Current biodiesel mandate in transportation sector	0.10	dmnl
d	Current biodiesel mandate in industrial sector	0.07	dmnl
e	Current biodiesel mandate in other sector	0	dmnl

3.3.5.2 Scenario setting run

One of SD main attribute is providing a platform to do experimentation of various scenarios on the developed model. Through various scenario experimentation, the impact of policies implementation in the future can be evaluated effortlessly without involving serious post-policy implementation cost. Three different scenarios of simulation have been conducted. Each scenario is crafted representing all policy variables and their influence towards CPO production.

SCENARIO 1: Pushing to replant

Due to the scarcity of potential plantation land, it is important for our industry to increase the productivity that refer to productivity per hectare or the number of FFB yield per hectare. This also has long been targeted in the ETP under EPP number 2. EPP 2 set to achieve average 25 tonne/ha FFB across all plantation owner by 2020 (PEMANDU, 2010). In order to increase FFB yield given a limited plantation area, the replanting rate has to be increased due to the huge difference of FFB yield per hectare in mature and ageing area.

Scenario where replanting is at higher level is simulated and the behaviour of CPO production as well as other important variables were observed. It is assumed that government has managed to find a way to convince plantation company and smallholders to perform aggressive replanting programme. In this scenario, the average replanting is set from 50,000 hectare to 300,000 hectare per year. The new replanting programme is set to start in 2017.

SCENARIO 2: Expanding the mechanization adoption rate

Another way to increase FFB yield per hectare is to ensure that we get the most yield out of every tree. This include ensuring sufficient nurturing (the quality fruit can be produced) and complete harvesting (minimizing loose fruit). To achieve this we have to supply optimal number of labour in the industry. However, the depleting labour particularly from Indonesia is inevitable because theoretically we cannot stop the growth of Indonesian plantation. As labour shortage is bound to happen, adopting mechanization is a way forward to sustain and increase productivity. However, current mechanization adoption is at unsatisfying level due to various factors including inadequate technology development on mechanization and high initial adoption cost.

A scenario where mechanization adoption is at satisfying high level was simulated. It is assumed that government has come out with appropriate scheme to convince both plantation company and smallholder to adopt mechanization. The mechanization adoption rate was increased from 20 percent to 100 percent. The new adoption rate is set to start in year 2017.

SCENARIO 3: Progressing the biodiesel programme

The need of increasing palm oil output is of essence due to the advancement of biodiesel programme. The current blend mandates may be increased in the future as part of the government commitment in stimulating biodiesel industry growth set under the National Biofuel Policy (NBP). With increase blend mandates, this means high demand of CPO will take place and supress the supply resulting to high CPO price. Similar things happen if government decides to widen the implementation of blend mandates in other sector aside of transportation and industrial sector. The sufficient palm oil output will help in stabilizing the high CPO price stem from blend mandate increase.

A scenario was simulated where the parameter of biodiesel blend mandate in transportation, industrial and other sector were increased starting year 2020 (four years after the latest announcement of new blend mandate in 2016). In transportation sector the mandate will be increase from 0.10 to 0.15, industrial sector from 0.07 to 0.10, and other sector from 0 to 0.05. This scenario also indicates the government has started to enforce biodiesel blend mandates into the other sector.

3.4 Genetic Algorithm as Search Algorithm

Developing GA is the second phase of the research methodology, which is also part of the process to achieve the second research objective. As aligned by Duggan (2008), a process of searching optimal solutions in an SD model using any search method fundamentally has to involve some essential steps, which include:

1) SFD must be completed and robust.
2) The policy variables have to be selected.
3) The upper and lower bound for each policy variables has to be defined.
4) The output which serve as the payoff have to be identified to serve as objective function.

In reference to this guideline, an SD model of Malaysia palm oil industry has been developed and various test has been performed to validate its robustness as presented in Chapter 4.1. Further, the policy variables were selected based on the main factor that influence CPO production which has been identified previously as illustrated in Figure 3.27. The determination of policy variables were done according to their impact on CPO production and validated by the expert opinion. The respective upper and lower bound for each policy variables has been defined as presented in Chapter 4.4. Finally, CPO production is chosen as the payoff or objective function in this research. Table 3.22 explains the description of each policy variables.

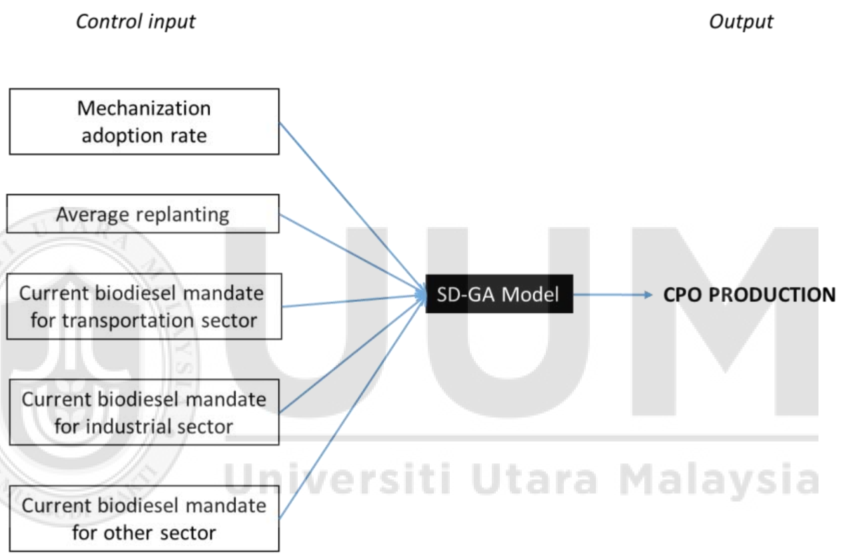

Figure 3.22. The relationship mapping between input and output of optimization module

Table 3.12

The Description of Policy Variables

Variables	**Sub-model**	**Description**
Mechanization adoption rate	Labour	The rate of all plantation in Malaysia adopting mechanized equipment to assist plantation activities
Average replanting	Oil palm plantation sector	Average replanting works done in all plantation in Malaysia per annum.

Biodiesel mandate in transportation sector	Biodiesel	The biodiesel mandate launched by the government targeting transportation sector.
Biodiesel mandate in industrial sector	Biodiesel	The biodiesel mandate launched by the government targeting industrial sector.
Biodiesel mandate in other sector	Biodiesel	The biodiesel mandate launched by the government targeting sector other than transportation and industrial.

In this research, as GA is integrated with SD model, the model allows autonomous control of the policy variable constraint. This comes from the feedback structure in SD model. For instance one of the policy variables - the average replanting rate - has to be capped by the current ageing area. The structure of the SD model has already captured the feedback process between these variables and autonomously refrain average replanting rate from exceeding current ageing area. On that account, there is no need in using penalty as adopted in other studies with GA only method.

The objective behind developing the SD-GA model is to find the sufficiently good solution for the set of aforementioned policy variables in order to achieve the desired CPO production level in certain year. Thus the objective function is to minimize the absolute value between the CPO production and its desired level in a desired time in the model time line as shown in Equation 3.75.

$$Objective\ function = MIN\left|CPO_{p(t)} - CPO_{p(t)}{}^{*}\right| \quad (3.75)$$

Where

$CPO_{p(t)}$ is the CPO production at time t

$CPO_{p(t)}*$ is the target CPO production at time t

The following sub-sections explain the working steps of the developed algorithm, the corresponded GA operator used, and the integration mechanism with Malaysia palm oil SD model.

3.4.1 Working Procedure of Genetic Algorithm

The sequential steps involved in the development of GA in this research are illustrated by flowchart as in Figure 3.23. The development of the algorithm is done on visual basics platform in Microsoft Excel 2013. Microsoft Excel 2013 was chosen because it offers the spreadsheet layout that is helpful for tabulating all the genes of chromosome in the population. Furthermore, the underlying visual basics (VB) programming in Microsoft Excel 2013 helps in coding the GA and the system interface, and the output from GA can be tabulated using the spreadsheet in Microsoft Excel 2013. Moreover, Vensim Dynamic Link Library (DLL) provides the leverage to integrate with Microsoft Excel thus facilitating the integration between SD and GA.

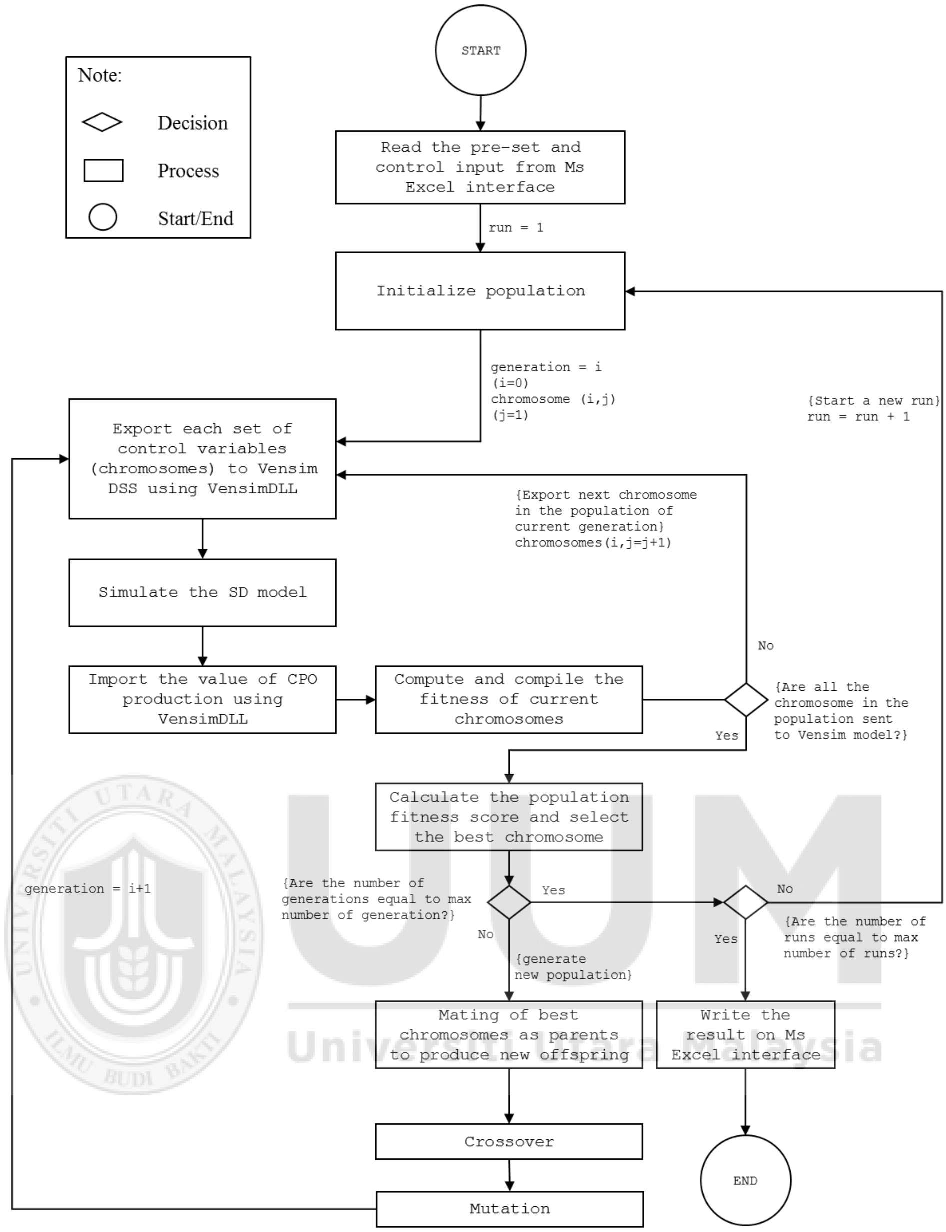

Figure 3.23. Workflow of the genetic algorithm on visual basic platform in Microsoft Excel 2013

STEP 1. Read the control input: The first step in the algorithm is reading the value range for policy variables. The value and range has to be defined before starting the algorithm. Table 3.13 compiles the value for number of population, number of generation and number of run. The number of generation is set as the stopping criterion for the optimization process, in which in this model the process will be stopped after the generation reach 30. This is based on the experimentation results done with various number of generation as presented in Chapter 4.2. The results show that at the 30th generation, sufficiently good solution has been produced with acceptable amount of time. As for the population number, 20 has been chosen as appropriate population size. A number of experiment has been done to decide the best generation and population number which produce the best solution in the shortest possible time as presented in Chapter 4.2. Finally, number of run is simply the number of running the optimization process and 30 is deemed sufficient for comparison purpose in this research.

Table 3.13

Genetic Algorithm Operator Used in this Study

GA operator	**Value**
Number of generation	30
Number of population	20
Number of run	30

STEP 2. Initialize the population: The algorithm generate an initial population in semi-random operation based on pre-defined upper and lower bound of policy variables as shown by the pseudo-code in Figure 3.21. The number of solutions (or chromosomes) in the population is based on the population number set during the coding process. The solution is represented by an array of 1x5 encoded real values which correspond to the five policy variables. Figure 3.24 shows the steps to generate the initial solution. Table 3.14 listed the policy variables and their respective code with representation of solution illustrated in Figure 3.25. The number of solutions in the population remains the same until the stopping criteria is met.

```
Generate an initial population using equation
for i = a, b c, d, e
IPOPj = rand|Li, Ui|
where Li is the policy variable lower bound
      Ui is the policy upper bound
      j is the number of population
```

Figure 3.24. Pseudo-code for generating initial population

Table 3.14

Policy Variables code

Variables	**Codes**
Mechanization adoption rate	*a*
Average replanting	*b*
Current biodiesel mandate for transportation sector	*c*
Current biodiesel mandate for industrial sector	*d*
Current biodiesel mandate for other sector	*e*

$$\left\{\ \begin{array}{|c|c|c|c|c|}\hline a & b & c & d & e \\ \hline\end{array}\ \right\}$$

Figure 3.25. Solution representation structure

STEP 3. Fitness evaluation and new population generation: Next is the sub-steps which are performed on the population of each generation until a specified number of run are performed.

1) The generated solutions are exported to Vensim DSS using Vensim Dynamic Link Library (VensimDLL). Vensim DSS will run the simulation using these values and produce the CPO production value in desired year as simulation output. The output is then imported by GA and evaluated of its fitness. The

fitness of a chromosome is measured by its corresponded CPO production value. Fitness of each chromosome is calculated following computation as shown by the pseudo-code in Figure 3.26. The code calculate the difference between the target CPO production and the current generation chromosome fitness. The calculation is expected to return between 0 and 1, where highest value denotes as the fittest chromosome.

```
Compare the CPO production, CPO(i) with the targeted CPO
production, CPO*, then compute fitness score, FS

For i = 1 to population number

If CPO(i) < CPO* then
FS(i) = CPO(i)/CPO*

If CPO(i) > CPO* then
FS(i) = CPO*/CPO(i)
```

Figure 3.26. The pseudo-code for fitness value evaluation

2) Then, the fittest chromosomes will be selected as parents to produce new offspring for next generation. The selection is done using the roulette wheel selection process. The idea is to select chromosomes with a probability of selection proportional to the chromosomes' fitness scores. Chromosomes with the highest fitness scores have greater probabilities of being selected, while chromosomes with lower scores have lower probabilities of being selected. The pseudo-code of roulette wheel selection is shown in Figure 3.27 as adapted from Bourg (2006). In this research, roulette wheel selection operator selects parents from population based on crossover probability rate dependent on the number of solutions which has been selected as elitist. Elitist is selected based on elitism mechanism.

```
i.  Generate a random number, Rnd
ii. Calculate fitness value, FV
    FV = Rnd * sum of fitness score

iii.Using a loop, calculate the fitness total, FT of all
    solutions which accumulates until FT > FV
    Do while,
    With (i = 1 to population number),
    FT = FT + FitnessScore(i)
    When FT > FV, the selection is obtained.

iv. Process i to iii is repeat for next selection.
```

Figure 3.27. The pseudo-code for roulette wheel selection

3) Selected chromosomes become the parents needed for mating or crossover process. The probability of crossover, *Pc* is equal to 0.95. This means that all offspring except one elitist from previous generation is made by crossover to ensure the diversity of the population. Crossover process is done using a simple single point crossover because the chromosome have a short structure with only five genes. The usage of multipoint crossover on the other hand will result into population become homogenous after many generations as stated by Spears and De Jong (1990). The cutting point is in the ratio of 2:3 as illustrated in Figure 3.28. The logic behind this cutting point is that the last three genes are of same category which is the biodiesel mandates. Thus, retaining or changing the last three genes is for the purpose of maintaining the properties of the chromosome. Figure 3.29 shows the pseudo-code for the single point crossover process.

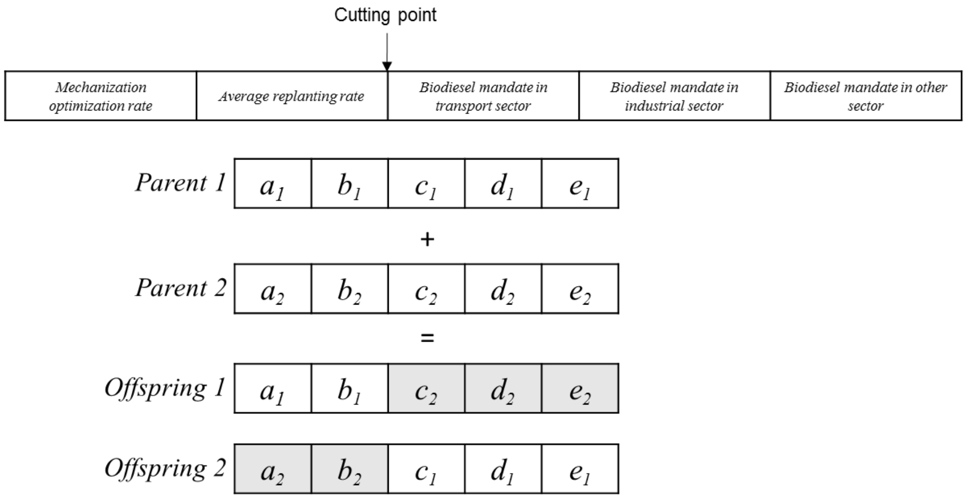

Figure 3.28. Example of single point crossover

```
i.   Choose cutting point in parent 1 and parent 2
     Ratio of cutting = 2:3 = a,b|c,d,e
ii.  For offspring 1, take gene a and b from parent 1 and
     take gene c, d, and e from parent 2.
iii. For offspring 2, take gene a and b from parent 2 and
     take gene c, d, and e from parent 1.
```


Figure 3.29. One point crossover pseudo-code

4) After crossover process, the new chromosomes will undergo mutation process. Mutation process is done using uniform mutation. That is, each gene has equal opportunity to be mutated based on random value between the constrain range (Michalewicz ,1994). The reason of using uniform mutation is that all gene in the chromosome in this research are assumed to have similar weigh to be mutated. Hence, there is no need of having index controlled mutation as offered by power mutation. Firstly, a random number is generated between 0 and 1. If the random number is less than the mutation probability rate, the mutation process is performed. The mutation probability used in this study is 0.01. Otherwise, the solution will not be mutated. The purpose of using low mutation

rate is to limit the number of mutated chromosome. If the mutation is performed, a random number between 0 and 1 is generated again. If the random number fall in the specific range, the correspondent gene is mutated. This scheme gives each gene a 20 percent chance of being mutated. The gene is mutated by generating random number within the lower and upper bound again. The mutation algorithm is illustrated in Figure 3.30 as adapted from Bourg (2006).

```
i.   Generate random number, Rnd1
ii.  Compare Rnd1 with mutation probability rate, Pm.
     If Pm < Rnd1 then
     proceed with the mutation process.
     Else
     cancel mutation process.
iii. If Pm < Rnd1, generate random number, Rnd2 again.
iv.  Compare Rnd2 with the uniform probability of each
     gene in a solution. Mutation of a gene is the re-
     generation of that gene in its correspondent upper
     and lower bound.
     If Rnd2 < 0.2, mutate gene a;
     If 0.2 < Rnd2 < 0.4, mutate gene b;
     If 0.4 < Rnd2 < 0.6, mutate gene c;
     If 0.6 < Rnd2 < 0.8, mutate gene d; and
     If 0.8 < Rnd2 < 1, mutate gene e.
```


Figure 3.30. Pseudo-code for mutation process

5) In this research, elitism mechanism is used to select the best solutions from the current population to be forwarded to next generation without undergoing crossover and mutation process. The mechanism select one solution with the highest fitness score from current population and bring it to the next generation without any gene modification. The remaining population in the next generation will be formed through the selection, crossover and mutation process using current population. The elitism mechanism is illustrated in Figure 3.31.

```
i.   Sort the solutions in current generation in descending
     order of its fitness.
ii.  Select the solution with the highest fitness score and
     bring it to the next generation.
iii. Other solutions in the next generation are obtained through
     selection, crossover and mutation process of current
     generation.
```

Figure 3.31. The pseudo-code for elitism mechanism.

STEP 4. *Process repeating:* After all the generation has been evaluated, next run will be performed. In this research, the number of run is 30. The number of run is deemed sufficient for comparison purpose in this research. Furthermore, performing several runs are important as GA is stochastic in nature thus repeating the whole process will increase the chances of getting the best of the best solution.

STEP 5. *Displaying the result:* When all run has been performed, the system will compile all the best solutions (chromosomes) from each run in Microsoft Excel 2013 interface for comparison and interpretation purpose.

The interface is developed on Microsoft Excel spreadsheet to allow the input of GA setting including the number of generation, number of population, and mutation rate as shown in Figure 3.32. Furthermore, it allows the input of policy variables' lower and upper boundary. On the left side of the interface, the list of genes of all chromosomes in all population are displayed in list. By checking the 'show progress' button, the system will show updated list from each generation throughout the optimization process. However, user may choose to uncheck the 'show progress' button which will render the system to only display the list of genes of chromosomes in the final generation. For reference, the system also display the total execution time of the whole optimization process.

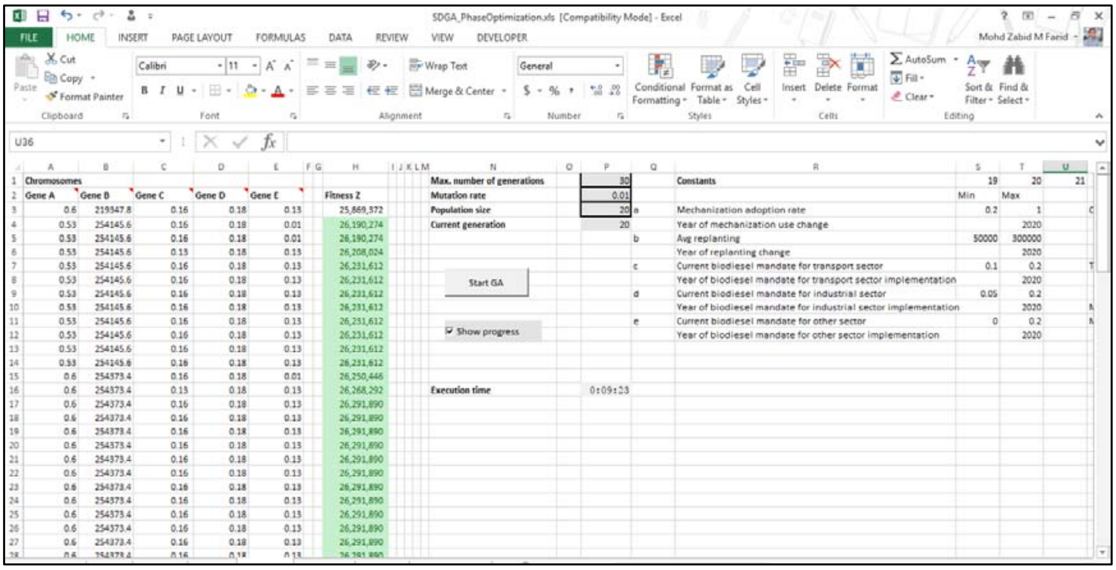

Figure 3.32. The system interface.

3.5 Searching for Optimal Policy Options

To achieve our research objective of improving CPO production, the policy variables has to be optimized. Performing optimization for multiple variables manually using SD alone can be time-consuming. Furthermore, successful optimization process may result into better result for searching the optimal policy options. Thus we seek the helps from GA from metaheuristics family by integrating it with SD. In optimization process, there is an objective function, the constraints and the results. In this study, the objective function is to minimize the absolute value between the targeted CPO production and simulated CPO production. By achieving this objective function, CPO production can be improved to the desired level. The constraints are lower and upper bound of five policy variables namely mechanization adoption rate, average replanting, biodiesel mandated for transportation sector, biodiesel mandate for industrial sector, and biodiesel mandate for other sector. Each optimization process will be performed in 30 runs where the best result will be chosen for policy interpretation.

There are three optimization process performed using SD-GA model where each are conducted with exclusive objective function. The optimization process was done as part of the requirement to achieve the second research objective. The best solution from each optimization is meticulously interpreted for possible real life policy implementation.

3.5.1 Optimization 1

In optimization 1, the absolute value of the difference between CPO production in 2050 ($CPO_{P(t=2050)}$)and maximum value CPO production in 2050 ($Max\ CPO_{P(t=2050)}$) by searching for appropriate values of each policy variables (Equation 3.76). Table 3.15 list the parameter range for all policy variables. All policy variables will be the genes in the chromosome with the correspondent value as the gene's allele. At the end of optimization, the best chromosome will be the best so far solution. After 30 run, these best so far solution will be compared to choose the best solution.

$$Objective\ function = MIN\ |(CPO_{P\ (t=2050)}) - (Max\ CPO_{P\ (t=2050)})| \tag{3.76}$$

Table 3.15

Parameter Setting for Policy Variables Tested in Optimization 1

Code	Policy variable	Range	Starting year	Description
a	Mechanization adoption rate	0.2 – 1	2017	The adoption of mechanization is in the range of 20% to 100%.
b	Average replanting	50,000 – 300,000	2017	The minimum replanting rate is the current replanting rate (50,000 ha) and maximum is at 300,000 ha.
c	Blend mandate for transportation	0.10 – 0.20	*2020	New mandate start at year 2020 with the range of B10 to B20.
d	Blend mandate for industrial	0.07 – 0.20	*2020	New mandate start at year 2020 with the range of B7 to B20.
e	Blend mandate for other sector	0 – 0.20	*2020	New mandate start at year 2020 with the range of 0 to B20.

*Because latest mandates has been announced in 2016 and scheduled to be implemented in 2017, the starting point for all new mandates implementation are in 2020.

3.5.2 Optimization 2

In optimization 2, assuming that it is hard to implement new policies in 2017 due to time constraint, therefore the new policies are planned to be implemented in year 2020 (4 year's time frame). Equation 3.77 shows the objective function for optimization 2. Note that the objective function is similar with that of optimization 1. The difference of these two optimization however is the year of policy variable changes. The input and control parameter are listed in Table 3.16.

$$Objective\ function = MIN\ |\left(CPO_{P\ (t=2050)}\right) - \left(Max\ CPO_{P\ (t=2050)}\right)| \tag{3.77}$$

Table 3.16

Parameter Setting for Policy Variables in Optimization 2

Code	Policy variable	Parameter /Range	Starting year	Description
a	Mechanization adoption rate	0.2 – 1	2020	The adoption of mechanization is in the range of 20% to 100%.
b	Average replanting	50,000 – 300,000	2020	The minimum replanting rate is the current replanting rate (50,000 ha) and maximum is at 300,000 ha.
c	Blend mandate for transportation	0.10 – 0.20	2020	New mandate start at year 2020 with the range of B10 to B20.
d	Blend mandate for industrial	0.07 – 0.20	2020	New mandate start at year 2020 with the range of B7 to B20.
e	Blend mandate for other sector	0 – 0.20	2020	New mandate start at year 2020 with the range of 0 to B20.

3.5.3 Optimization 3

Optimization 3 takes a different approach in utilizing SD-GA model as compared to optimization 1 and 2. While trying to maintain the progress of policy variables, however, the solution produced in both optimization 1 and 2 may not be sensible in the real world policy implementation. In a nutshell, any improvement on the policy has to be done in phases to ensure the participation of the industry players as well as deterring any unwarranted shock in the industry. On this account, the capability of the SD-GA model in setting the policy variables in any desired years can be utilized in order to perform phase optimization process. Say the policy makers are not planning to maximize the CPO production through one shot policy changes. However, they prefer to disaggregate the path to achieve the goal and set specific value to be achieved in certain year. This is important in helping the policy maker to formulate a realistic and achievable goal.

By using the hybrid SD-GA model, the 'phased optimization processes' where policy changes are done phase by phase to achieve desired CPO production has been introduced. Each phase has individually tailored objective function and parameter range for policy variables formulated in continuum as illustrated in Table 3.17. The time interval between the phases is five years where the process start in year 2017 and ended in year 2050. The target for CPO production in year 2020 is increased by 4 percent of CPO production in year 2017[6]. Next, CPO production target in year 2025 is increased by 4 percent of CPO production target in 2020. Then, the following five years interval will have CPO production target of 26 million tonne without any increment from the

[6] The reason we increase 4% instead of finding the maximum CPO production at the particular year is to avoid the sudden high increase in policy variables, which will defeat the very purpose of phase optimization process.

previous target. This is due to the physical limitation of the model, where the highest CPO production achievable is at 26 million tonne. Finally, the target CPO production will remain until year 2050, or in other words the maximum CPO production is targeted until year 2050. Equation 3.78 shows the objective function for optimization 3.

$$Objective\ function_{(t=n)} = MIN\ |\left(CPO_{P\ (t=n+1)}\right) - \left(CPO_{P\ (t=n+1)}{}^{*}\right)| \tag{3.78}$$

Where,

n = number of phase (n = 1,…, 7)

Table 3.17

The Parameter Setting in Phase Optimization Process

Policy variable	Phase 1 2017-2020	Phase 2 2020-2025	Phase 3 2025-2030	Phase 4 2030-2035	Phase 5 2035-2040	Phase 6 2040-2045	Phase 7 2045-2050
Mechanization adoption rate	0.2 – 0.3	0.3 – 0.5	0.5 – 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	0.99 – 1
Average replanting	50,000 – 100,000	100,000 – 150,000	150,000 – 200,000	200,000 – 300,000	200,000 – 300,000	200,000 – 300,000	200,000 – 300,000
Biodiesel mandate in transport	0.10 – 0.10	0.10 – 0.15	0.13 – 0.2	0.17 – 0.25	0.18 – 0.3	0.24 - 0.35	0.33 – 0.4
Biodiesel mandate in industrial	0.07 – 0.07	0.07 – 0.10	0.08 – 0.15	0.14 – 0.2	0.18 – 0.25	0.18 – 0.3	0.23 – 0.35
Biodiesel mandate in other	0 - 0	0 – 0.05	0.02 – 0.10	0.04 – 0.15	0.08 – 0.2	0.08 – 0.25	0.22 – 0.3
TARGET CPO production (Year)	25,000,000 (2020)	26,000,000 (2025)	*26,000,000 (2030)	*26,000,000 (2035)	*26,000,000 (2040)	*26,000,000 (2045)	*26,000,000 (2050)
Increment from previous target	+ 4%	+ 4%	0	0	0	0	0

* CPO production cannot be increased further than 26,000,000 tonne due to physical limitation of the model.

Through phased optimization processes, it helps to identify the room for gradual policy implementation and avoid post-policy implementation shock to the industry.

3.6 Model evaluation

For evaluation purpose, all optimization results are compiled and compared. The evaluation is based on the CPO production produced as well as the appropriateness of the solution to be implemented in the real world situation. Further, the discussions will involve the findings comparison with previous studies. This is done as the requirement to achieve the third research objective, which is to evaluate the propose hybrid model for assessing CPO production in Malaysia.

3.7 Summary

In this chapter, research design and process are explained in detail. This includes the SD model development process and GA working procedure. Both SD and GA area integrated using user interface developed in Ms Excel 2013. The best solution from each run is compiled at the end of the process for comparison purpose. Next chapter present the results of experimentation and analysis derived from this research using the propose SD-GA model.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

This chapter starts with the presentation of the outcome of various validation tests. Then, the simulation results from the model under various policy interventions are presented. Next, the results for several SD-GA optimization to find the optimal policy options are presented. Finally, the obtained optimal policy options from all optimization were compared to select the best policy appropriate for real world implementation. The chapter ends with the conclusion.

4.1 Model Validation

4.1.1 Structural and parameter assessments

In structural assessment test, the boundary adequacy of the model the appropriateness of variables were examined, which was initially done by having a close look on causal loop diagram (CLD). The CLD capture the main component in Malaysia palm oil market including palm oil supply and demand, plantation sector, labour availability, and palm-based biodiesel sector. The main components of CLD were referred from key papers as were in Yahaya et al. (2006), Shri Dewi et al. (2010), Shri Dewi et al. (2015), and Mohammadi et al. (2016).

The next process involved with the conversion of CLD into stock and flow diagram (SFD). In this process, the main component were modeled in individual sub-model and eventually combined into a main model. Again, the fundamental structure and behaviour of SFD were referred from key papers as in Yahaya et al. (2006), Shri Dewi et al. (2010), Shri Dewi et al. (2015), and Mohammadi et al. (2016). Modification has been made however for the model to achieve the research objective. The non-linear relationship was also being incorporated using system dynamics lookup function to permeate higher accuracy in depicting the real industry situation. Further, both CLD and SFD mechanism and feedback process were validated by expert opinion through interview session with industry members. Table 4.1 shows the process involve in validation process with the expert in the industry. Conclusively, after the validation process it was found that the fundamental structure and feedback process of both CLD and SFD were closely conformed to the previous studies and in-line with expert opinion.

Table 4.1

Model Validation Process with Expert in the Industry

Date	**Experts rank and affiliation**	**Process**	**Action taken**
9 September 2016	Deputy President, Malaysia Biodiesel Association	• Defining the reference mode • CLD structure and feedback checking • SFD structure and feedback checking • Policy analysis	• CLD structure and feedback loops were accepted. • Biodiesel sub-model in SFD has been improved in terms of mandate impact on CPO demand. • Policy changes on mandate and its impact on model behaviour was accepted.
14 September 2016	Director, Malaysian Palm Oil Board	• Defining the reference mode • CLD structure and feedback checking • SFD structure and feedback checking • Policy analysis	• CLD structure was corrected in terms of CPO prices, supply and demand relationship. • CPO price setting mechanism in SFD has been corrected. • Policy changes on replanting rate and mechanization and their impact on model behaviour were accepted.
7 October 2016	Manager, Performance Management and Delivery Unit	• Defining the reference mode • CLD structure and feedback checking • SFD structure and feedback checking • Policy analysis	• CLD structure and feedback loops were accepted. • SFD structure and behaviour were accepted. • Policy changes on all policy variables and their

			impact on model behaviour were accepted.
10 October 2016	Director, Ministry of Plantation Industries and Commodities	• Defining the reference mode • CLD structure and feedback checking • SFD structure and feedback checking • Policy analysis	• CLD structure and feedback loops were accepted. • SFD structure and behaviour were accepted. • Policy changes on all policy variables and their impact on model behaviour were accepted.

*CLD = Causal Loop Diagram; SFD = Stock and Flow Diagram

Next, for parameter assessment test, sub-chapter 3.33 can be referred for detailed explanation on the source of parameter as well as reasons behind the assumptions made in each sub-model. Conclusively, all variables and assumptions were taken from published literature, government bodies, and interview with industry members.

4.1.2 Dimensional consistency test

Dimensional consistency test is done by checking both hand sides of equations in the model. For better understanding, Table 4.2 presents the dimensional consistency analysis of main equation from each sub-models. Furthermore, the built-in dimensional consistency test provided in Vensim has been performed and the result shows all unit are consistence as demonstrated in Figure 4.1.

Table 4.2

Dimensional Consistency of Selected Equations from Each Sub-Models

Sub-model	Equation number	Equation	Dimensional analysis
Palm oil supply and demand	3.3	$CPO_{p(t)} = \int_{to}^{t} r_{CPOp}\, dt + CPO_{p(to)}$	[tonne] = [tonne/year]*[year]+[tonne]
	3.4	$r_{CPOp} = (OER \times FFBY_T)/t_{CPOp}$	[tonne/year] = [dmnl]*[tonne]/[year]
	3.5	$CPO_{i(t)} = \int_{to}^{t} r_{CPOi}\, dt + CPO_{i(to)}$	[tonne] = [tonne/year]*[year]+[tonne]
	3.9	$CPO_{x(t)} = \int_{to}^{t} r_{CPOx}\, dt + CPO_{x(to)}$	[tonne] = [tonne/year]*[year]+[tonne]
	3.16	$TD_{CPO} = CPO_x + CPO_B + CPO_{PPO}$	[tonne] = [tonne]+[tonne]+[tonne]
	3.18	$PPO_{l(t)} = \int_{to}^{t} r_{PPOl}\, dt + PPO_{l(to)}$	[tonne] = [tonne/year]*[year]+[tonne]
	3.23	$PPO_{x(t)} = \int_{to}^{t} r_{PPOx}\, dt + PPO_{x(to)}$	[tonne] = [tonne/year]*[year]+[tonne]
	3.28	$TD_{PPO} = PPO_l + PPO_x$	Total PPO demand
	3.29	$P_{CPO(t)} = \int_{to}^{t} r_{PCPO}\, dt + P_{CPO(to)}$	[RM] = [RM/year]*[year]+[RM]
Oil palm plantation	3.36	$A_{pre(t)} = \int_{to}^{t} r_{plant} - r_{mat}\, dt + A_{pre(to)}$	[hectare] = ([hectare/year]-[hectare/year])*year+[hectare]
	3.46	$A_{mat(t)} = \int_{to}^{t} r_{mat} - r_{age}\, dt + A_{mat(to)}$	[hectare] = ([hectare/year]-[hectare/year])*year+[hectare]
	3.49	$A_{age(t)} = \int_{to}^{t} r_{age} - r_{cut}\, dt + A_{age(to)}$	[hectare] = ([hectare/year]-[hectare/year])*[year]+[hectare]
	3.51	$T_{FFBY} = \left(FFBY_{mat} + FFBY_{age}\right) \times f_{weather,FFBY} \times f_{L,FFBY}$	[tonne] = ([tonne]+[tonne])*dmnl*dmnl
	3.52	$FFBY_{mat} = FFBY_{avg,mat} \times A_{mat}$	[tonne] = [tonne/hectare]*[hectare]
	3.53	$FFBY_{age} = FFBY_{avg,age} \times A_{age}$	[tonne] = [tonne/hectare]*[hectare]
Biodiesel	3.54	$B_{p(t)} = \int_{to}^{t} r_{Bp}\, dt + B_{p(to)}$	[tonne] = [tonne/year]*[year]+[tonne]
	3.55	$r_{Bp} = TD_B$	[tonne] = [tonne]
	3.56	$TD_B = D_{Btrans} + D_{Bind} + D_{Bother}$	[tonne] = [tonne]+[tonne]+[tonne]
Labour	3.60	$L_{(t)} = \int_{to}^{t} r_{Lin} - r_{Lout}\, dt + L_{(to)}$	[labour] = ([labour/year]-[labour/year])*[year]+[labour]

3.61	$r_{Lin} = f_{rLin} \times L_{gap}$	[labour/year] = [1/year]*[labour]
3.66	$r_{Lout} = f_{Lout} \times L/T_{contract}$	[labour/year] = [dmnl]*[labour]/[year]

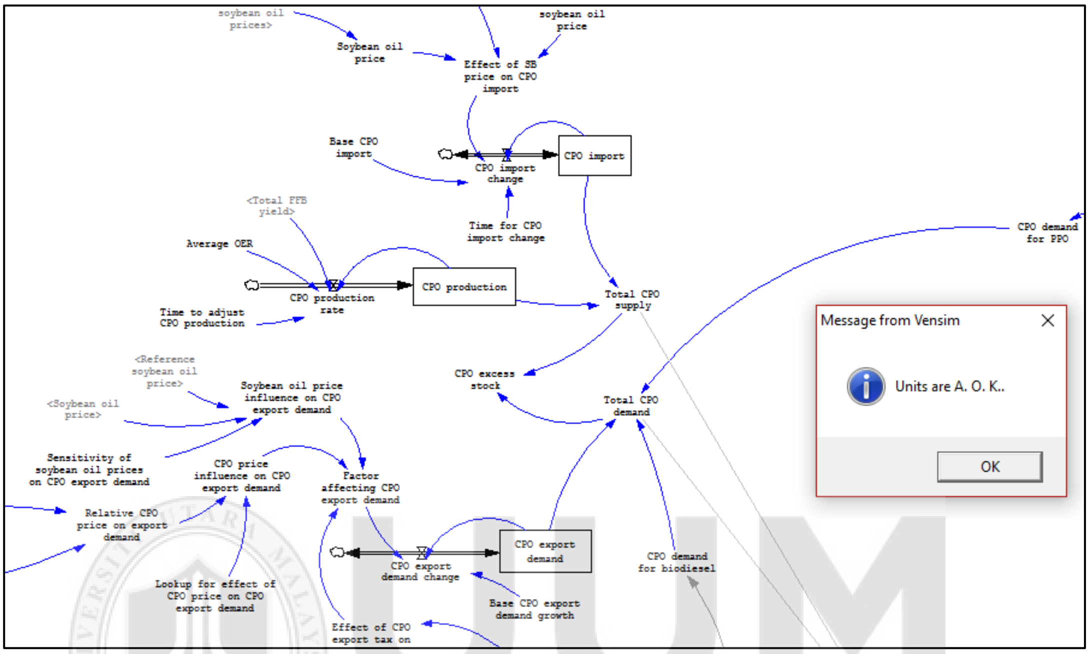

Figure 4.1. Successful unit test performed in Vensim

4.1.3 Extreme condition test

The trend for selected variables from each sub-models were observed while changing the correspondent parameters to extreme value. Table 4.2 shows the extreme condition test setup, expected outcome and the results of the test. All the expected outcome realized in each sub-model after the test is illustrated in Figure 4.2 until Figure 4.3. As a conclusion, result obtained from the test indicates that the model has passed the extreme condition test.

Table 4.2

Extreme Condition Test of the Model

Sub-model	Test	Value	Expected outcome	Illustration
1. Palm oil supply demand	Oil extraction rate become extremely low at zero.	0	CPO production become zero	Figure 4.1
2. Oil palm plantation	Replanting rate become extremely low at zero.	0	Premature and mature area become zero; Ageing area equal to total planting area.	Figure 4.2
3. Palm-based biodiesel	Biodiesel mandate for each sector become maximum at 100 percent.	1	Biodiesel demand increase.	Figure 4.3
4. Labour	Mechanization adoption rate become maximum at 100 percent	1	Labour productivity increase.	Figure 4.4

For the first test, when oil extraction rate become zero (for instance when there is no mills to process FFB), this means that there will be no oil extracted from FFB. Even though the FFB yield is at very high level, without mills to process the CPO production will become zero as illustrated in Figure 4.2.

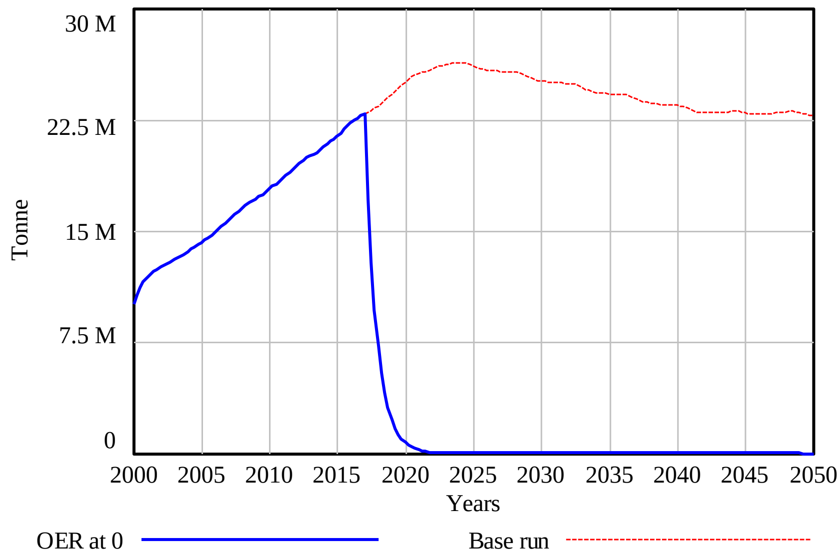

Figure 4.2. Behaviour of CPO production for extreme condition test

For the second test, Replanting rate set at zero means there is no replanting works done in the oil palm plantation sector. When this happen, there will be no premature area because no new replanting at the end of simulation. The mature area also become zero at the end of the simulation as all area become ageing area. Eventually, ageing area will be equal to total plantation area, which means all planted area in the beginning of the simulation has become ageing area due to no replanting works to replace ageing trees as shown in Figure 4.3.

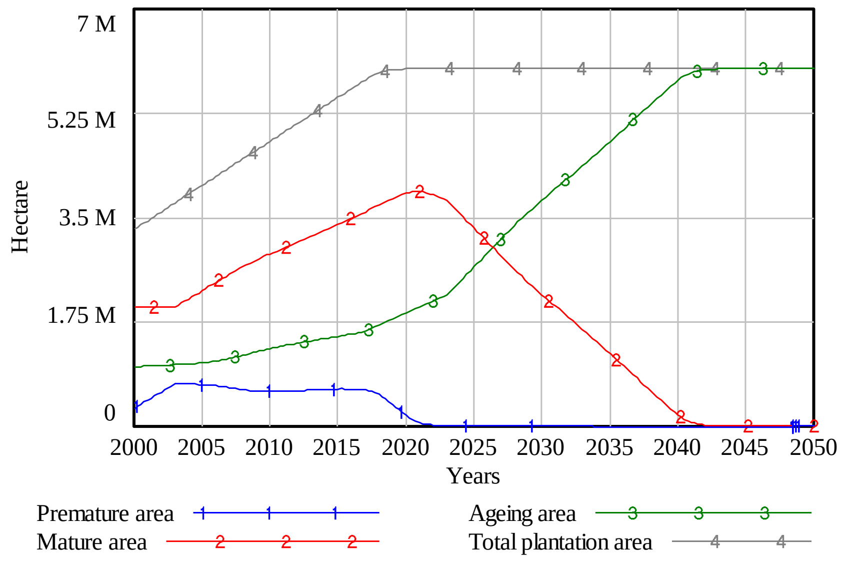

Figure 4.3. Behaviour of all plantation area for extreme condition test

For the third test, when biodiesel mandates in all sector become maximum (or become B100), biodiesel demand will be significantly increase due to demand from biodiesel producer to fulfill the mandate requirement as illustrated in Figure 4.4. This also means that all petrol diesel usage has been completely replaced by the used of pure biodiesel or B100.

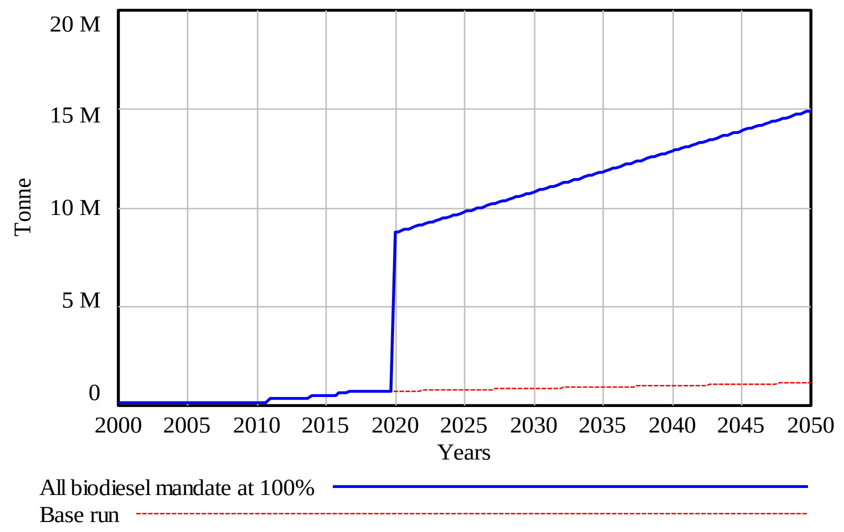

Figure 4.4. Behaviour of biodiesel demand for extreme condition test

Finally, in the fourth test, when all plantation sector has adopted mechanization (where mechanization adoption rate become 100 percent), the productivity of labour will significantly increase and boosted the FFB yield and CPO production as shown in Figure 4.5.

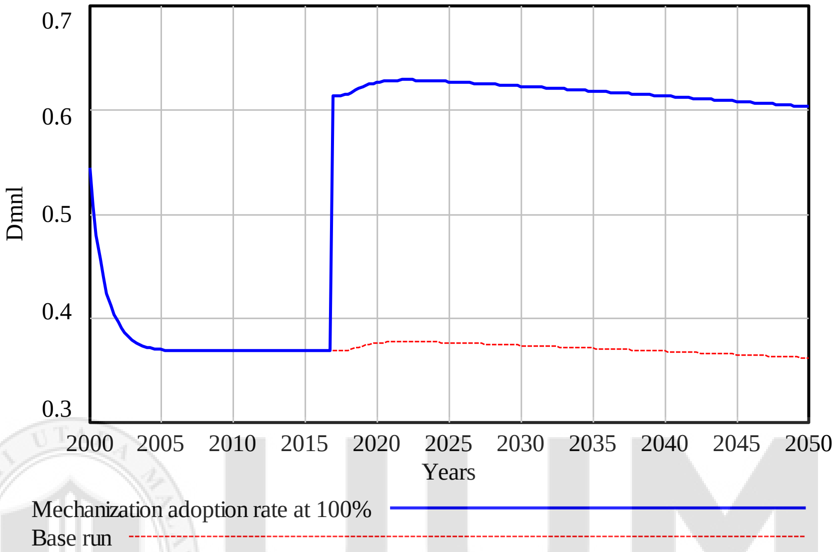

Figure 4.5. The behaviour of labour productivity for extreme condition test

4.1.4 Integration error test

For integration error test, three values of time step namely 0.25, 0.125 and 0.0625 were chosen and the main stock variable from each sub-model were observed. As Figure 4.6 and 4.7 shows insignificant change in behaviour, it can be concluded that the model has passed the integration error test.

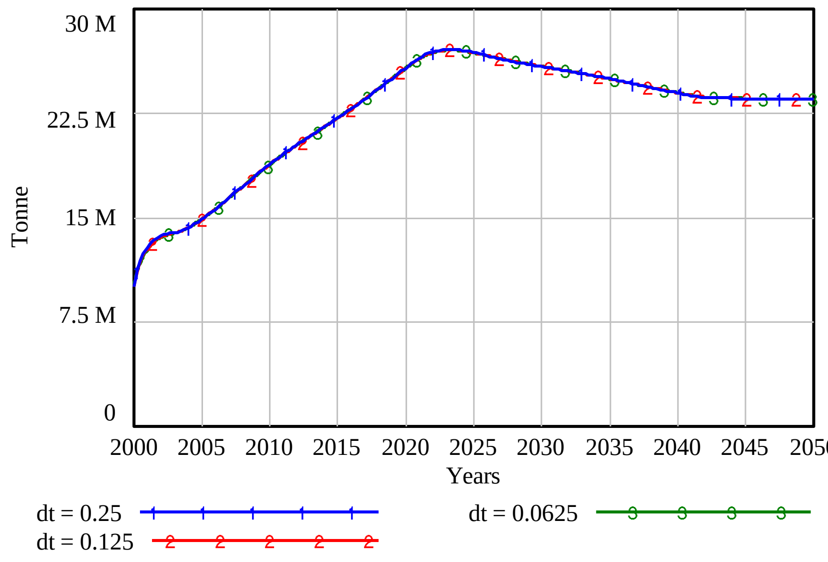

Figure 4.6. CPO production in different delta time (*dt*) for integration error test

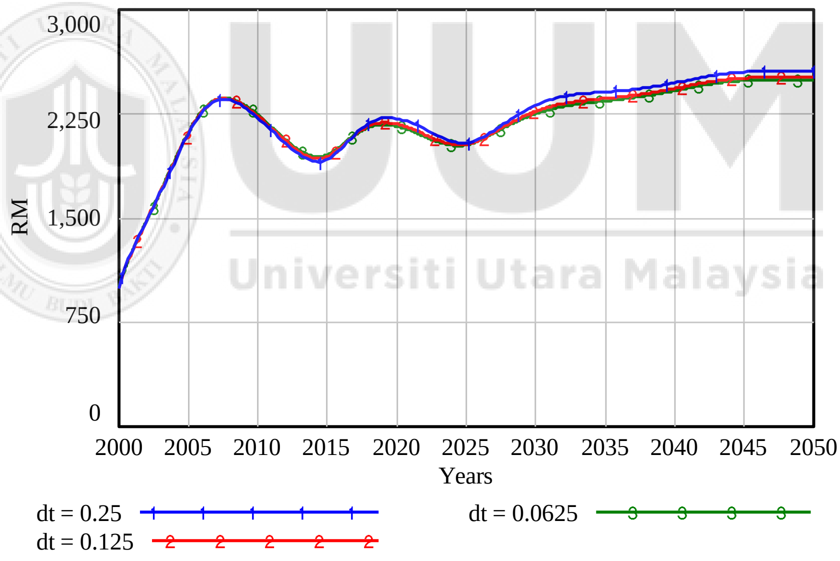

Figure 4.7. CPO price in different delta time (*dt*) for integration error test

4.1.5 Sensitivity test

For sensitivity test, six policy variables from each sub-model were chosen namely average oil extraction rate, average replanting, and biodiesel mandate for transportation, industrial and other sector. The result from sensitivity analysis illustrated in Figure 4.8 and 4.9. The figure show that the pattern of CPO production and CPO prices respectively has similar range of values with no irregular pattern was observed from the pattern. Towards the end of the simulation, CPO production and CPO prices move to the attainment of equilibrium. It can be explained that the overall pattern consistency is of critical as compared to numerical values as argued by Hekimoglu and Barlas (2010). On that ground, we concluded that the model has passed the sensitivity analysis test.

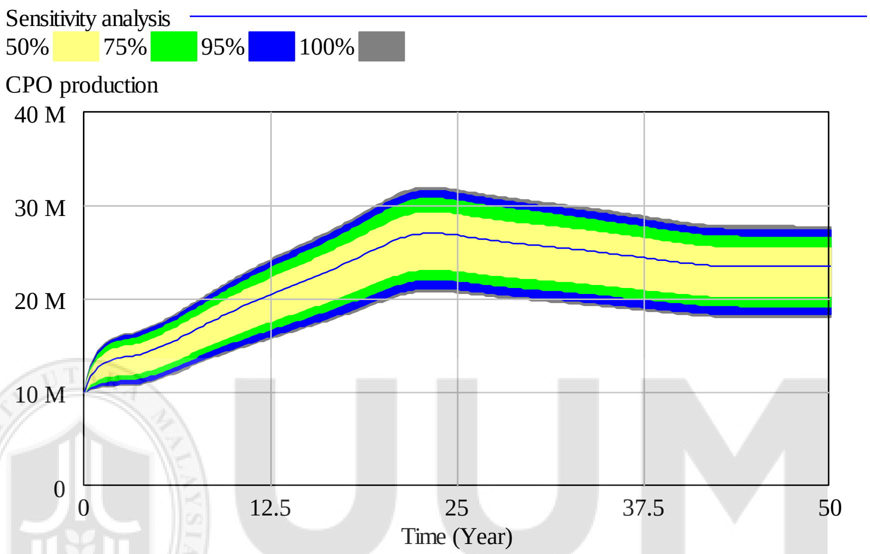

Figure 4.8. CPO production in multi-variate sensitivity analysis

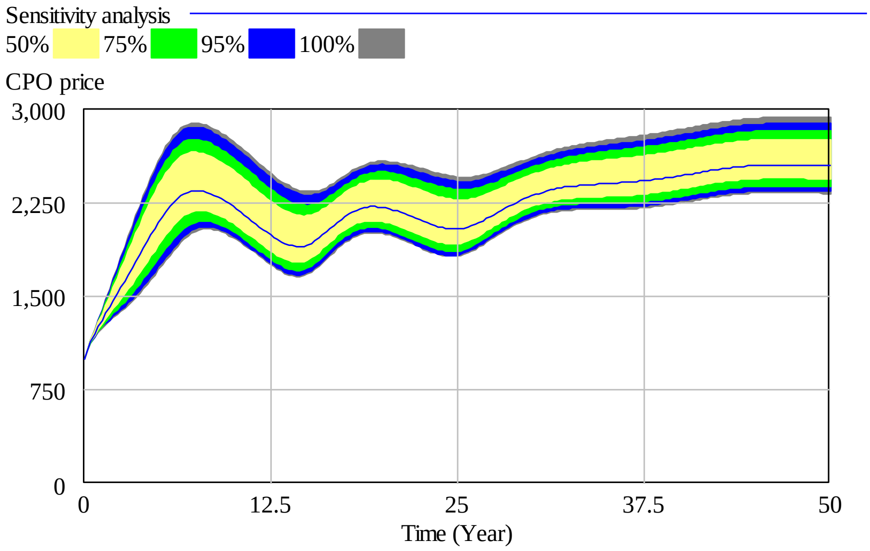

Figure 4.9. CPO price in multi-variate sensitivity analysis

4.1.6 Behaviour validity test

The behaviour validity test is executed using the calibration module provided in Vensim. Table 4.3 compile the value derived from parameter estimation process for all non-control variables in the model. The value has resulted into better fit of simulation result against historical data as shown in Figure 4.10 to 4.15.

Table 4.3

Parameter Estimation Results

Variables	Values
Base CPO export demand growth	3.00
Base PPO export demand growth	0.201
Base PPO local demand growth	0.155
Fraction of labour taking rate	0.250
Sensitivity of soybean prices on PPO local demand	0.479
Sensitivity of soybean oil price on CPO export	0.001
Sensitivity of soybean oil price on CPO import	0.100
Sensitivity of soybean oil price on PPO export demand	0.004
Time for CPO price adjustment	2.000

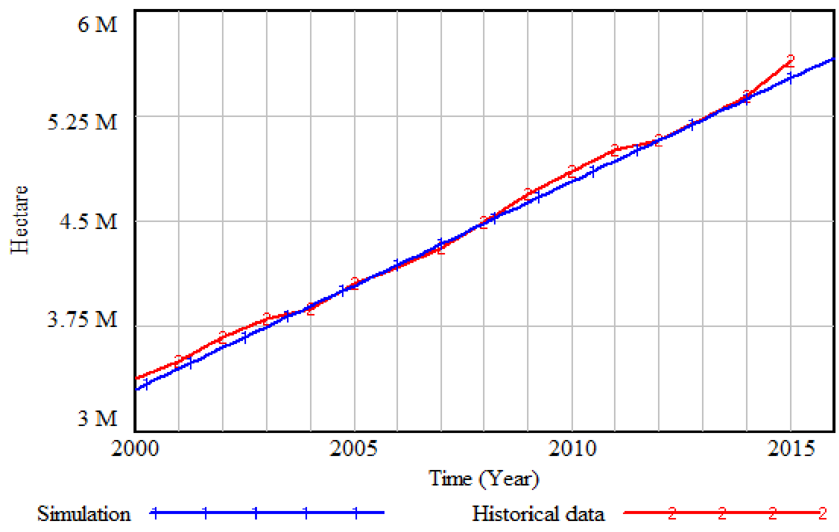

Figure 4.10. Total plantation area simulation result against historical data

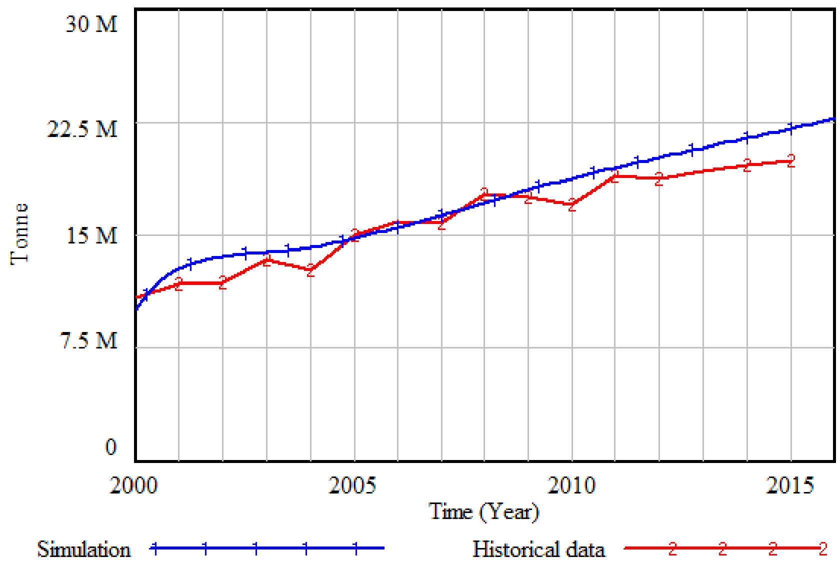

Figure 4.11. CPO production simulation result against historical data

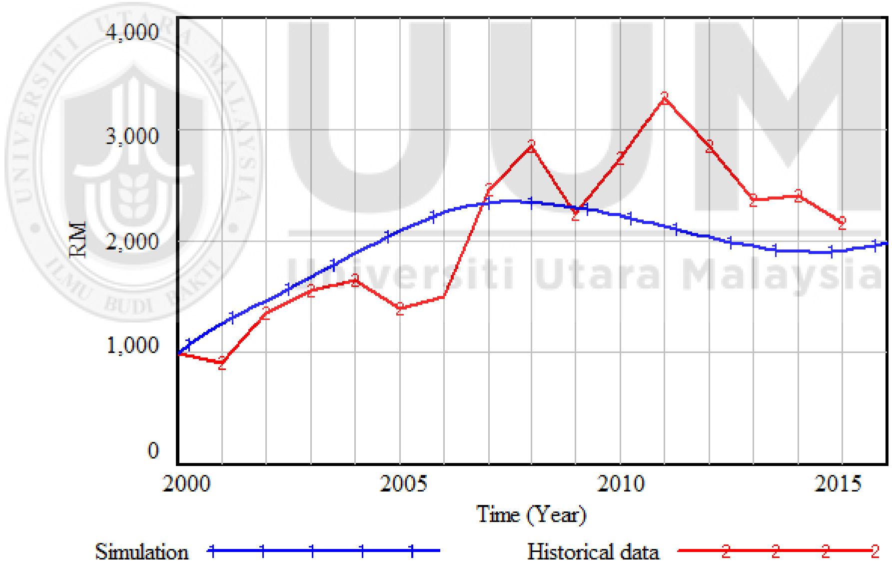

Figure 4.12. CPO price simulation result against historical data

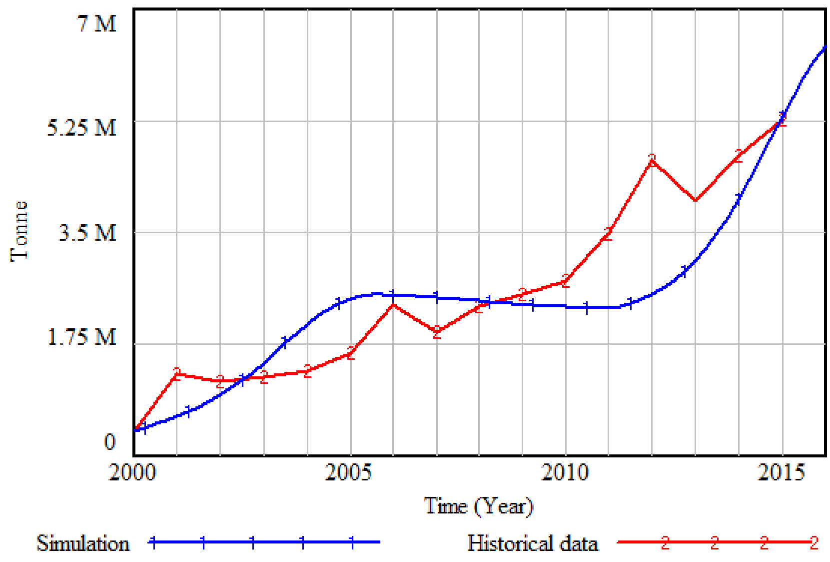

Figure 4.13. CPO export demand simulation result against historical data

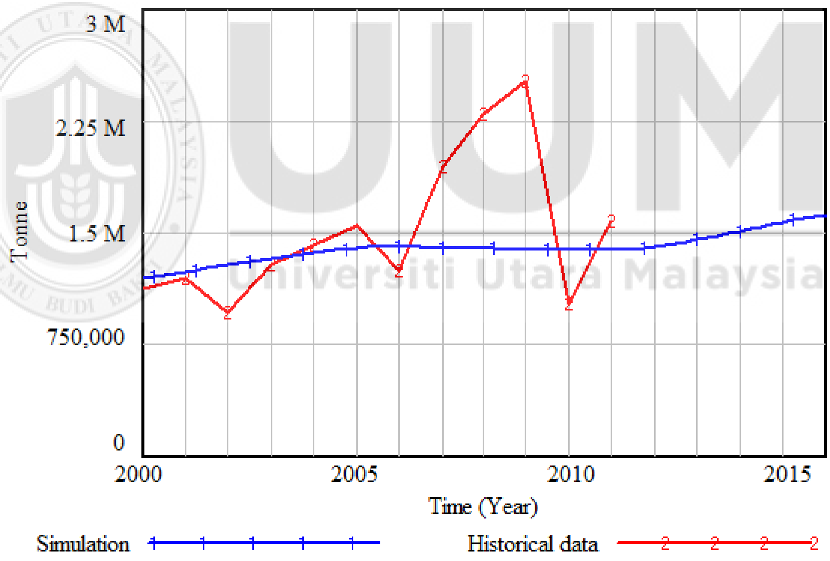

Figure 4.14. PPO local demand simulation result against historical data

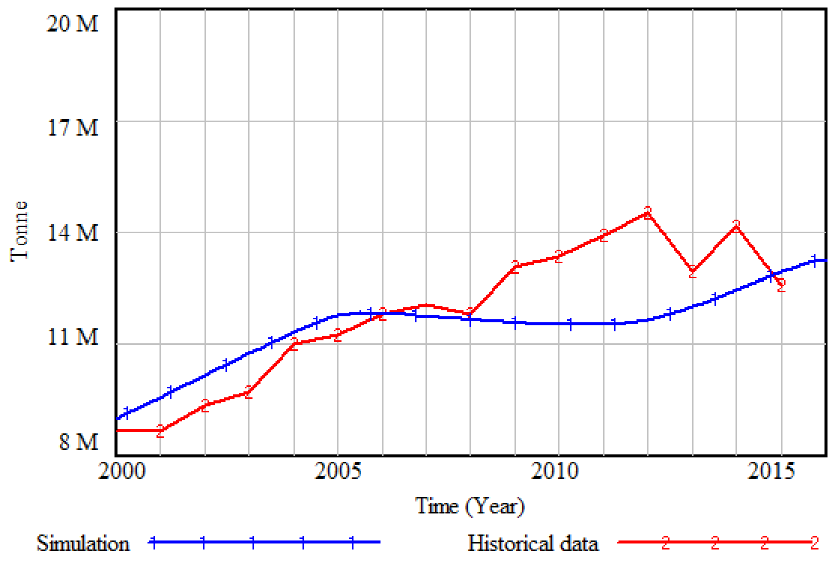

Figure 4.15. PPO export demand simulation result against historical data

The results of statistical analysis test are compiled in Table 4.4. The RMSPE are below ten percent with the exception of CPO price, CPO export demand and PPO local demand. The small total errors for total plantation area, CPO production, and PPO export demand show the model adequately tracks the major variables.

Table 4.4

Statistical Error Analysis of Selected Variables

Variable	**RMSPE (%)**	**Theil's Inequality Coefficients**		
		U^M	U^S	U^C
Total plantation area	1.28	0.41	0.01	0.59
CPO production	7.75	0.44	0.11	0.45
CPO price	25.59	0.06	0.37	0.58
CPO export demand	29.81	0.09	0.11	0.80
PPO local demand	24.48	0.12	0.75	0.13
PPO export demand	9.84	0.13	0.45	0.43

However, there are explanations on large errors on the variables. According to Sterman (2000), the larger error often leads to questions about the assumption of the model. Consider the CPO price with RMSPE of 25.59 percent. Plotting the simulated and actual data in Figure 4.12 reveals that the model does not capture the short-term fluctuation in CPO price. The reason can be traced from the difficulty of depicting the CPO supply and demand imbalance. As the demand comes from several sources including CPO export and PPO local demand (which also have high RMSPE) this has highly the chance to be the reason why CPO price RMSPE produce a high value.

Other than CPO price, both CPO export and PPO local demand are influenced by the soybean oil price. The soybean oil price is the closest substitutes of palm oil and may be the choice for importing countries in the midst of low CPO demand. The short term demand from major importing country like China, India and the European Union contribute to the short term fluctuation of demand. This normally caused by market sentiment like forecasted adverse weather or exporting tax bill that affects both CPO production and demand. In this study however, the demand fluctuation based on market sentiment is not captured due to the difficulty of incorporating them in the model.

Another main reason why the CPO price simulated trend missed some turning point as compared to the actual data is due to the simulation time. The change of CPO price in this study were done per year, while in reality the annual CPO price published in palm oil statistic report were the average price for 12 month in a year. As the demand and market sentiment changes every month, the model in this study is unable to capture the monthly variation in demand which shaped the fluctuation in real data. On that account, because the model in this study uses longer time (of annually rather than monthly), it inevitably introduce delays that cause the simulated trend miss key turning points and shifts in growth rate (Sterman, 2000).

Nevertheless, the inequality coefficient shows low value indicating that for all tested variables, the simulated trend is vary point-by-point but following the behaviour of the actual data (Sterman, 1989). Fitting the historical data alone does not necessarily prove that a model is correct and simply shows the replicability of behaviour in the real world (Morecroft, 2007; Olaya, 2014). Thus, as the model in this study has the purpose of studying the long term behaviour of CPO production and policy analysis as opposed to short term point-by-point forecasting, the large RMSPE error for some variables did not compromise the conclusions of this study (Sterman, 1984; 2000).

4.2 Identification of Parameters Value for Genetic Algorithm

The number of generation and population were identified through various numbers of experimentation. In this research, the best values were determined based on the quality of desired output and time taken for best solutions to converge. Table 4.5 list the parameters used in this research determined from series of experimentation.

Table 4.5

Parameters Value for Generation and Population Number

Properties	**Value**
Generation number	30
Population number	20

The population number has to be large enough to support sufficient genetic variations (Chinneck, 2006). However, having extremely large population will lead to intolerable long running time. The criteria for choosing the most appropriate population and generation number in this research is based on the best fitness score under the shortage running time for the output to converge. Experiments with various population number were run with the result listed in Table 4.6.

Table 4.6

Results of Experimentations with Various Population Number

Population number	**Average run time [minute]**	**Latest converging point [Generation]**	**Best fitness score**
10	4.50	G36	0.999612
20	9.78	G27	0.999998
30	14.23	G24	0.999997
40	18.21	G24	0.999992
50	21.94	G23	0.999994

Each experiment of correspondent population number is done in 30 run. The first column is the population number. Second column is the average run time of the process. The third column denotes the latest point where the best output converge. Finally in the fourth column, best fitness score obtained from the 30 run is selected. Except for population 10, all populations produced a sufficiently high best fitness score. As the population increase, the output converge in the earlier generation but with increase run time. This indicates that the higher the population, the earlier the output tend to converge but with longer run time. From this result, it is thus acceptable to choose population number of 20 which consume the shortest run time in obtaining the best solution. Further, because all populations tested converged at generation below than 30 (accept for population number of 10), it is thus acceptable to cap the generation at 30 which will help in further reducing the run time.

4.3 Output from the Run of Simulation Model

With the model being validated in the previous section, a sufficient level of confidence has been instilled in the model. This permeates its usage for simulation in an attempt to achieve our research objective. There are two simulation run conducted namely base run and scenario setting run.

4.3.1 Base run

The base run for CPO production until year 2050 is presented in Figure 4.16. CPO production achieve its maximum value by year 2024 at around 25.6 million tonne. However, it started to decline and settle at around 23.3 million tonne until 2050. As compared to Indonesia (in 2015 at approximately 34 million tonne), our production is far-fetched. The reason of such a low production can be traced from various sources by examining each sub-model.

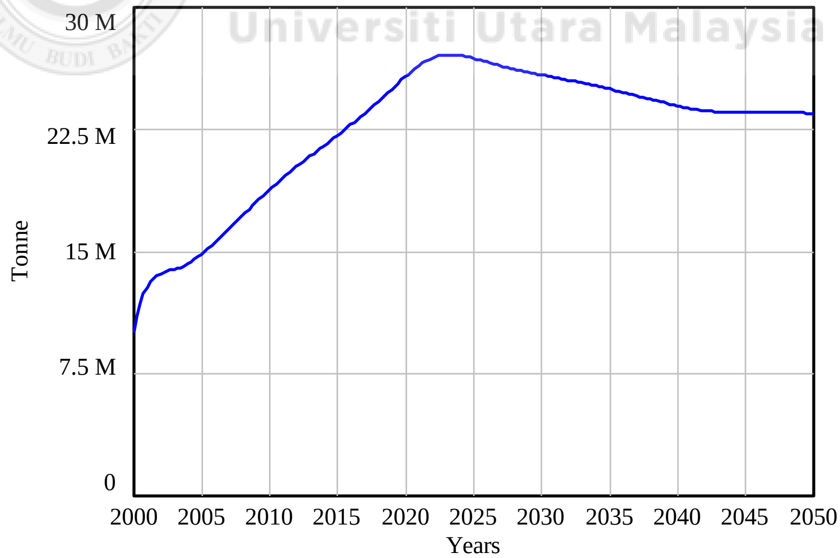

Figure 4.16. The behaviour trend of CPO production for base run

First, we look at the oil palm plantation sub-model as it is known that FFB yield exert direct impact on CPO production. One of the determinants of FFB yield is the area of mature and ageing area. Figure 4.17 shows the output for all plantation area including premature, mature and ageing area. Note that the assumption made in this study where our plantation land is at maximum 6 million hectare due to scarcity of potential land available. At average 50,000 hectare of replanting every year, mature area achieve its peak at 4.11 million hectare in 2022 before declining and settle at 1.18 million hectare. On the contrary, ageing area steeply increase starting 2022, and settle at much higher level of 4.64 million hectare. FFB yield for mature and ageing area difference diverge as much as 20% which explain the low CPO production. It will be good if the replanting rate can be sufficiently increased to sustain high mature area while reducing the accumulation of ageing area thus increasing the CPO production by 2050.

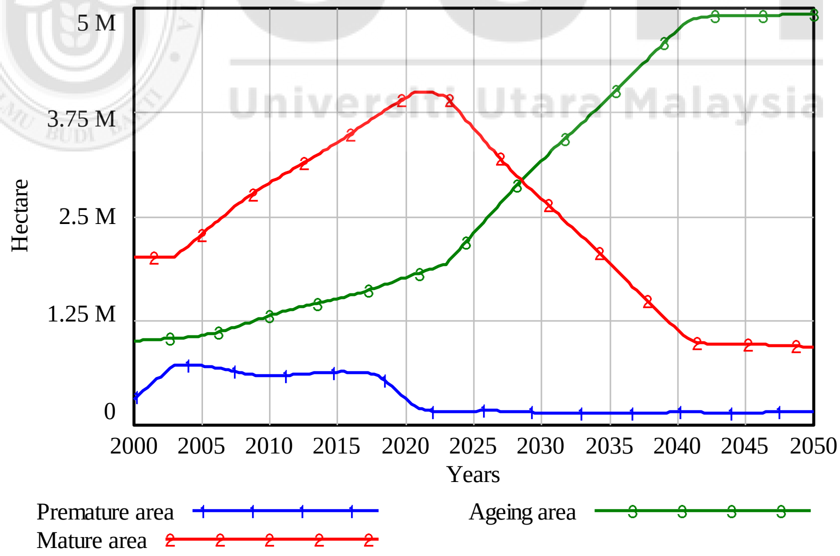

Figure 4.17. The behaviour trend of oil palm plantation area for base run

However, increasing the replanting rate is not an easy task as it involves both big plantation and smallholder (which account approximately 40% of total plantation owned). The former may aware the need of vigorous replanting for sustainable high yield. The latter on the other hand act in different way and anchoring their response for replanting based on CPO price. The smallholder tends to delay their replanting plan during high CPO price to reap as much profit they can get regardless the mature or premature area (Wahid & Simeh, 2010; PEMANDU, 2010). They also tend to avoid replanting because newly planted area is not productive for at least three years and during this transition period, they may suffer loss. Moreover, the replanting takes extensive works and high cost. The run from simulation capture this dynamic where the low replanting rate below average in the high CPO price period is observed as in Figure 4.18. The government has launched one-off replanting scheme to stimulate replanting among smallholders but these has not given huge impact on replanting rate (Wahid & Simeh, 2010).

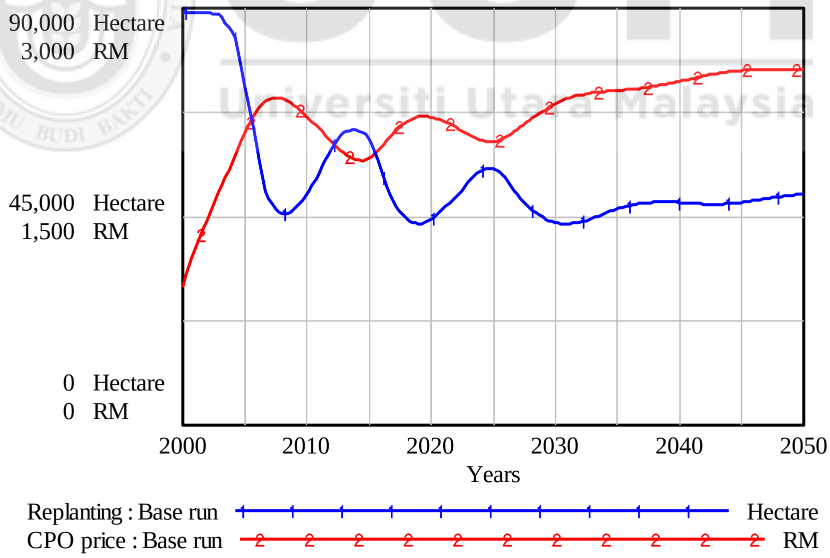

Figure 4.18. The behaviour of replanting against CPO price for base run

With the stagnant CPO production couple with the continuation of current blend mandate (0.10 for transportation sector, 0.07 for industrial sector, 0 for the other sector), this has pushed the CPO price up as illustrated in Figure 4.19. Although CPO consumption from biodiesel sector is comparatively modest as compared to non-biodiesel sector, additional demand from biodiesel sector has played some part in further suppressing CPO supply. Low supply relative to its demand will increase CPO price. With the assumption of no market intervention in the future, the CPO price will fluctuate around RM2,500 per tonne by 2050. High CPO price will discount the CPO demand from other sector which will end up decreasing the price. However, the reduce of CPO demand is modest due to the facts that CPO is a commodity and long-term high CPO price will gradually be accepted by importer as other substitutes also increase in price when they shift their purchase towards substitutes. When CPO and its substitute's purchasing power are level, their price will settle at higher level pegging new benchmark price for the commodity. If government continue increasing the mandate in the future, it is possible that CPO price will go even higher. Unless there is huge market intervention (e.g. abrupt demand shortage that resort into sudden supply glut) will there be significant drop in CPO price.

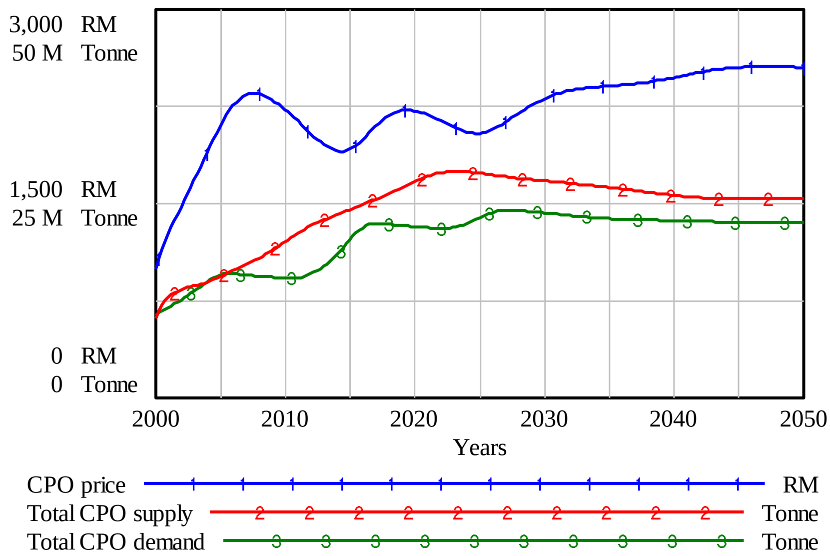

Figure 4.19. The behaviour trend of CPO price against supply and demand for the base run

Another factor affecting FFB yield is the number of labour. Even though the effect is modest, our palm oil industry is moving towards serious labour shortage. The model capture the dynamic of losing the labour due to the increase attractiveness of Indonesia palm oil industry as illustrated in Figure 4.20. As the attractiveness of Indonesia palm oil industry increase due to the rapid industry growth which enhance the wage and working condition, Indonesian worker will prefer to work in their home country. However, the shortage of labour can possibly be resolved with the increase usage of mechanization. The current mechanization usage of 20 percent seems too low to help in increasing the labour productivity especially in the labour-intensive oil palm plantation sector. Government has to boost their effort to promote the usage of mechanization as well as offering financial assistance scheme especially for smallholder to overcome the substantial cost of mechanization adoption.

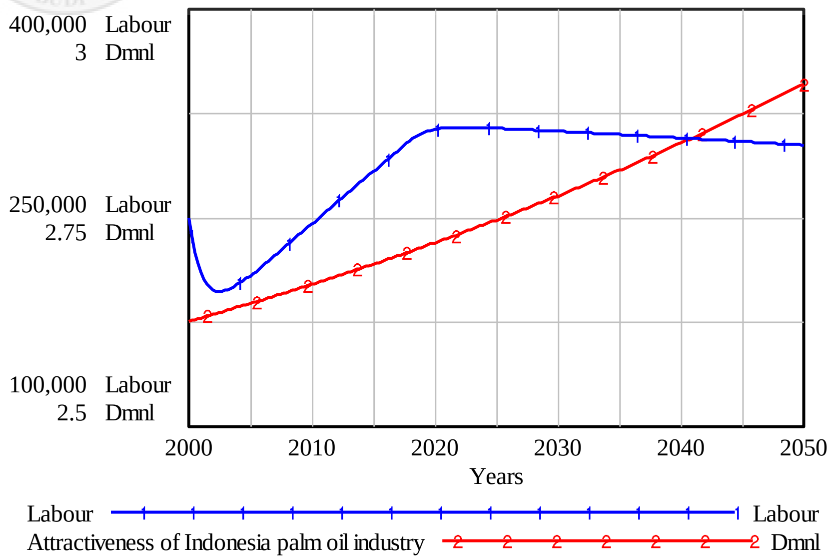

Figure 4.20. The behaviour trend of labour against attractiveness of Indonesia palm oil industry for the base run

4.3.2 Scenario setting run

SCENARIO 1: Pushing to replant

In scenario 1, the average replanting was increased from 50,000 hectare to 300,000 hectare per year. Figure 4.17 shows the simulated CPO production for scenario 1. Note that in the period of 2000 to 2016, the trend is similar to that of base run as the changes only made starting in 2017. Starting in 2017, CPO production is lower than that of base run. This is due to the new replanting programme taken place where 300,000 hectare of ageing area been cleared for replanting. With sustain 300,000 hectare replanting every year, CPO production settle at around 8.27 percent higher as compared to base run. This can also be observed from the increase of FFB yield per hectare as in Figure 4.21. The cause of this can be sourced from the high mature area and low ageing area at the end of simulation as illustrated in Figure 4.22. With wider productive area, the FFB yield per hectare increase as shown in Figure 4.23, thus increasing the CPO production. As CPO supply increase relative to its demand, this has caused CPO price to become lower as compared to the base run as shown in Figure 4.24.

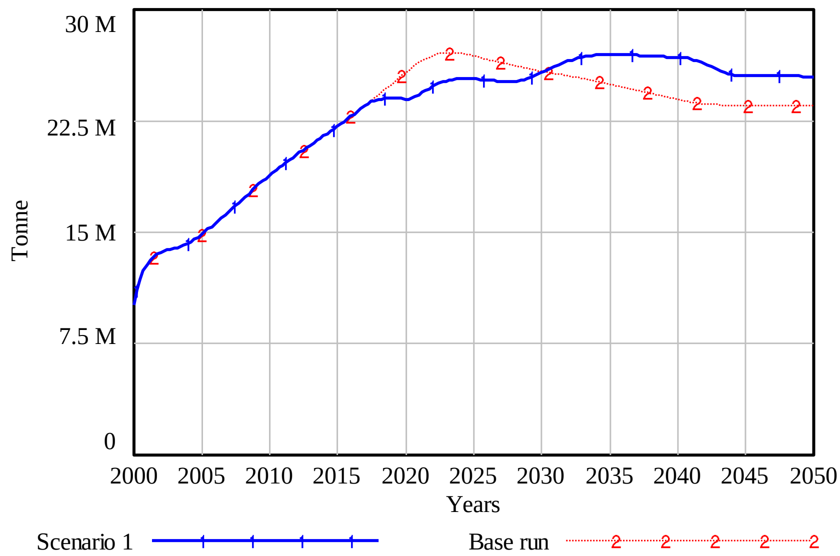

Figure 4.21. Behaviour trends of CPO production for scenario 1

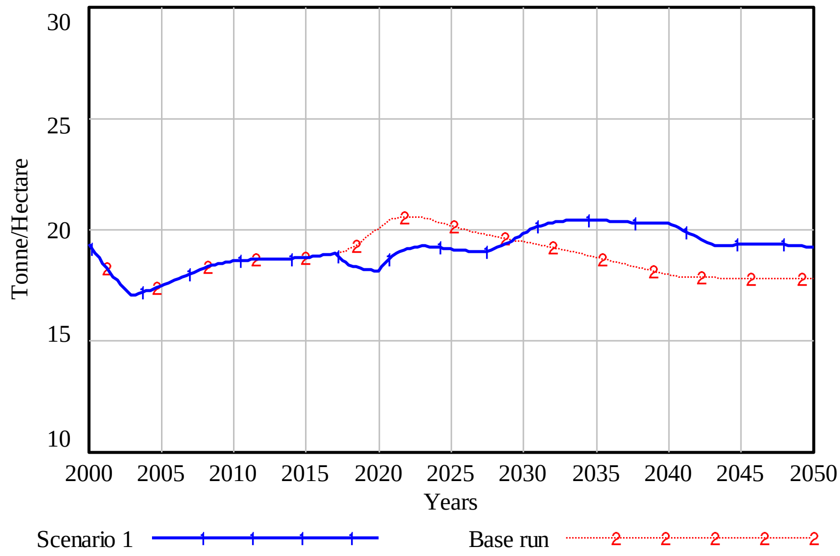

Figure 4.22. Behaviour trends of FFB yield per hectare for scenario 1

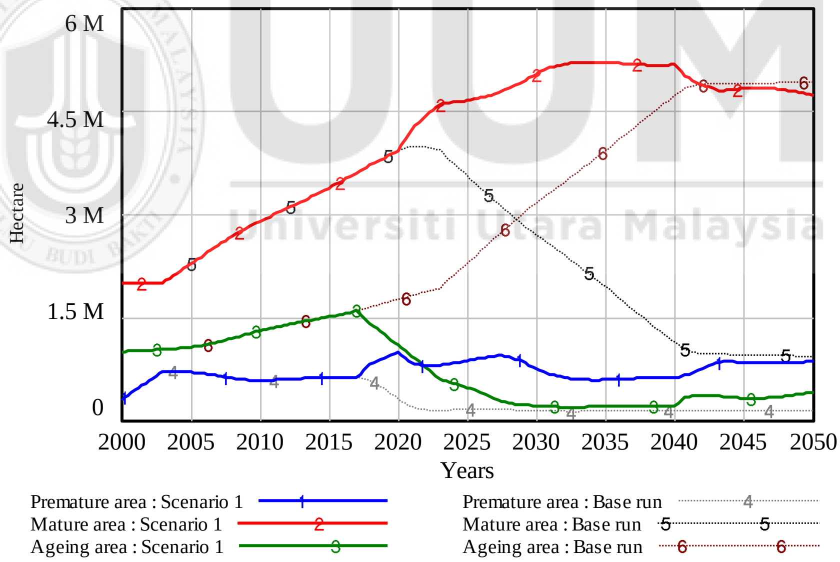

Figure 4.23. Behaviour trend of oil palm plantation area for scenario 1

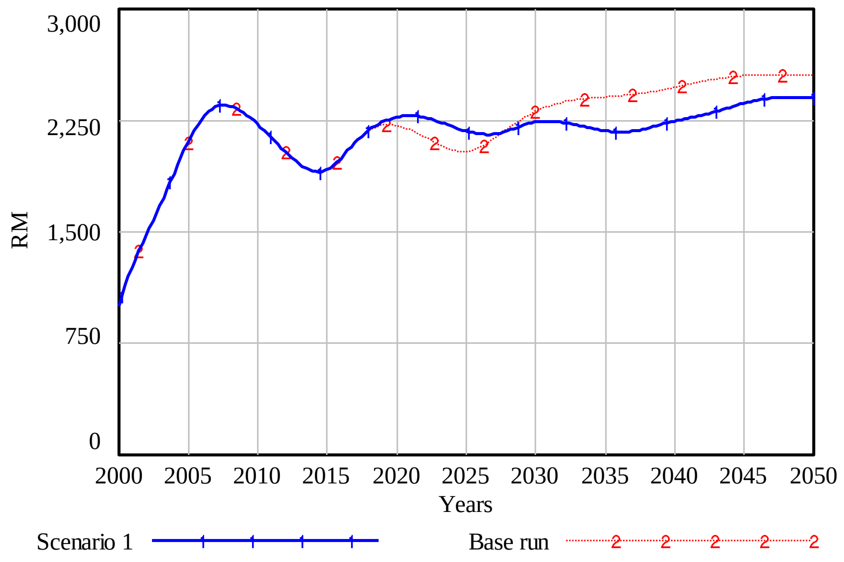

Figure 4.24. Behaviour trend of CPO price for scenario 1

Theoretically, increasing replanting rate can be accepted as one of the way to increase CPO production. However in reality, to enforce a sudden high replanting rate is challenging due to a low participation rate in replanting campaign especially from independent smallholders (PEMANDU, 2015). This is largely due to the temporary revenue loss in the transition period of replanting while waiting for the trees to be productive. Subsequently, this will also disrupt the supply of CPO in the market at the start of the new replanting rate which translates to substantial loss in terms of sales and taxes as observed in Figure 4.21. Furthermore, labour shortage is still a beleaguering problem in this scenario. Next scenario tested the circumstances where high mechanization adoption is at place.

SCENARIO 2: Expanding the mechanization adoption rate

In scenario 2, mechanization adoption rate was increased from 20 percent to 100 percent. The results from scenario 2 simulation shows an increased in CPO production as shown in Figure 4.25. As expected, CPO production shows little increase at around

1.40 percent with high mechanization adoption rate as compared to the base run. Observation on labour stock in Figure 4.26 shows no visible change on the labour stock with high mechanization adoption rate. This is because the sole purpose of mechanization is not to remove or deny the need of labour but rather to increase the productivity per hectare of labour due to critical labour shortage. Labour is very much important as they are still needed to operate the machine for daily plantation-related task. High mechanization adoption thus increases labour productivity per hectare and resulting into increase FFB yield per hectare as in Figure 4.27.

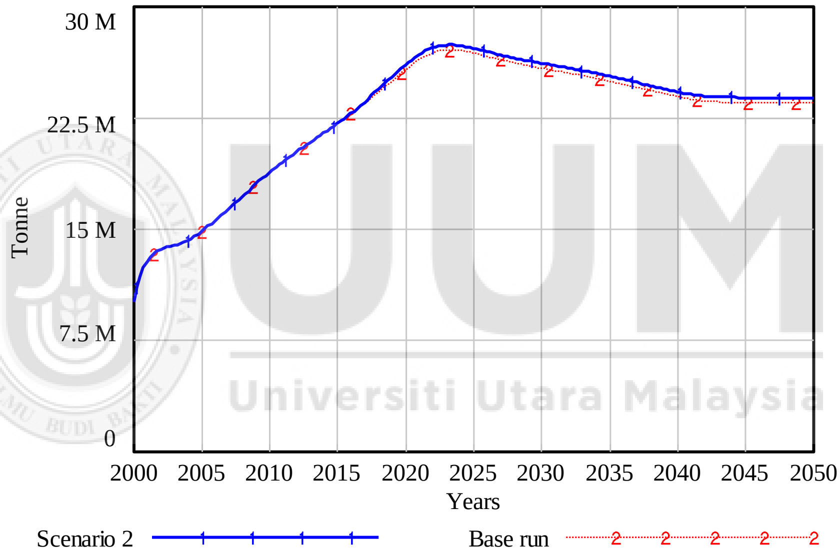

Figure 4.25. Behaviour trend of CPO production for scenario 2

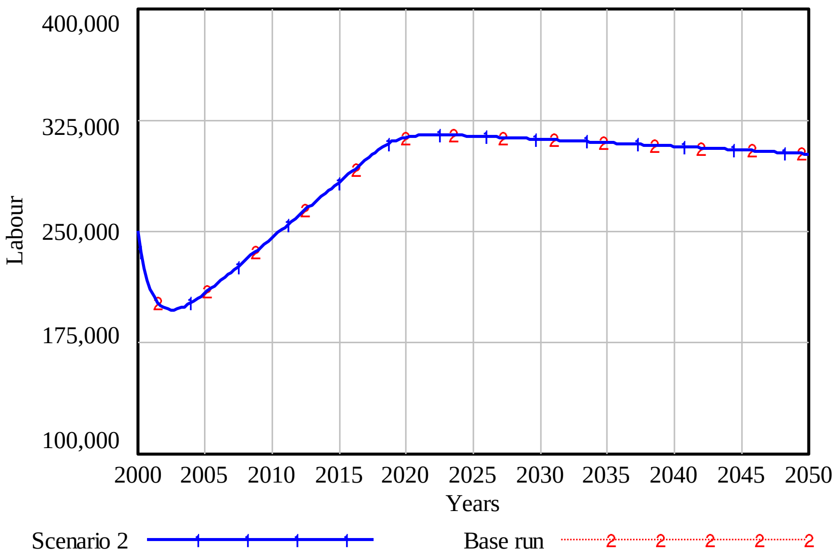

Figure 4.26. Behaviour trend of labour stock for scenario 2 compared to base run

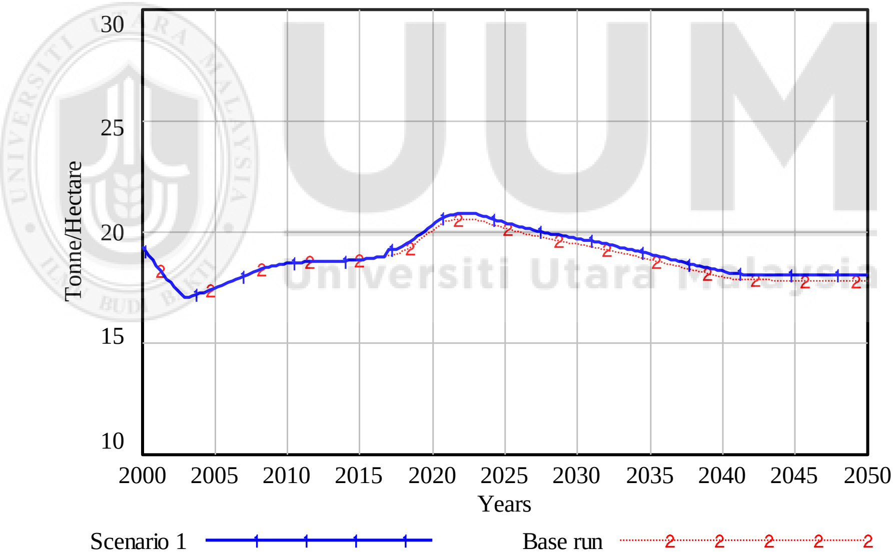

Figure 4.27. Behaviour trend of FFB yield per hectare for scenario 2 compared to base run

Nevertheless, increasing the adoption of mechanization does help in boosting CPO production through improved productivity per hectare. In addition, adoption of mechanization at satisfying level provides a direct resolution on the worrying labour shortage issue. However as argued previously, in reality the current mechanization adoption rate is still very low thus sudden enforcement on high adoption rate will be hardly possible.

SCENARIO 3: Progressing the biodiesel programme

In scenario 3, the biodiesel mandate in transportation sector was increased from 0.10 to 0.15, industrial sector from 0.07 to 0.10, and other sector from 0 to 0.05. Figure 4.28 shows the output from CPO production for scenario 3. The change in CPO production is hardly observable at 0.013% increase due to the total consumption of CPO from biodiesel sector is relatively small as compared to non-biodiesel sector. However, the implementation of new mandate did slightly increase CPO price as can be seen in Figure 4.29.

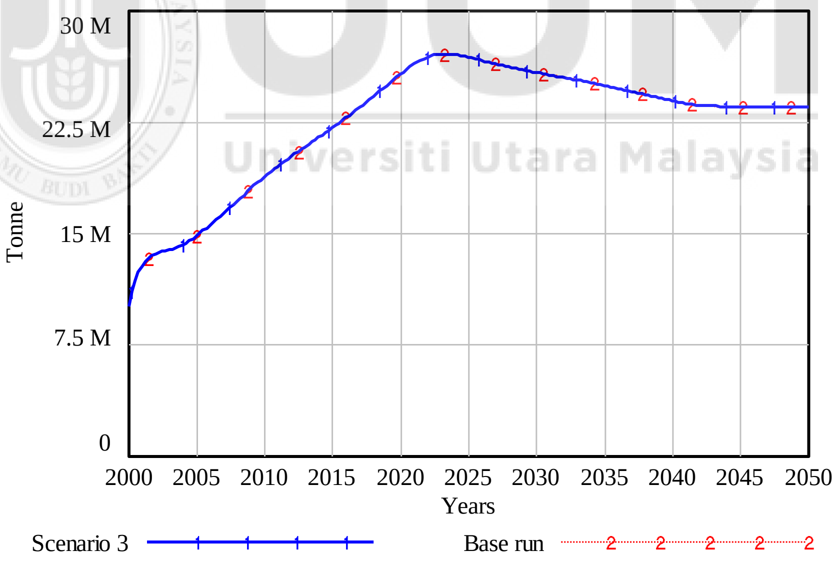

Figure 4.28. Behaviour trend of CPO production for scenario 3 compared to base run

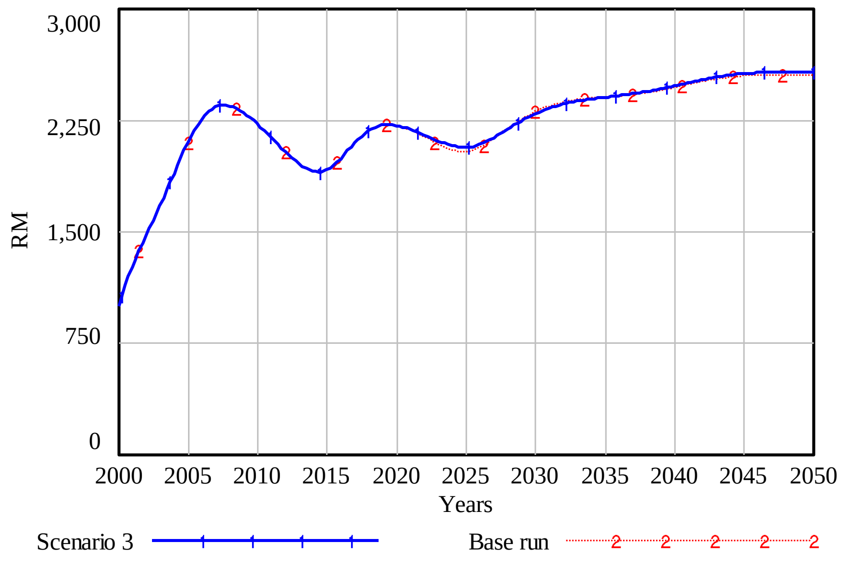

Figure 4.29. Behaviour trend of CPO price for scenario 3 compared to base run

Even though there is a hardly visible change to CPO production from the implementation of higher mandate, CPO price do pose slight increase indicating the urgency to strengthen the CPO production to cater the biodiesel demand. Particularly as highlighted previously the government will continue the biodiesel programme and increase the mandate in the future as part of its commitment in promoting the growth of the industry. By increasing the CPO production through means presented in the scenario 1 and scenario 2, high CPO price can be stabilized while ensuring adequate supply of CPO during its demand boom period.

Generally, the parameter for each policy variables and CPO production from all scenarios is summarized in Table 4.7.

Table 4.7

Summary of Output from All Scenario Run

Scenario	**Policy variables**					**CPO production in 2050**
	a	*b*	*c*	*d*	*e*	

Base run	0.20	50,000	0.10	0.07	0.00	23,457,100
1	0.20	300,000	0.10	0.07	0.00	25,397,600
2	1.00	50,000	0.10	0.07	0.00	23,786,000
3	0.20	50,000	0.15	0.10	0.05	23,460,100

As explained previously, even though CPO production from Scenario 1 recorded the highest value as compared to other scenario, the sudden increase in replanting rates may not be plausible to be implemented in reality. This is also applied to other policy variable changes in Scenario 2 and Scenario 3. On that account, the search for the right value of policy variables can be done by using GA.

4.4 Searching for Optimal Policy Options

From the base run and scenarios setting run, the means of increasing productivity per hectare so that CPO production can be boosted has been identified. It is also known that the labour shortage issue pose a serious threat to our plantation sector and has to be resolved to avoid degrading the productivity per hectare. Further, the government will continue the biodiesel mandate programme in the future which will boost demand and impact CPO price. In a nutshell, while putting an effort to improve CPO production, it is important to take into account of the progression of policies.

4.4.1 Optimization 1: Maximizing CPO production in year 2050 by changing policy variables in year 2017

The top five best solutions from the run of optimization 1 can be obtained from Table 4.8, while Table 4.9 compile the comparison between base run and the best solution. From the simulation run, it is found that the maximum CPO production value retrieved in year 2050 was at 26,293,476 tonne.

Table 4.8

Top Five Best Solution from Optimization 1

Run	a	b	c	d	e	Fitness score	CPO production
1	0.88	254170.9	0.17	0.1	0.17	0.999980	26,293,476
2	0.74	249449.1	0.16	0.15	0.12	0.999970	26,293,214
3	0.72	250540.5	0.19	0.15	0.05	0.999961	26,292,968
4	0.6	254152.3	0.19	0.15	0.1	0.999794	26,288,584
5	0.84	244910.2	0.18	0.11	0.19	0.999598	26,283,440

Table 4.9

Comparison between Base Run and the Best Solution of Optimization 1

Run	Mechanization adoption rate, *a*	Average replanting, *b*	Blend mandate for transportation, *c*	Blend mandate for industrial, *d*	Blend mandate for other, *e*	CPO production in 2050
Base run	0.2	50,000	0.10	0.07	0	23,457,078
Optimization 1	0.88	254,170.9	0.17	0.1	0.17	26,293,476
+/-change	+0.68	+408.34%	+0.07	+0.03	+0.17	+12.09%

CPO production has recorded an increase of 12.09% as compared to the base run as illustrated in Figure 4.30. This is huge improvement as it translates to approximately 2.8 million of extra CPO production in 2050. However, due to high replanting rate, there is a disruption in CPO supply during the transition period of replanting (from 2017 to 2030. This is in accordance with the feedback loops in the SD model which incorporate the delays in planting phases. The supply disruption unfortunately can cause a potential substantial loss of revenue from sales and taxes.

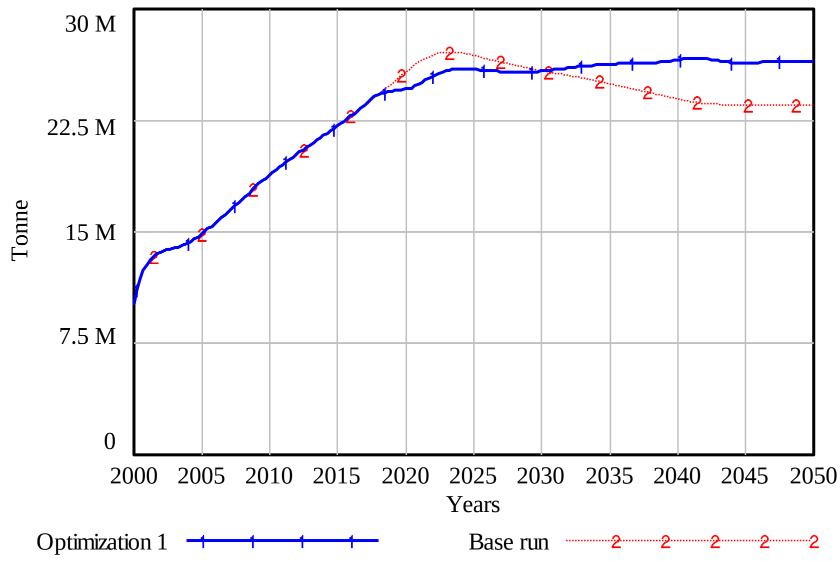

Figure 4.30. Behaviour trend of CPO production for optimization 1 compared to base run

Figure 4.31 shows the impact of the new policy on CPO price. Starting 2017, CPO price has increased which is caused by interruption in CPO supply due to sudden high replanting. The CPO price then settle at new price and exhibit a more stable pattern (but lower) as compared to the base run.

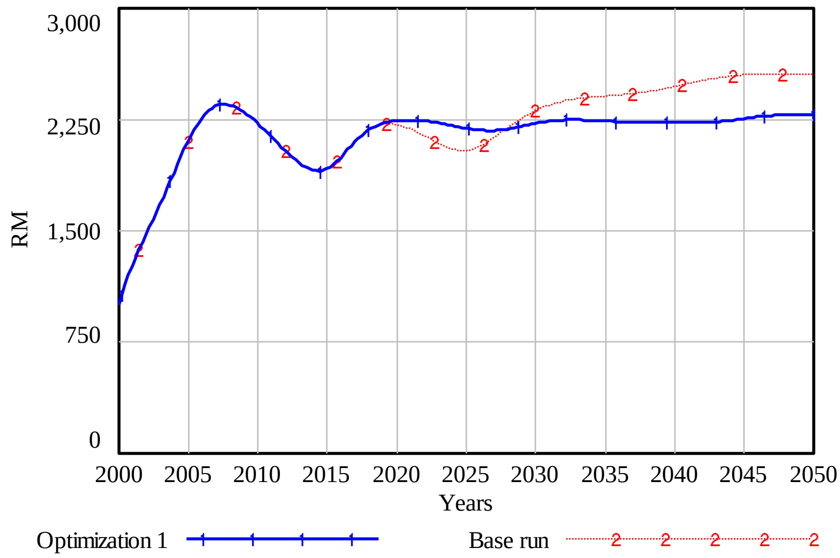

Figure 4.31. Behaviour trend of CPO price for optimization 1 compared to base run

Looking at the policy variable, both blending mandate for transportation and industrial sector were increased from the previous value. In addition, the increase of blend mandate for other sector to 0.17 indicate the expandability of biodiesel usage aside of in transportation and industrial sector. However, the huge increase in mechanization adoption rate may seems implausible to be achieved in a short time frame, particularly the advancement in mechanization technology in plantation is still at low pace technology- and cost-wise.

On the other hand, Figure 4.32 shows the changing trend in plantation area from optimization 1. High replanting rate has effectively lowered the accumulation of ageing area while increasing the mature area. In reality, the sudden increase of replanting rate may be hardly possible to be enforced in such a short time frame giving the current low replanting rate as highlighted in the latest ETP report by PEMANDU (2015).

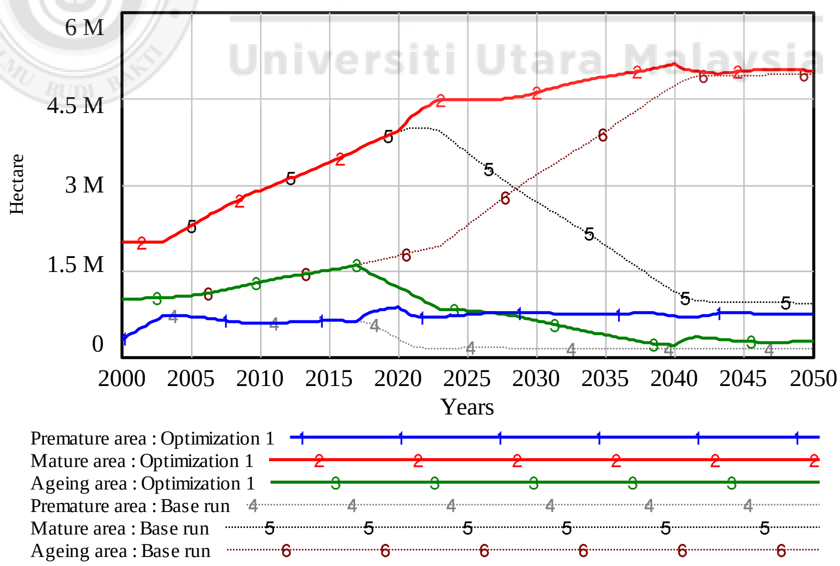

Figure 4.32. Behaviour trend of mature and ageing area for optimization 1 compared to base run

4.4.2 Optimization 2: Maximizing CPO production in year 2050 by changing policy variables in year 2020

The top five best solutions from the run of optimization 2 can be obtained from Table 4.10, while 4.11 compile the comparison between base run and the best solution. From the simulation run, it was found that the maximum CPO production value retrieved in year 2050 was at 26,328,130 tonne.

Table 4.10

The Top Five Best Solution from Optimization 2

Run	a	b	c	d	e	Fitness score	CPO production
1	0.69	254363.6	0.19	0.14	0.18	0.999997	26,328,130
2	0.62	250672.3	0.17	0.06	0.14	0.999718	26,320,772
3	0.99	250286.6	0.20	0.12	0.06	0.999455	26,313,862
4	0.72	253956.4	0.16	0.08	0.17	0.999192	26,306,918
5	0.6	254373.4	0.16	0.18	0.13	0.998621	26,291,890

Table 4.11

Comparison between Base Run and the Best Solution from Optimization 2

Run	Mechanization adoption rate, *a*	Average replanting, *b*	Blend mandate for transportation, *c*	Blend mandate for industrial, *d*	Blend mandate for other, *e*	CPO production in 2050
Base run	0.2	50,000	0.10	0.07	0	23,457,078
Optimization 2	0.69	254,363.6	0.19	0.14	0.18	26,328,130
+/- change	+0.49	+408.73%	+0.09	+0.07	+0.18	+12.24%

From the analysis, it is found that CPO production recorded a 12.24% increase in year 2050 as compared to the base run, which translates to around 2.9 million tonne of increase in CPO production as illustrated in Figure 4.33. Moreover, a sustained high CPO production has been produced in comparison with the base run but with steeper decline during the transition period of replanting. Again, there is a disruption in supply and may cause substantial loss to the industry.

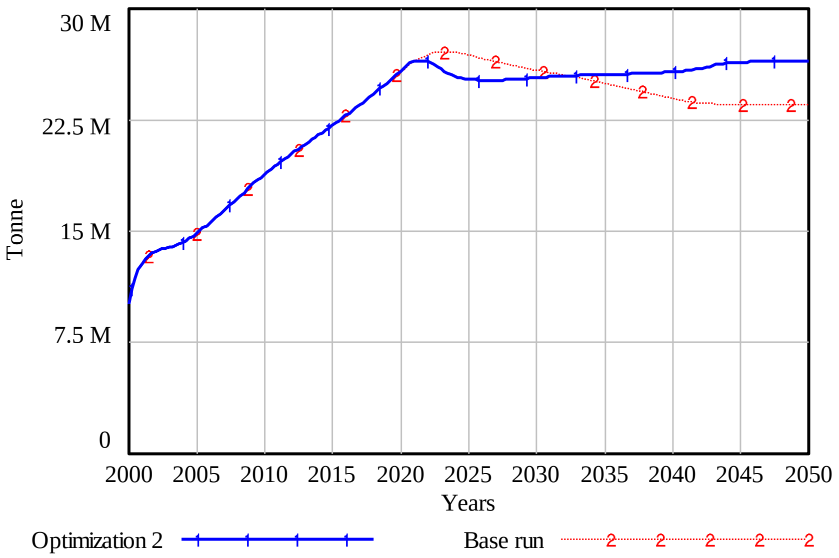

Figure 4.33. CPO production for optimization 2 against base run

CPO prices comparison in Figure 4.34 shows an increase after 3 years of policy implementation as compared to base run. The outcome is pretty similar with that of optimization 1. CPO prices increase initially but stabilize at lower level towards the end as compared to the base run.

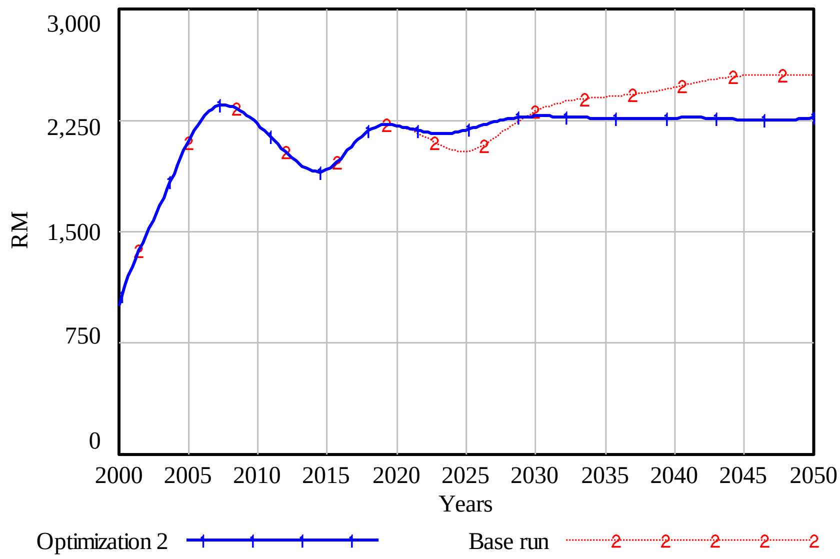

Figure 4.34. CPO price for optimization 2 against base run

As for the policy variables, the solution suggest the increase of biodiesel blend mandates in all sector, which is good for the growth of biodiesel industry. As for the mechanization adoption rate, a huge increase in 2020 from 2017 may seem a doable (but still difficult) effort because of the longer time frame (as opposed to optimization 1) to new policy implementation. High mechanization adoption rate will be a direct solution to labour shortage in the industry but giving the current sluggish development in mechanization technology development as reported in ETP by PEMANDU (2015), reaching high mechanization adoption rate in three years can still be considered as technically ambiguous.

Finally, the solution suggest huge increase of annual replanting from the base run which will be more than enough in reducing the ageing plantation area as shown Figure 4.35. Nevertheless, enforcing very high replanting rate can be highly challenging in reality especially on the smallholders similar to findings in optimization 1.

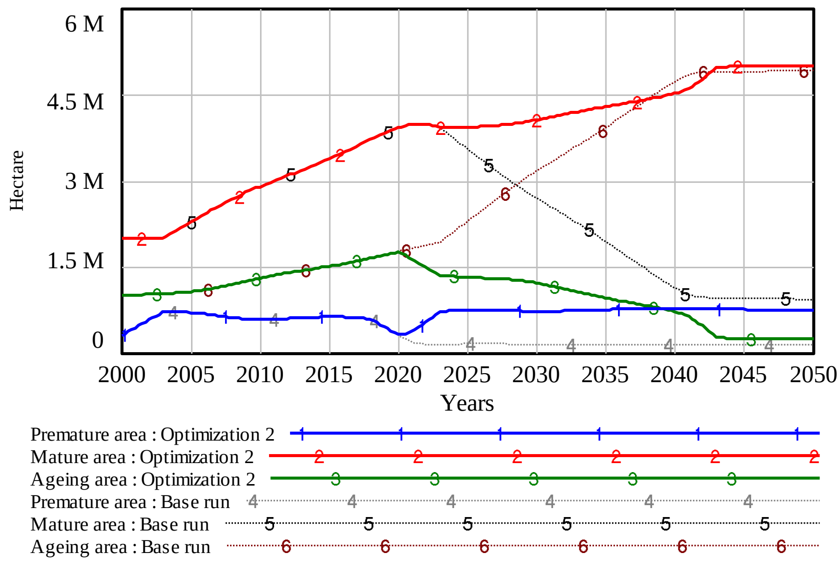

Figure 4.35. Plantation area from optimization 2 against base run

Optimization 1 and 2 has successfully demonstrated the usage of SD-GA model for searching optimal policy options in dynamic environment. That is, the parameter to be optimized can be set in year 2017 or 2020, or even any year. The findings obtained from the two optimization exhibit a rather similar outcome which suggest that any improvement attempted through one time policy changes will only produce sudden increase of policy variables' parameters. While this seems like a good policy option in theory, enforcing them in reality is highly challenging and hardly possible.

4.4.3 Optimization 3: Phased optimization process

The top five best solutions of each phase from the run of optimization 3 can be obtained from Table 4.12, while Table 4.13 compare the output from optimization 3 against the base run. From the simulation run, it was found that the maximum CPO production value retrieved in year 2050 was at 25,796,430 tonne.

Table 4.12

Top Five Best Solutions for Each Phase from Optimization 3

Phase	Run	a	b	c	d	e	Fitness score	CPO production
1	1	0.2	99482.9	0.10	0.05	0	0.999765	25,005,870
	2	0.2	98175.4	0.10	0.05	0	0.999393	25,015,186
	3	0.22	96694.8	0.10	0.05	0	0.998276	25,043,170
	4	0.21	95581.6	0.10	0.05	0	0.998307	25,042,388
	5	0.2	99145.7	0.10	0.05	0	0.999669	25,008,274
2	1	0.38	165875.1	0.11	0.08	0	0.999792	26,005,420
	2	0.45	176717.1	0.15	0.09	0.04	0.999398	25,984,342
	3	0.39	167373.2	0.11	0.07	0.01	0.999946	26,001,408
	4	0.33	160478.1	0.10	0.09	0.01	0.999600	26,010,392
	5	0.49	177772.8	0.14	0.08	0	0.999987	26,000,330
3	1	0.6	202954	0.19	0.11	0.09	0.980777	25,500,204
	2	0.63	202392.8	0.20	0.14	0.07	0.981021	25,506,540
	3	0.59	200276.7	0.20	0.13	0.1	0.981994	25,531,838
	4	0.67	200726.4	0.19	0.14	0.09	0.981599	25,521,584
	5	0.57	204020.4	0.18	0.13	0.09	0.980247	25,486,422
4	1	0.76	251244.3	0.24	0.2	0.15	0.969410	25,204,664
	2	0.74	252208.7	0.24	0.15	0.15	0.969024	25,194,616
	3	0.7	250169.4	0.25	0.17	0.13	0.969740	25,213,232
	4	0.89	252064.9	0.25	0.19	0.14	0.969254	25,200,606
	5	0.8	250217.3	0.24	0.19	0.14	0.969625	25,210,254
5	1	1	202091.7	0.29	0.24	0.2	0.984801	25,604,820
	2	0.97	200160.8	0.30	0.22	0.2	0.985650	25,626,908
	3	0.96	200670.5	0.30	0.21	0.18	0.985281	25,617,294
	4	0.94	203510.4	0.30	0.24	0.19	0.984408	25,594,614
	5	0.95	200416.2	0.30	0.24	0.19	0.985494	25,622,854
6	1	1	200678.9	0.34	0.28	0.25	0.988662	25,705,208
	2	0.97	200863.5	0.35	0.29	0.24	0.988714	25,706,570
	3	0.97	200143.4	0.35	0.3	0.24	0.988984	25,713,576
	4	0.98	200015.1	0.34	0.27	0.25	0.988888	25,711,084
	5	1	201120.1	0.34	0.28	0.2	0.988040	25,689,032
7	1	0.99	203038	0.38	0.35	0.26	0.990527	25,753,710
	2	0.98	201378.4	0.39	0.35	0.29	0.991607	25,781,784
	3	1	200273	0.38	0.3	0.3	0.991830	25,787,572
	4	0.99	200017.6	0.39	0.34	0.3	0.992170	25,796,430
	5	0.98	202031.2	0.40	0.3	0.3	0.991612	25,781,916

Table 4.13

Comparison between Base Run and Best Solution from Optimization 3

Run	Mechanization adoption rate, *a*	Average replanting, *b*	Blend mandate for transportation, *c*	Blend mandate for industrial, *d*	Blend mandate for other, *e*	CPO production in 2050
Base run	0.2	50,000	0.10	0.07	0	23,457,078
Optimization 3	0.99	200017.6	0.39	0.34	0.3	25,796,430
+/- change	+0.79	+408.73%	+0.09	+0.07	+0.18	+9.97%

Optimization 3 shows 9.97% increase of CPO production in 2050 than that of the base run as illustrated in Figure 4.36. Similarly important, the CPO production trend is much more stable than that of base run. The CPO production cannot go any higher than this (with current policy variables parameters) due to the physical limitation of the model. Close inspection on the model has concluded that in order for CPO production to go any higher, the industry has to break the 'plantation land' limitation and expand the oil palm plantation area beyond 6 million hectare[7]. Still, the CPO production settle at higher level as compared to the base run.

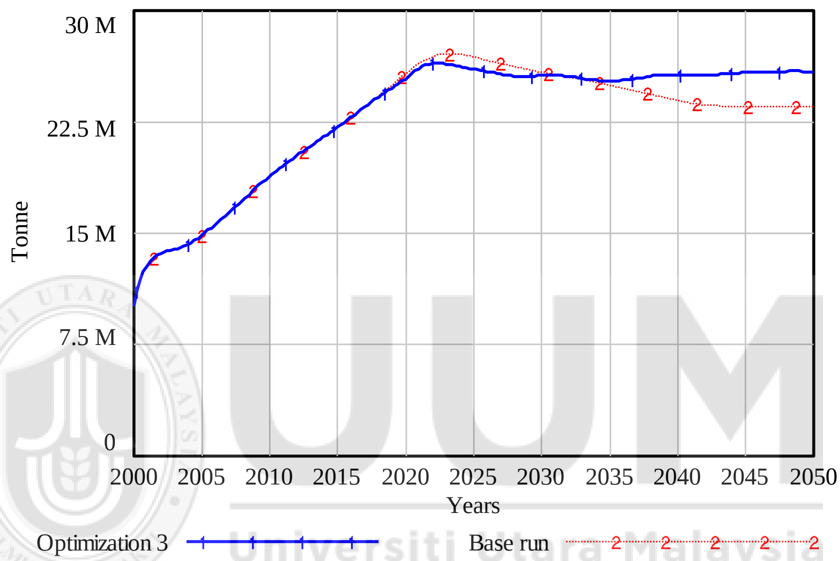

Figure 4.36. CPO production for optimization 3 against base run

Figure 4.37 shows the CPO prices from optimization 3. It is interesting to observe only slight increase of magnitude and similar pattern with the base run. Lower price is observed in optimization 1 and 2 in 2050 even though optimization 1, 2 and 3 produced high CPO production in 2050. The reason behind this behaviour is due to the existence of feedback loops between CPO supply and demand which influence the CPO price setting. Due to the fact that optimization 3 changes its policy variables in phases (every

[7] 6 million hectare is the maximum limit for available potential land to be converted to oil palm plantation assumed in this study.

five years), this also has influenced the demand reaction to the changes of prices in each phase.

The feedback structure in SD model dictate that every change in CPO supply demand ratio will inversely affect CPO price. After some delay, these changes in price will influence the purchase of CPO (the demand). When policy changes are done using the same rate of policy variables through the period as demonstrated in optimization 1 and 2, this has caused a sudden change of CPO supply thus changing its price, which causes demand to react in inverse way. On the other hand, in the case of optimization 3, because policy changes were implemented in phases, the supply and demand reaction loop change in each phase, where in every phase the ratio changes and produce new price resulting to high CPO price at the end of the process. From another perspective, high CPO prices in 2050 is good in the sense of it gives higher revenue to the palm oil industry.

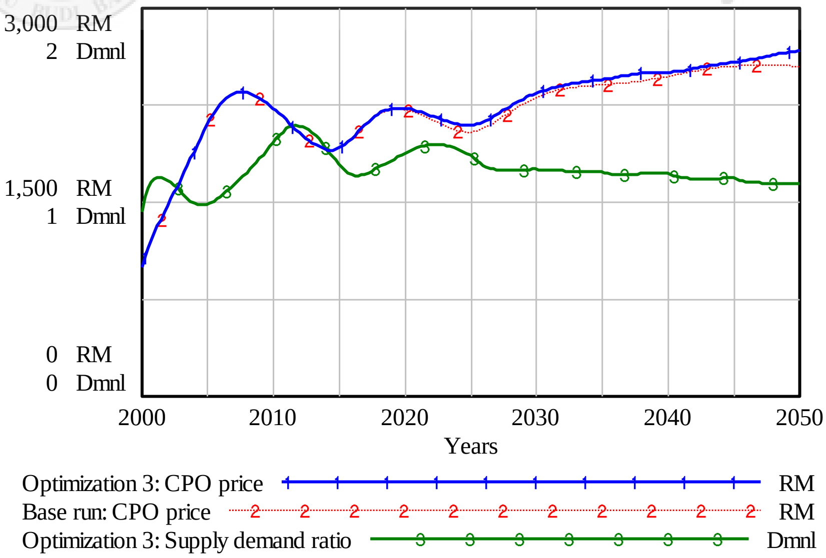

Figure 4.37. CPO prices from optimization 3 against base run

Although the changes for all policy variables are high, note that the policy variables has undergone gradual changes as oppose to drastic single change in optimization 1 and 2. The summary of the policy variable changes are compiled in Table 4.14.

Table 4.14

Summary of the Solutions from Optimization 3

Year of implemen_ tation	**Mechanization adoption rate, *a***	**Average replanting, *b***	**Biodiesel mandate for transportation, *c***	**Biodiesel mandate for industrial, *d***	**Biodiesel mandate for other, *e***
2017	0.2	99482.9	0.10	0.05	0
2020	0.49	177772.8	0.14	0.08	0
2025	0.59	200276.7	0.20	0.13	0.1
2030	0.7	250169.4	0.25	0.17	0.13
2035	0.97	200160.8	0.30	0.22	0.2
2040	0.97	200143.4	0.35	0.3	0.24
2045	0.99	200017.6	0.39	0.34	0.3

Mechanization adoption rate for instance was increased from 0.2 to 0.99 gradually in the period of 28 years (sufficient for any enforcement effort to achieve the adoption rate). This is also true for biodiesel mandates in the transportation, industrial and other sector. Although the increment of each mandate in reality is subject to the development of research and engine compatibility, optimization 3 at the least level is capable of mapping the pathway for the mandates to be implemented in the plausible time frame. Finally, the solution suggest the replanting to be increased gradually until it reach around 250,000 hectare in 2030, before being lowered down to around 200,000 per hectare until the end of the simulation. This can be pictured as one of the systematic replanting scheme which avoid rush replanting and align a doable replanting campaign. Notice that the solution in the end suggest an optimal 200,000 hectare replanting that is higher in comparison with the recommendation by Wahid & Simeh (2010) of 150,000 hectare. Higher average replanting means less accumulation of ageing area. With gradual increment of replanting along an acceptable time frame, the participation from the planters can be highly anticipated, as well as it gives the government ample time to formulate and plan their compensation scheme.

One of the largest contributors to high CPO production equilibrium is the high productive plantation area. As shown in Figure 4.38, ageing area has been reduced significantly whilst mature area has been hugely increased as compared to the base run. Further, both ageing and mature area has been successfully sustained both at low and high level respectively. This contributes to a higher FFB yield per hectare shown in Figure 4.39.

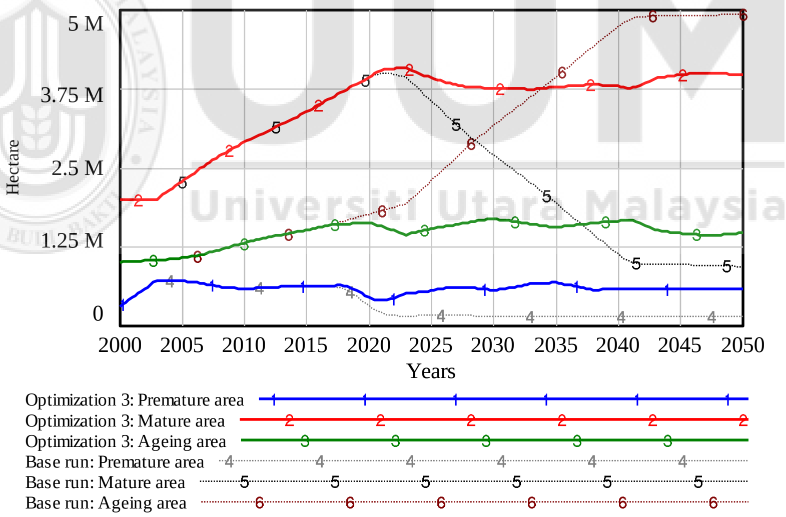

Figure 4.38 Plantation area for optimization 3 against base run

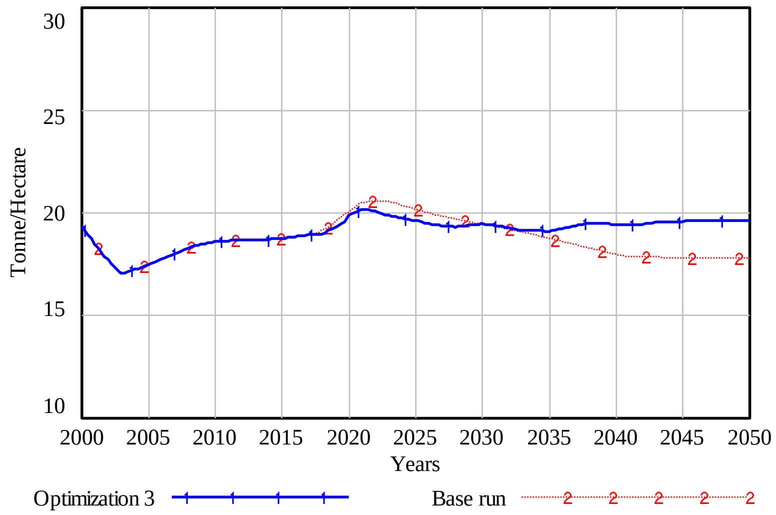

Figure 4.39. FFB yield per hectare for optimization 3 against base run

Optimization 3 produce rather satisfying result compared to base run in terms of CPO production. Furthermore, this has been achieved by gradually progress the policy variables. In next section, the comparison between all optimization are presented where ultimate verdict on the best solution to be converted into policy is discussed.

4.4.4 Evaluation of all policy optimization

Figure 4.40 shows that the highest CPO production in 2050 is produced by optimization 1 and 2. However, there is a long period of production disruption in optimization 1 (even longer in optimization 2) before it bounce back higher (than base run) until 2050. These period exhibits the substantial loss of opportunity cost (as compared to base run) for a longer time. Even though meticulous cost-benefit analysis may be required, it is suffice at this level to conclude that loss of opportunity cost will claim its toll through lower taxes collection and backlashes government revenue from oil palm industry. On the other hand, CPO production produced by optimization 3 is equally stable with only slight disruption on CPO production with higher equilibrium level than base run. As conclusion, with minimal disruption in supply, it can be concluded that CPO production produced by optimization 3 is the most favourable.

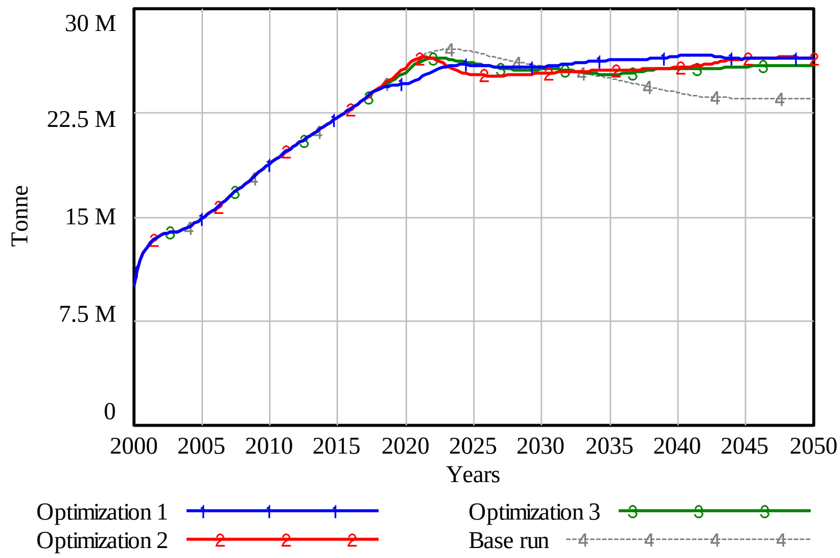

Figure 4.40. CPO production for all optimization

Further analysis has to be made in terms of the policy variables changes in each optimization. Not only optimization 3 produced favourable CPO production, it has also progressed all policy variables in a sensible manner. Firstly, looking at mechanization adoption, the rate has been successfully increased to maximum by year 2045 with stages of implementation as illustrated in Figure 4.41. It is always great to have high adoption rate as soon as possible (as in optimization 1 and 2) but in reality, such implementation necessitates sufficient time frame particularly with currently low adoption largely due to costly purchase and maintenance of the machine, not to mention the sluggish development of mechanization technology. Having the target adoption rate increase every 5 years will give ample time for the enforcer to materialize their strategy to increase adoption rate as well as pushing forward the research and development on mechanization technology.

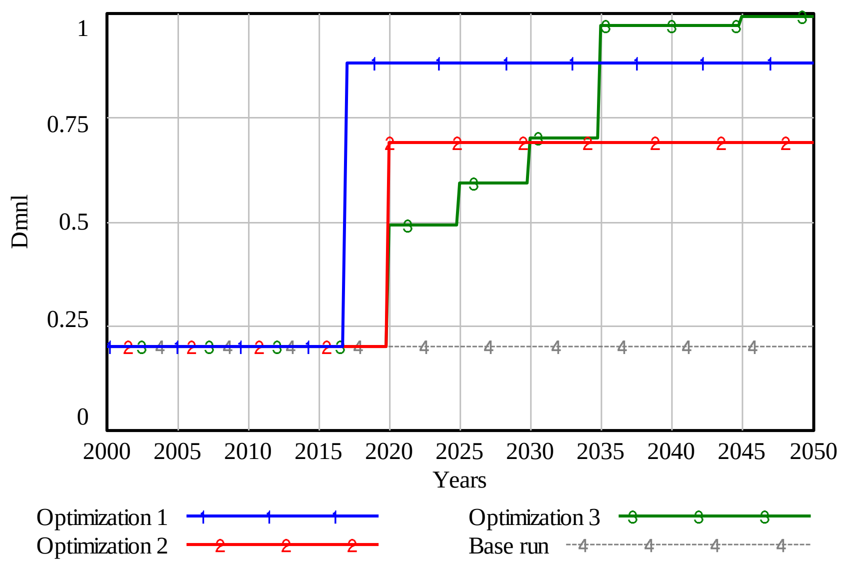

Figure 4.41. Mechanization adoption rate for all optimization

Similarly, enforcing a sudden high replanting rate also bring a huge shock to the industry as exemplified by optimization 1 and 2 in Figure 4.42. The most challenging part is to enforce the high replanting rate among the planters especially independent smallholders. In principal, to do this, certain compensation package has to be taken into consideration to convince planters to enter into replanting phase. Rush replanting (as termed by Wahid & Simeh, 2010) thus will result into high compensation package and disrupt the palm oil supply for some period of time (as illustrated by CPO production in Figure 4.41). However, gradual increase in replanting rate (exemplified by optimization 3 in Figure 4.43) reduce the degree of shock in the industry and gives ample time for the enforcer to launch the replanting campaign among planters. Moreover, gradual change will not financially burden the government if somehow they agree to release some compensation package to planters during the non-productive replanting period. This also minimizes the disruption in palm oil supply resorted from rush replanting effect. Figure 4.43 captures this dynamic comparison between all the three optimization runs.

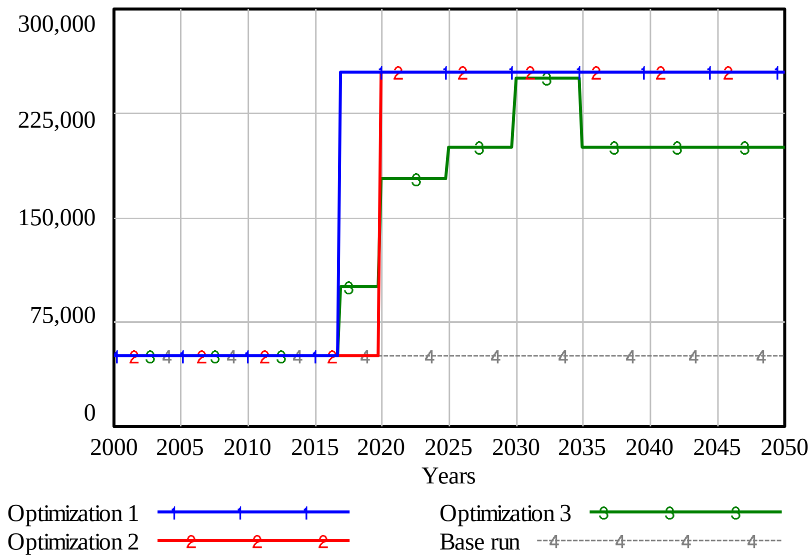

Figure 4.42. Replanting rate for all optimization

The final policy variable is the biodiesel blend mandates in all sector. As explained in chapter 1, biodiesel is a very important emerging sector where government has aligned its commitment to develop this industry through NBP (2006), continuing in Malaysia's Tenth Plan and Malaysia's Eleventh Plan. Thus, ensuring the increase of the mandate programme will warrant the progress of this industry. As shown in Figure 4.43 – Figure 4.45, optimization 3 keeps the increment of biodiesel in all sector in check, where highest achievable mandate is at B39 by year 2050 in transportation sector. Depending on the interpretation, 30 years for B39 may seem a slow progress but notice that the mandate is reviewed every 5 years by assuming that 5 years is the time taken for the implementation being fully accepted. This assumption is rather fair because it has come to our knowledge that even current B10 mandate implementation is bombarded with resistance from automakers and has resulted into several delays of implementation by the government. While looking onto optimization 1 and 2, one time huge increase not only being non-sensible for real world implementation, but also hinders the growth and development of biodiesel sector.

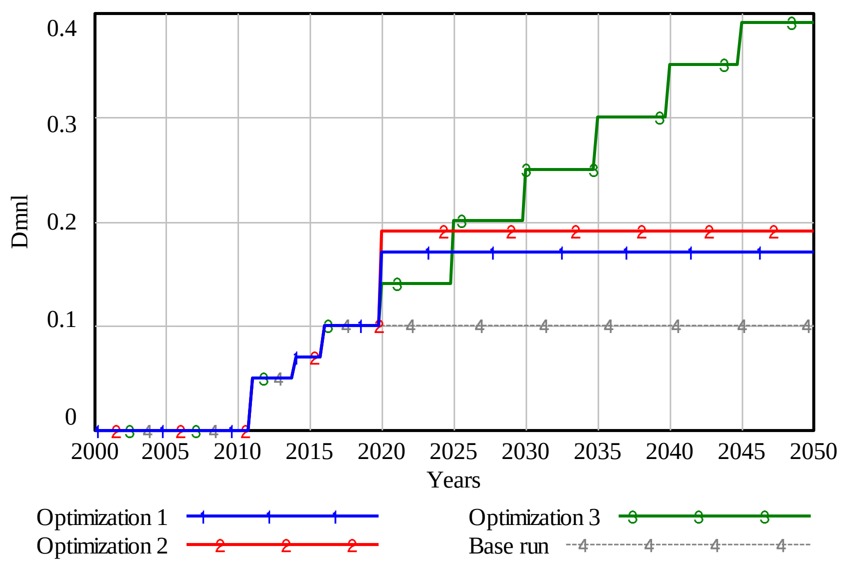

Figure 4.43. Biodiesel mandate for transportation sector in all optimization

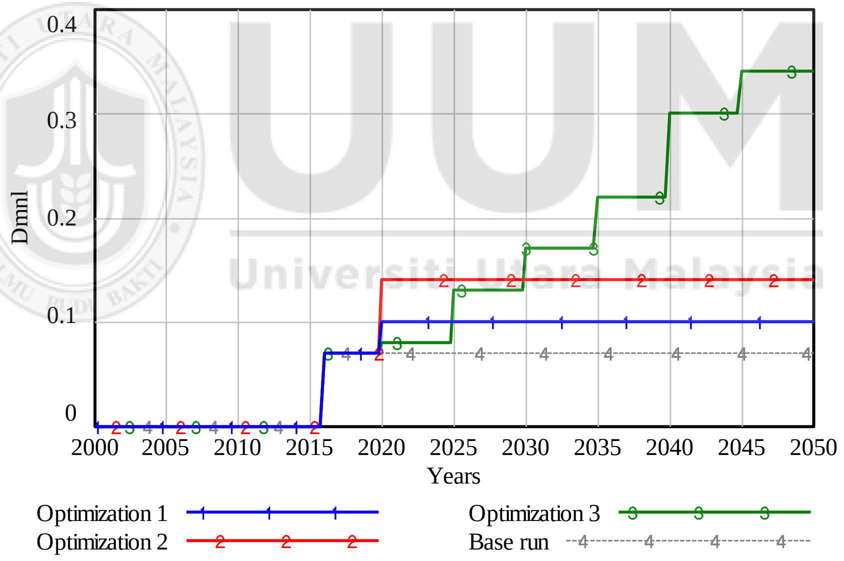

Figure 4.44. Biodiesel mandate for industrial sector in all optimization

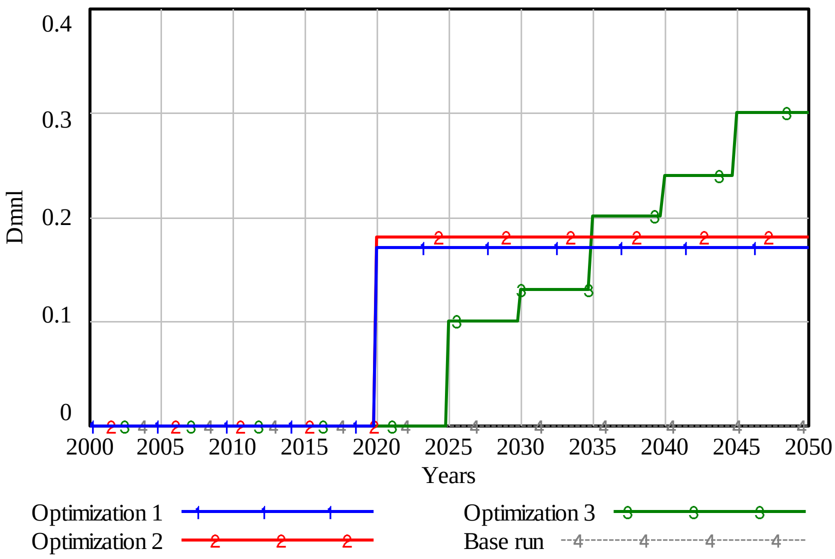

Figure 4.45. Biodiesel mandate for other sector in all optimization

From the comparison, it can be concluded that in order to improve the CPO production, implementation of policies in phases are the most effective means (exemplified by optimization 3). One time policy implementation is not effective for long term CPO production particularly due to the shock it may impose to the industry and shorter time frame that is deemed not plausible for implementation in the real world (exemplified by optimization 1 and 2).

Table 4.15 summarizes the parameter value for each policy variables and CPO production in seven phases from 2017 until 2050 from all optimization.

Table 4.15

Summary of Output from All Optimization

Variables	Run	2017	2020	2025	2030	2035	2040	2045	2050
Mechanization	Base run	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
adoption rate, *a*	Optimization 1	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
	Optimization 2	0.20	0.69	0.69	0.69	0.69	0.69	0.69	0.69
	Optimization 3	0.20	0.49	0.59	0.70	0.97	0.97	0.99	0.99
Average	Base run	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000
replanting, *b*	Optimization 1	254,171	254,171	254,171	254,171	254,171	254,171	254,171	254,171
	Optimization 2	50,000	254,364	254,364	254,364	254,364	254,364	254,364	254,364
	Optimization 3	99,483	177,773	200,277	250,169	200,161	200,143	200,018	200,018
Biodiesel	Base run	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
mandate in	Optimization 1	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
transportation	Optimization 2	0.10	0.19	0.19	0.19	0.19	0.19	0.19	0.19
sector, *c*	Optimization 3	0.10	0.14	0.20	0.25	0.30	0.35	0.39	0.39
Biodiesel	Base run	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
mandate in	Optimization 1	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
industrial sector,	Optimization 2	0.07	0.14	0.14	0.14	0.14	0.14	0.14	0.14
d	Optimization 3	0.05	0.08	0.13	0.17	0.22	0.30	0.34	0.34
Biodiesel	Base run	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
mandate in other	Optimization 1	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
sector, *e*	Optimization 2	0.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00
	Optimization 3	0.00	0.00	0.10	0.13	0.20	0.24	0.30	0.30
CPO production	Base run	23,438,702	25,674,296	26,826,812	25,806,422	24,937,752	23,913,356	23,510,624	23,457,078
	Optimization 1	23,438,700	24,544,000	25,882,300	25,757,800	26,234,000	26,515,000	26,329,000	26,415,900
	Optimization 2	23,438,700	25,674,300	25,213,200	25,295,400	25,504,500	25,699,300	26,333,800	26,416,900
	Optimization 3	23,438,700	25,327,700	26,007,700	25,582,000	25,221,600	25,639,400	25,774,100	25,850,200

4.5 Discussions

In Chapter 2, the need of a dynamic model to assist in finding optimal policy options to improve CPO production in palm oil industry was highlighted. In the context of Malaysia, reviewed of past studies mostly focus on the modeling of palm oil industry with less emphasizing in finding optimal solutions to improve the model as in Yahaya et al. (2006), Shri Dewi et al. (2010), Shri Dewi et al. (2015), and Mohammadi et al. (2016). It is admittedly that past studies had successfully model palm oil industry and understand the underlying mechanism in the system. However, the analysis mostly stopped at the simulation of related policies scenarios in order to improve the model. Further, based on the review made, it is found that there was no analytical method adopted to find the best policy option to improve the model. On the other hand, policies to improve the model were recommended based on the simulation outcome and backed with the expert opinions.

In this study, a SD-GA hybrid model was found to be capable of modeling the palm oil industry and searching for optimal policy options. The scenario simulation was initially done to understand the impact of imposed policy variables on the CPO production. From the simulation outcome, GA helps the SD model to find the best parameters for policy variables in order to achieve maximum CPO production in the long term investment planning.

On the other hand, review of past studies that adopt hybrid SD-GA model found that the integration process of the two methods was done by totally converting the SD model to other programming language before being integrated with GA code as in Grossman

(2002) and Duggan (2008). This process is found to be inefficient and impractical especially for a highly complex model like palm oil industry. Furthermore, SD-GA model in past studies has had only one change made in the policy variable done at the beginning of the simulation (Grossman, 2002; Duggan, 2008). This has been argued in this research of non-practicality and implausibility to be implemented in reality.

To address this limitation, this study proposed a hybrid SD-GA model that integrates SD and GA in a different platform (Vensim for SD model and Visual basics for GA code) that facilitate the process even for highly complex model like palm oil industry. Moreover, the propose hybrid SD-GA model are able to set the objective function as well as the policy variables at any point of the model timeline. This is very effective in designing time sensitive policies and has not been featured in the past studies. In addition, this feature has been utilized for phase optimization process in which the process of finding best solution were done in seven phases along the simulation timeline. As a result, the phase optimization process has become the best way to maximize CPO production in a long term, by gradually progressing all policy variables and making sure that the implementation is technically plausible in reality.

The output from this research were compared with the study by Mohammadi et al. (2016). The author simulated the increase of biodiesel mandate in 2014 to B15. Note that these were solely based on the author assumption in an attempt to observe the dynamic behaviour of the palm oil industry model. Only one policy variable were changed (that is biodiesel mandate) and no optimization method involve to find optimal solution. The findings suggest that CPO production were expected to increase to 27.8 million tonne in year 2025 by increasing biodiesel mandate to B15. On the contrary, through phase optimization, this research found that by 2025, biodiesel mandate will be increased to B20 (for transportation sector), B13 (for transportation sector), and B10 (for other sector). The CPO production was expected to increase to 25.5 million tonne in 2025 (8 percent lower than that of Mohammadi et al., 2016). The difference of CPO production in 2025 are due to several reasons. Firstly, the assumption made in the model. Mohammadi et al. (2016) assumed that maximum land available for oil palm plantation at more than 6 million hectares, whereas in this research, it assumed that the maximum land is at 6 million hectares. Higher plantation land will surely result into higher FFB yield and more CPO production.

Secondly, Mohammadi et al. (2016) did not take replanting rate as one of the policy variable, but instead assumed that the replanting rate as fix at certain percentage of decay rate. On the other hand, this research had explicitly modeled oil palm plantation phases with replanting rate as one of policy variables and modeled using batch function (that render more realistic planting phases rather than using decay rate. More explanation in Sub-chapter 3.3.3.2). Thus, the CPO production projected in Mohammadi et al. (2016) may not be accurate as the model did not represent the actual dynamic behaviour in oil palm plantation sector.

Thirdly, Mohammadi et al. (2016) had only one policy variable change (that is biodiesel mandate) in their simulation. Thus, higher CPO production were expected because the model did not take into account the changes in other policy variables. In contrary, this research considered five policy variables which are average replanting rate, mechanization adoption rate (labour factor), and biodiesel mandates (which also being further disaggregated based on transportation, industrial and other sector, as oppose to

Mohammadi et al. (2016) without aggregation of biodiesel usage in various sectors). The optimization method in this research simulate and change all five policy variables simultaneously while finding best solution for CPO production. Hence, the finding of this research is far more comprehensive as compared to that of Mohammadi et al. (2016).

And finally, Mohammadi et al. (2016) simulate their model based on assumption and with only one time increment of policy variable. This research on the other hand used third party method (that is GA) to help in finding best solution to improve CPO production. Furthermore, as argued previously, one time policy variable change may not be sensible for real world implementation. This explains the high CPO production in 2025 in Mohammadi et al. (2016). As a matter of facts, one time policy variables change exemplified by optimization 1 and 2 (refer Sub-chapter 4.4.1 and 4.4.2) also showed higher CPO production at the end of the simulation. However, the question is whether it is relevant for real world implementation, given that optimization 1 and 2 suggest sudden drastic one time increase of policy variables. On this account, the finding from phase optimization was the most sensible for real world policy implementation with its gradual change of policy variables.

Conclusively, the phase optimization process using the proposed SD-GA model has found that:

- The best way to have maximum CPO production (with current plantation area) in Malaysia is by increasing the policy variables namely mechanization adoption rate, replanting rate and biodiesel mandate in transportation, industrial and the other sector in seven phases (where each phase consist of five years interval) until 2050.

- The gradual increase of all policy variables in phases can possibly be implemented in reality because the five years interval in each phase will give ample of time for strategy planning and execution. Further, the gradual policy variables progression will avoid unwarranted shock in the palm oil industry as opposed to the sudden high increase of policy variables. As example, this has been shown in the report by PEMANDU (2015) which shown very low replanting rate and mechanization adoption rate despite many campaigns were launched by the government to increase both rates.

- Through the phase optimization process, CPO production can be maximized to satisfied level while ensuring all policy variables to progress simultaneously.

4.6 Summary

Generally, the model has been structural and behavioural validated as explained at the beginning of the chapter. With high confidence in the model, base and scenario setting simulation run has been conducted. The simulation found the importance of policy variables namely mechanization adoption rate, average replanting and biodiesel mandates in improving CPO production. Using the SD-GA hybrid model, optimization process is performed to find the optimal parameter for the policy variables. Three optimization concluded that phase optimization is the best mean to improve CPO production in the long run in terms of the logic of policy implementation in the real world as well as avoiding unnecessary shock in the industry.

Question may arise on the appropriateness of policy designing based on the reliance on numerical orientated solution derived from SD-GA model optimization process. The most appropriate answer for that question is that although the optimal parameter obtained seems too simplistic of an assumption for possible system improving effort, the SD-GA model proposed in this study is (at the least level) capable of highlighting the impact of existing policy changes (under various economic scenarios) on CPO production in the future. This can serve as scientifically supported evidence in assisting policy designing process relating to palm oil industry.

CHAPTER FIVE
CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the summary of the research findings and evaluates the contributions of the study where policy implication has been derived. Furthermore, the chapter highlights some limitation of the study and finally offer some recommendations for future research.

5.1 Conclusions

Malaysia palm oil industry at the current state is facing a stagnant CPO production growth compared to Indonesia. This shows that Malaysia's CPO production is lagging behind. There are various factors that cause the slow growth. This study focuses on three main factors namely the scarcity of plantation area, the shortage of labour and the rapid development of palm-based biodiesel industry. Contrary with Indonesia, the available land for plantation area is limited thus the productivity of the plantation sector (measure by FFB yield per hectare) has to be increased as the mean to improve CPO production. Labour shortage on the other hand is inevitable because in the future the number of workers from Indonesia is reducing due to vigorous growth of Indonesia palm oil industry. Low labour plantation ratio negatively effects the FFB yield (due to poor agro-management) thus to overcome this the labour productivity (measure by plantation area per labour) can be increased through the adoption of mechanization. Finally, the progress of biodiesel programme cannot be stopped as it is part of government commitment underlined in the National Biofuel Policy and continued in Malaysian Tenth Plan and Malaysian Eleventh Plan. The increment of biodiesel mandate in the future will require strong CPO production to avoid supply disruption.

There are three specific objectives in this study. The first objective is to determine the factors that influence CPO production in Malaysia palm oil industry. The factors had been determined through the review of literature which include published studies and reports from Malaysian Palm Oil Board (MPOB). Further, the latest updates on the current situation of Malaysian palm oil industry were obtained by attending the related conferences and conducting informational interviews with the industry members. Three main factors influencing CPO production has been identified namely the scarcity of plantation area, labour shortage, and demand surge from palm-based biodiesel sector.

The second objective is to optimize parameters for assessing CPO production in a dynamic environment. SD was applied to understand, evaluate, and model the Malaysian palm oil industry. The development of SD model starts with model conceptualization (further explanation can be referred to sub-chapter 3.3). A conceptual model was produced using causal loop diagram (CLD) which capture the main component of Malaysian palm oil industry, their inter-relationships and underlying feedback processes. Referring to CLD, the next stage is the development of stock and flow diagram (SFD) was constructed to quantify these inter-relationships in the form of stock and flow. The SFD consist of four sub-models namely palm oil supply and demand, oil palm plantation sector, palm-based biodiesel sector, and labour. The final model has passed six validation tests which include structural and parameter test, dimensional consistency test, extreme condition test, integration error test, sensitivity test, and behavioural validity test. Five policy variables were identified in the model which are mechanization rate (from labour sub-model), replanting rate (from oil palm plantation sector sub-model), and biodiesel mandate for transportation, biodiesel mandate for industrial and biodiesel mandated for other sector (from palm-based biodiesel sector sub-model). Next, a base run and three simulations setting run had been conducted to observe the impact of these policy variables on CPO production. The simulation period were from year 2000 until 2050. Findings from simulation suggest the change of the policy variables exert some impacts on CPO production.

Following through, GA code was developed to be integrated with SD model (further explanation can be referred to sub-chapter 3.4). A generation and population of 30 and 20 respectively were chosen through several experimentations based on the best output quality and shortest running time. Furthermore, roulette wheel selection was chosen for selection method with single point crossover and uniform mutation. The integration of SD and GA were performed in different platform behind a user interfaces which act as control panel for the integration. The upper and lower bound for each policy variables were set as the input with objective function to minimize the absolute value between simulated CPO production and desired CPO production. Firstly, a semi-random population is produced by GA which will be fed into SD model for simulation. The output from the simulation (the CPO production) is imported by GA and will be computed of its fitness score. Then, new population will be generated via selection, crossover and mutation process, which will be fed again to SD model. The process is repeated until the stopping criterion (number of generation) is met. The whole process is performed for 30 runs. The best output from the 30 runs are compiled and the best output with lowest fitness score will be chosen.

Three optimization processes were performed towards achieving this objective. Optimization 1 maximises CPO production in 2050 by changing the policy variables in

2017 (current year). The final output found that CPO production has been increased to 12.09% from base run. However, mechanization adoption rate and average replanting has to be drastically increased from 22% to 88% and from 50,000 hectare to 254,170.90 respectively. The drastic increase was deemed impossible to be achieved in one year. Next, optimization 2 maximize CPO production in 2050 by changing policy variables in 2020 (four years from current year). The final output found that CPO production has been increased to 12.24% from base run. Similarly, both mechanization adoption rate has to be drastically increased from 20% to 69% and 50,000 hectare to 254,363.60 hectare respectively. It is a challenging move and Malaysia can hardly implement the optimization in four years time.

On the other hand, optimization 3 maximize CPO production in 2050 by changing policy variables in phases. There are seven phases of implementation year which are 2017-2020, 2020-2025, 2025-2030, 2030-2035, 2035-2040, 2040-2045, and 2045-2050 has been conducted. The best policy options were searched in current phase and revised in the following phase. The phases optimization process leverage the ability of the proposed SD-GA model which is able to set policy variables and objective function at any specific time in the simulation timeline (further explanation is in sub-chapter 3.5.3). The final output found that CPO production has been increased to 9.97% from base run. Even though the increment of CPO production is lower than that of optimization 1 and 2, it was found that the implementation of policy in optimization 3 were more realistic and plausible in real world due to implementation in phases. Furthermore, another advantage of policy implementation in phases is that it avoids unwarranted shock to the industry.

The third and final objective is to evaluate the proposed hybrid SD-GA model for assessing CPO production in Malaysia. Optimization 1, 2, and 3 were compared in terms of their output in maximizing CPO production in Malaysia palm oil industry (further explanation in sub-chapter 4.4.4). It is found that although optimization 1 and 2 were capable of increasing CPO production higher than that of optimization 3, but they are not suitable for real world policy implementation. This is due to the drastic increase of policy variables which is deemed impossible to be done in such a short time frame. On the other hand, progressing the policy variables in phases through optimization 3 is more suitable for real world policy implementation.

5.2 Policy Recommendations

From the results, the output were analysed for policy interpretation, which led to policy recommendations. It is concluded that to improve CPO production in the long run, the best mean is through progressing the policy variables in phases. For instance, mechanization adoption rate is currently low in the palm oil industry due to technology and cost constraints. On that account, sudden increase of mechanization adoption rate is hardly possible to be implemented thus having the target revised in phase (every five years) provides sufficient time for research and development of mechanize equipment.

Further, implementing sudden increase in replanting rate may also become highly challenging especially among smallholders given the current low replanting rate in the industry. This also may resort into sudden shock in the industry and backlashing Malaysian revenue from palm oil sector due to interruption on palm oil supply. On that account, it is recommended to increase replanting rate in phase since it gives an ample time to gain participation from planters as well as avoiding the unwarranted shock in the industry. In addition to increasing replanting rate, there is a need of educating smallholders on the importance of replanting because without awareness among planters, any replanting campaign is hardly to be successful. Alternatively, government may offer some financial assistance to compensate the loss during the replanting period as the mean of encouraging the planters to participate in replanting campaign.

Finally, implementing policy in phases is a good option for progression of biodiesel industry. As the commitment of the government to uphold biodiesel industry were showed through National Biofuel Policy (NBP), having revised target in phases to increase biodiesel mandates in every sector will greatly help the policy maker in mapping the roadmap of biodiesel industry and anticipate its impact on CPO production in the future.

5.3 Research contributions

This study contributes to the body of knowledge and managerial aspects as explained below.

5.3.1 Body of knowledge contribution

The concept of methodology is the centre for contribution to the body of knowledge. This study proposed an improved version of hybrid of SD and GA model as proposed by previous studies the like of Grossman (2002); Duggan (2008); Alborzi (2008); and Cheng, Tu and Jeng (2011). The integration of SD and GA proposed in this study offers an optimization capability where its objective function can be set to be achieved in a desired time in the model time line as needed by policy requirement.

In addition, the model optimization process permeate the setting of policy variables in any desired time in the model time line which added further flexibility in policy designing process. As illustrated in sub-chapter 4.3, the policy maker is capable of finding the variable parameters of optimal policy in any desired year such as in year 2020 and 2035. Moreover, objective function can also be formulated to be achieved, for instance, in year 2040 or 2045 or in any desired year.

Next, through the usage of the SD-GA hybrid model this study has proposed the phase optimization process that utilizes the flexibility of the model (i.e. to set policy variables and objective function in any time period) for effective long term improvement of CPO production. This method successfully found the sufficiently good solution value needed for policy variables (in every time interval) in order to achieve desired objective function.

The SD-GA hybrid model proposed in this study also provides alternative method of solving the problem of time-dependant dynamic optimization (DO) using the combination of traditional GA and SD. In evolutionary computing field, solving DO problem requires the exploitation of GA code to adapt the dynamic nature of a system (Branke, 1999). However in the proposed hybrid of SD and GA model, traditional static GA is used where its integration with SD allowed the hybrid model to solve optimization problem in the dynamic environment.

5.3.2 Managerial contribution

For managerial contribution, this study focuses on the application of SD-GA hybrid model for real world policy design process. Previous studies has been found limited to the modeling of palm oil industry with less emphasizing on the searching of optimal policies to improve the model. The development of SD-GA hybrid model in this study addresses this need and offers a platform to evaluate, experiment and design new policies towards the achievement in the improvement of CPO production. This study can thus shed a light of possible changes to be implemented for improving CPO production. Specifically, this research will help:

1) The government to assess the effectiveness of ETP toward strengthening palm oil industry in Malaysia.

2) Malaysian Palm Oil Board (MPOB) in evaluating the impact of current policy on the palm oil industry. As the authority in the industry, MPOB can used the developed model to test new policy options before its implementation to avoid costly consequences in the long term.

3) Industry members to evaluate their current strategy on CPO production improvement and designing new strategy to stay competitive in palm oil industry such as planters, palm oil producers and traders.

Finally, with appropriate parameter and minor modification this framework can also be used for assisting the policy design process in other commodity industries such as cocoa, coconut and rice.

5.4 Limitations of the research

There are some limitations in this study as listed below.

1) This study did not explicitly model the influence of soybean oil on the CPO production. It would be better if soybean oil can be modeled endogenously where it will exhibit its role as the main substitutes for palm oil and influence the model dynamic. However, modeling endogenous soybean oil price will resort into highly detailed and complex model.

2) Similarly, the influence of adverse weather on FFB yield also was modeled as exogenous. Although the weather effect has become a critical issue recently in determining palm oil output, it is found to be an incontrollable variable and modeling it in high detail will make the model become overly complex.

5.5 Recommendations for future work

The SD-GA hybrid model developed in this study has demonstrated its capability in searching for optimal policy to improve CPO production in Malaysia. Further exploration can be made to make the system dynamic model more realistic.

1) The addition of more factors influencing Malaysian palm oil industry in the model will expand the understanding of the dynamic of the industry. For instance, the incorporation of world CPO supply and demand as well as Indonesia palm oil industry may add further element in the dynamic of palm oil world market. In addition, the dynamic of soybean oil supply and demand can be explored to capture its influence on Malaysia palm oil industry. Moreover,

the influence of adverse weather can be included as endogenous weather for better capturing its influence on FFB yield.

2) The proposed SD-GA hybrid model may be effective for searching optimal policy that lead to the improvement in CPO production, however its potential can only be realized by the experts in modeling. In the future, the proposed model can be converted into interactive user interface to allow the non-expert to operate the model. This can be done through the development of micromodel or using commercial programming language like visual basics or C++.

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APPENDIX

APPENDIX A: Palm Oil Supply Demand Sub-Model Equations

Average OER= 0.22
Units: Dmnl

Base CPO export demand growth= 3
Units: 1/Year

Base CPO import=
60000+RAMP(200000,0,3)+RAMP(80000,3,5)+RAMP(500,5,8)+RAMP(400000,8,11)+RAMP(5000,11,70)
Units: Tonne/Year

Base PPO export demand growth= 0.201
Units: 1/Year

Base PPO local demand growth= 0.155
Units: 1/Year

Biodiesel production= INTEG (Biodiesel production rate, 0)
Units: Tonne

CPO demand for biodiesel= Biodiesel production
Units: Tonne

CPO demand for PPO=Total PPO demand
Units: Tonne

CPO excess stock=Total CPO supply-Total CPO demand
Units: Tonne

CPO export demand= INTEG (CPO export demand change,400000)
Units: Tonne

CPO export demand change=
CPO export demand*Base CPO export demand growth*Factor affecting CPO export demand
Units: Tonne/Year

CPO export tax=
STEP(Lookup for CPO tax structure(CPO price),13)
Units: Dmnl

CPO import= INTEG (CPO import change, 46000)
Units: Tonne

CPO import change= Base CPO import*Effect of SB price on CPO import-CPO import
Units: Tonne/Year

CPO price= INTEG (CPO price change, 990)
Units: RM

CPO price change= Indicated CPO price/Time for CPO price adjustment
Units: RM/Year

CPO price influence on CPO export demand=
Lookup for effect of CPO price on CPO export demand (Relative CPO price on export demand)
Units: Dmnl

CPO production= INTEG (CPO production rate, 1e+007)
Units: Tonne

CPO production rate=
(Average OER*Total FFB yield-CPO production)/Time to adjust CPO production
Units: Tonne/Year

CPO supply demand ratio= Total CPO supply/Total CPO demand
Units: Dmnl

Effect of CPO export tax on demand=
1+STEP(-1+Lookup for effect of CPO export tax on CPO export(CPO export tax /Reference CPO export tax),13)
Units: Dmnl

Effect of CPO supply demand ratio on CPO price=
Lookup for effect of CPO SD on CPO price(Relative SD ratio)
Units: RM

Effect of SB price on CPO import=
(Soybean oil price/Reference soybean oil price)^Sensitivity of soybean oil price on CPO import
Units: Dmnl

Factor affecting CPO export demand=
CPO price influence on CPO export demand*Soybean oil price influence on CPO export demand*Effect of CPO export tax on demand
Units: Dmnl

Factor affecting PPO export demand=
PPO price influence on PPO export demand*Soybean oil price influence on PPO export
Units: Dmnl

Factor affecting PPO local demand=
PPO price influence on PPO local demand*SBO price influence on PPO local demand
Units: Dmnl

Historical soybean oil prices= Lookup for historical SBO prices (Time)
Units: USD/Tonne

Indicated CPO price= Effect of CPO supply demand ratio on CPO price

Units: RM

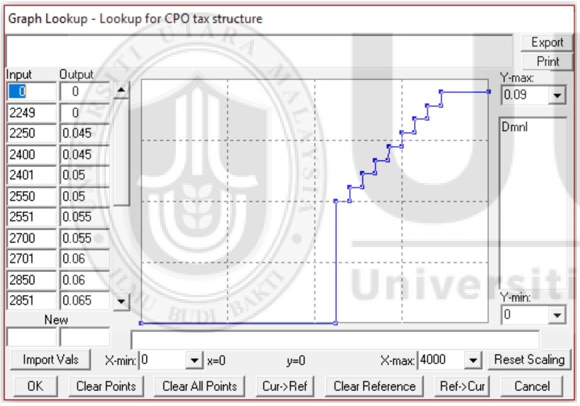
Initial CPO price references on CPO export demand= 3500
Units: RM

Initial PPO prices on PPO export demand= 3500
Units: RM

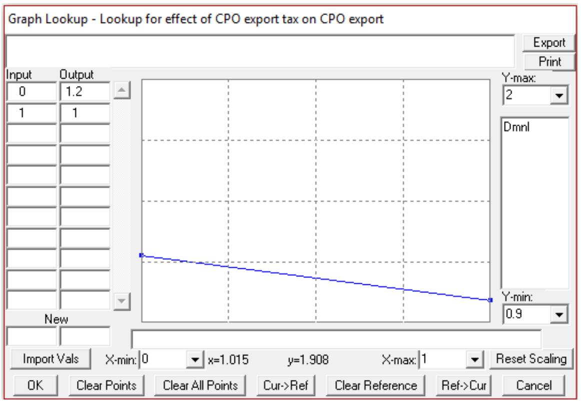
Initial reference CPO SD ratio= 1.5
Units: Dmnl

Initial reference PPO price on PPO local demand= 3500
Units: Dmnl

Lookup for CPO tax structure(
[(0,0)-(4000,0.09)],(0,0),(2249,0),(2250,0.045),(2400,0.045),(2401,0.05),(2550,0.05),(2551,0.055),(2700,0.055),(2701,0.06),(2850,0.06),(2851,0.065),(3000,0.065),(3001,0.07),(3150,0.07),(3151,0.075),(3300,0.075),(3301,0.08),(3450,0.08),(3451,0.085),(4000,0.085))
Units: Dmnl

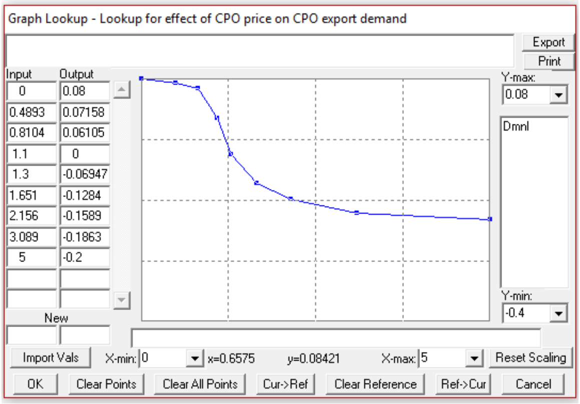


Lookup for effect of CPO export tax on CPO export(
[(0,0.9)-(1,2)],(0,1.05),(1,1))
Units: Dmnl

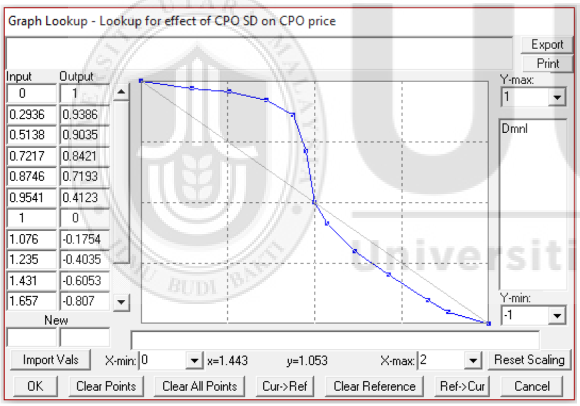


Lookup for effect of CPO price on CPO export demand(

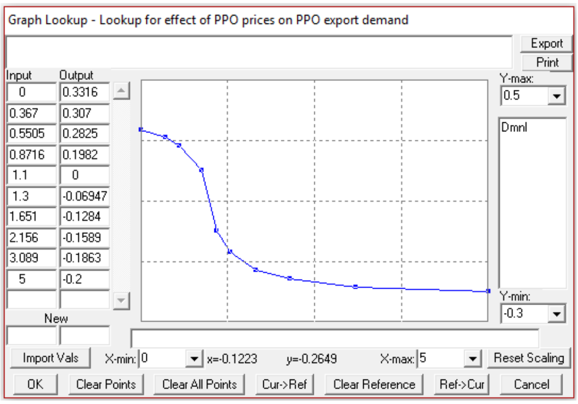
[(0,-0.4)-(5,0.08)],(0,0.08),(0.489297,0.0715789),(0.810398,0.0610526),(1.1,0),(1.29969,-0.0694737),(1.65138,-0.128421),(2.15596,-0.1589),(3.08869,-0.1863),(5,-0.2))
Units: Dmnl



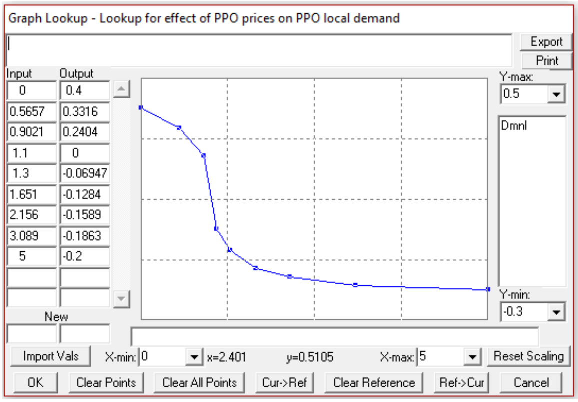
Lookup for effect of CPO SD on CPO price(
[(0,-1)-(2,1)],(0,1),(1,0),(2,-1)],(0,1),(0.293578,0.938596),(0.513761,0.903509),(0.721713,0.842105),(0.874618,0.719298),(0.954128,0.412281),(1,0),(1.07645,0.175439),(1.23547,-0.403509),(1.43119,-0.605263),(1.65749,-0.807018),(1.7737,-0.903509),(2,-1))
Units: Dmnl



Lookup for effect of PPO prices on PPO export demand(
[(0,-0.3)-(5,0.5)],(0,0.331579),(0.366972,0.307018),(0.550459,0.282456),(0.87156,0.198246),(1.1,0),(1.29969,-0.0694737),(1.65138,-0.128421),(2.15596,-0.1589),(3.08869, -0.1863),(5,-0.2))
Units: Dmnl



Lookup for effect of PPO prices on PPO local demand(
[(0,-0.3)-(5,0.5)],(0,0.4),(0.565749,0.331579),(0.902141,0.240351),(1.1,0)
,(1.29969,-0.0694737),(1.65138,-0.128421),(2.15596,-0.1589),(3.08869,-0.1863),(5,-0.2))
Units: Dmnl



PPO export demand= INTEG (PPO export demand change, 9e+006)
Units: Tonne

PPO export demand change=
Factor affecting PPO export demand*Base PPO export demand growth*PPO export demand
Units: Tonne/Year

PPO local demand= INTEG (PPO local demand change, 1.2e+006)
Units: Tonne

PPO local demand change=
Factor affecting PPO local demand*Base PPO local demand growth*PPO local demand
Units: Tonne/Year

PPO price= 1.03*CPO price
Units: RM

PPO price influence on PPO export demand=
Lookup for effect of PPO prices on PPO export demand (Relative PPO prices on export demand)
Units: Dmnl

PPO price influence on PPO local demand=
Lookup for effect of PPO prices on PPO local demand (Relative PPO prices on local demand)
Units: Dmnl

Reference CPO export tax= 0.045
Units: Dmnl

Reference CPO price on CPO export demand=

SMOOTH3I(CPO price,Time for CPO price references on CPO export demand,Initial CPO price references on CPO export demand)
Units: RM

Reference CPO SD ratio=
SMOOTH3I(CPO supply demand ratio, Time to perceived CPO SD ratio, Initial reference CPO SD ratio)
Units: Dmnl

Reference PPO price on PPO export demand=
SMOOTH3I(PPO price,Time for PPO price references on PPO export demand,Initial PPO prices on PPO export demand)
Units: RM

Reference PPO price on PPO local demand=
SMOOTH3I(PPO price,Time for PPO price references on PPO local demand,Initial reference PPO price on PPO local demand)
Units: RM

Reference soybean oil price= 980
Units: USD/Tonne

Relative CPO price on export demand=
CPO price/Reference CPO price on CPO export demand
Units: Dmnl

Relative PPO prices on export demand=
PPO price/Reference PPO price on PPO export demand
Units: Dmnl

Relative PPO prices on local demand=
PPO price/Reference PPO price on PPO local demand
Units: Dmnl

Relative SD ratio=
CPO supply demand ratio/Reference CPO SD ratio
Units: Dmnl

SBO price influence on PPO local demand=
(Soybean oil price/Reference soybean oil price)^Sensitivity of SBO prices on PPO local demand
Units: Dmnl

Sensitivity of SBO prices on PPO local demand= 0.479
Units: Dmnl

Sensitivity of soybean oil price on CPO import= 0.1
Units: Dmnl

Sensitivity of soybean oil price on PPO export demand= 0.004
Units: Dmnl

Sensitivity of soybean oil prices on CPO export demand= 0.9
Units: Dmnl
0.001

Soybean oil price= DELAY3(Historical soybean oil prices, 3)
Units: USD/Tonne

Soybean oil price influence on CPO export demand=
(Soybean oil price/Reference soybean oil price)^Sensitivity of soybean oil prices on CPO export demand
Units: Dmnl

Soybean oil price influence on PPO export=
(Soybean oil price/Reference soybean oil price)^Sensitivity of soybean oil price on PPO export demand
Units: Dmnl

Time for CPO price adjustment= 2
Units: Year

Time for CPO price references on CPO export demand= 5
Units: Year

Time for PPO price references on PPO export demand= 5
Units: Year

Time for PPO price references on PPO local demand= 5
Units: Year

Time to adjust CPO production= 1
Units: Year

Time to perceived CPO SD ratio= 5
Units: Year

Total CPO demand= CPO demand for PPO+CPO export demand + CPO demand for biodiesel
Units: Tonne

Total CPO supply= CPO production + CPO import
Units: Tonne

Total FFB yield=
Effect of labour on FFB yield*SMOOTH (Effect of adverse weather on FFB yield 4) *(Mature area yield + Ageing area yield)
Units: Tonne

Total PPO demand= PPO export demand + PPO local demand
Units: Tonne

APPENDIX B: Oil Palm Plantation Sub-Model Equations

Ageing area= INTEG (Ageing rate-Cutting rate, 1e+006)
Units: Hectare

Ageing area yield= Ageing area*Avg yield per ha for ageing area
Units: Tonne

Ageing period= 20
Units: Year

Ageing rate=
Fraction of ageing rate + (Initial mature area/Ageing period)*PULSE(0,20)
Units: Hectare/Year

Avg new planting= 150000
Units: Hectare

Avg replanting= 50000
Units: Hectare

Avg yield per ha for ageing area= 19
Units: Tonne/Hectare

Avg yield per ha for mature area= 25
Units: Tonne/Hectare

CPO price effect on replanting=
Lookup for CPO price effect on replanting (Relative CPO price on replanting)
Units: Dmnl

Cutting rate= MIN(Ageing area, Replanting)/Time for cutting
Units: Hectare/Year

Effect of adverse weather on FFB yield=
1+(-0.1*PULSE(0, 1))+(-0.1*PULSE(4, 1))+(-0.1*PULSE(8, 1))+(-0.1*PULSE(12, 1))+(-0.1*PULSE(16, 1))+(-0.1*PULSE(20, 1))+(-0.1*PULSE(24, 1))+(-0.1 *PULSE(28, 1))+(-0.1*PULSE(32, 1))+(-0.1*PULSE(36, 1))+(-0.1*PULSE(40, 1))+(-0.1*PULSE(44, 1))+(-0.1*PULSE(48, 1))+(-0.1*PULSE(52, 1))+(-0.1*PULSE (56, 1))+(-0.1*PULSE(60, 1))+(-0.1*PULSE(64, 1))
Units: Dmnl

Effect of labour on FFB yield=
Lookup for effect of labour on FFB yield(Relative labour land ratio)
Units: Dmnl

Effect of land availability on expansion plan=
Lookup for effect of land availability on expansion plan(Ratio of potential land for oil palm plantation)
Units: Dmnl

FFB yield per ha= Total FFB yield/Total plantation area

Units: Tonne/Hectare

Fraction of ageing rate= DELAY FIXED(Maturity rate, Ageing period , 0)
Units: Hectare/Year

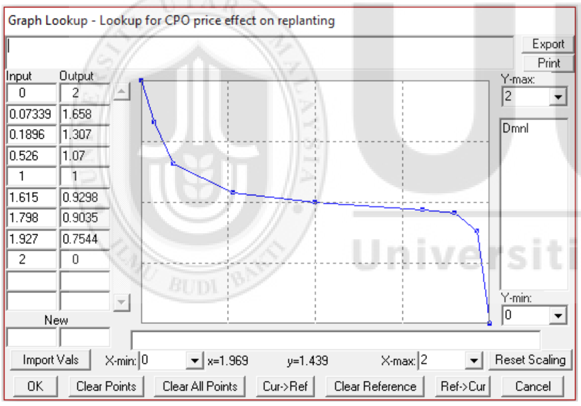
Fraction of maturity rate= DELAY FIXED(Planting rate, Maturity period , 0)
Units: Hectare/Year

Initial CPO price references on replanting=
5000
Units: Tonne

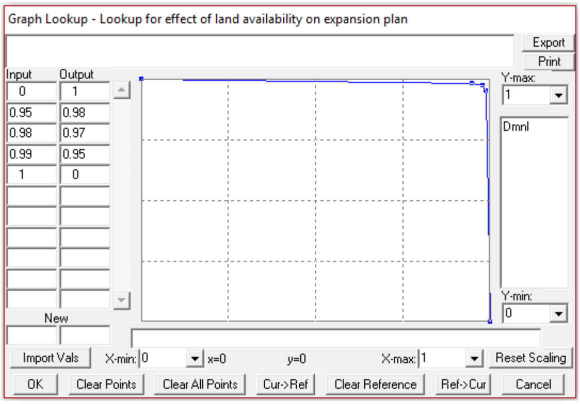
Initial mature area= 2e+006
Units: Hectare

Initial premature area= 300000
Units: Hectare

Lookup for CPO price effect on replanting (
[(0,0)-(2,2)],(0,2),(0.0733945,1.65789),(0.189602,1.30702),(0.525994,1.07018),(1,1),(1.61468,0.929825),(1.79817,0.903509),(1.92661,0.754386),(2,0))
Units: Dmnl



Lookup for effect of land availability on expansion plan(
[(0,0)-(1,1)],(0,1),(0.95,0.98),(0.98,0.97),(0.99,0.95),(1,0))
Units: Dmnl



Mature area= INTEG (Maturity rate-Ageing rate, Initial mature area)
Units: Hectare

Mature area yield= Mature area*Avg yield per ha for mature area
Units: Tonne

Maturity period=3
Units: Year

Maturity rate=
Fraction of maturity rate+(Initial premature area/Maturity period)*PULSE(0,3)
Units: Hectare/Year

Max land available= 6e+006
Units: Hectare

Motivation to replant= CPO price effect on replanting
Units: Dmnl

New planting=
MIN(Effect of land availability on expansion plan*Avg new planting, Vacant land)
Units: Hectare

Planting rate= (New planting + Replanting)/Time for planting
Units: Hectare/Year

Premature area= INTEG (Planting rate-Maturity rate,Initial premature area)
Units: Hectare

Ratio of potential land for oil palm plantation= Total plantation area/Max land available
Units: Dmnl

Reference CPO price on replanting=
SMOOTH3I(CPO price, Time for CPO price references on replanting, Initial CPO price references on replanting)
Units: RM

Relative CPO price on replanting= CPO price/Reference CPO price on replanting
Units: Dmnl

Replanting= MIN(Motivation to replant*Replanting rate, Ageing area)
Units: Hectare

Replanting rate=
50000+STEP(Avg replanting-50000,Year of replanting change-2000)
Units: Hectare

Time for CPO price references on replanting= 5
Units: Year

Time for cutting= 1
Units: Year

Time for planting= 1
Units: Year

Total FFB yield=
Effect of labour on FFB yield*SMOOTH(Effect of adverse weather on FFB yield, 4)*(Mature area yield + Ageing area yield)
Units: Tonne

Total plantation area= Premature area + Mature area + Ageing area
Units: Hectare

Total productive area= Mature area + Ageing area
Units: Hectare

Vacant land= MAX(Max land available-Total plantation area,0)
Units: Hectare

Year of replanting change= 2017
Units: Year

APPENDIX C: Palm-Based Biodiesel Sub-Model Equations

Biodiesel demand in industrial sector=
Total diesel use in industrial sector*Biodiesel mandate for industrial sector *STEP(1,16)
Units: Tonne

Biodiesel demand in other sector=
Total diesel use in other sector*Biodiesel mandate for other sector
Units: Tonne

Biodiesel demand in transport sector=
Biodiesel mandate for transport sector*Total diesel use on road
Units: Tonne

Biodiesel export= 100000
Units: Tonne

Biodiesel mandate for industrial sector=
STEP(0.07,16)+ STEP(Current biodiesel mandate for industrial sector-0.07, Year of biodiesel mandate for industrial sector implementation-2000)
Units: Dmnl

Biodiesel mandate for other sector=
STEP(Current biodiesel mandate for other sector, Year of biodiesel mandate for other sector implementation-2000)
Units: Dmnl

Biodiesel mandate for transport sector=
STEP(0.05,11)+STEP(0.07-0.05,14)+STEP(0.1-0.07,16)+STEP(Current biodiesel mandate for transport sector-0.1, Year of biodiesel mandate for transport sector implementation-2000)
Units: Dmnl

Biodiesel production= INTEG (Biodiesel production rate, 0)
Units: Tonne

Biodiesel production rate=
(Total biodiesel demand-Biodiesel production)/Time to adjust biodiesel production
Units: Tonne/Year

Current biodiesel mandate for industrial sector= 0.07
Units: Dmnl

Current biodiesel mandate for other sector= 0
Units: Dmnl

Current biodiesel mandate for transport sector= 0.39
Units: Dmnl

Time to adjust biodiesel production= 1
Units: Year

Total biodiesel demand=
STEP(1, 0)+Biodiesel demand in transport sector + Biodiesel demand in industrial sector + Biodiesel export + Biodiesel demand in other sector
Units: Tonne

TOTAL diesel consumption in all sector=
Total diesel use on road + Total diesel use in agriculture sector + Total diesel use in construction and mining sector + Total diesel use in industrial sector + Total diesel use in shipping and rail sector
Units: Tonne

Total diesel use in agriculture sector= 26803*Time+550316
Units: Tonne

Total diesel use in construction and mining sector= 10309*Time + 211659
Units: Tonne

Total diesel use in industrial sector= 8247.2*Time + 169327
Units: Tonne

Total diesel use in other sector=
Total diesel use in agriculture sector + Total diesel use in construction and mining sector + Total diesel use in shipping and rail sector
Units: Tonne

Total diesel use in shipping and rail sector= 26803*Time + 550316
Units: Tonne

Total diesel use on road= 134016*Time + 3e+006
Units: Tonne

Year of biodiesel mandate for industrial sector implementation= 2020
Units: Year

Year of biodiesel mandate for other sector implementation= 2020
Units: Year

Year of biodiesel mandate for transport sector implementation= 2020
Units: Year

APPENDIX D: Labour Sub-Model Equations

Actual labour land ratio= Labour stock/Total plantation area
Units: Labour/Hectare

Attractiveness of Indonesia palm oil industry=
1 + (0.3*Relative Indonesia palm oil growth+0.7*Relative wage rate)
Units: Dmnl

Contract duration= 5
Units: Year

Desired labour=
Total plantation area*Optimal labour land ratio
Units: Labour

Effect of labour on FFB yield=
Lookup for effect of labour on FFB yield (Relative labour land ratio)
Units: Dmnl

Effect of mechanization on labour=
0.2 + STEP(Mechanization adoption rate-0.2,Year of mechanization use change-2000)
Units: Dmnl

Factor affecting labour off rate= Attractiveness of Indonesia palm oil industry
Units: Dmnl

Fraction of labour taking= 0.25
Units: 1/Year

Gap of labour= Desired labour-Labour stock
Units: Labour

Indonesia palm oil industry growth= 3.4
Units: Dmnl

Indonesia wage= INTEG (Indonesia wage change, 300)
Units: RM

Indonesia wage change= Indonesia wage*Indonesia wage rate growth
Units: RM/Year

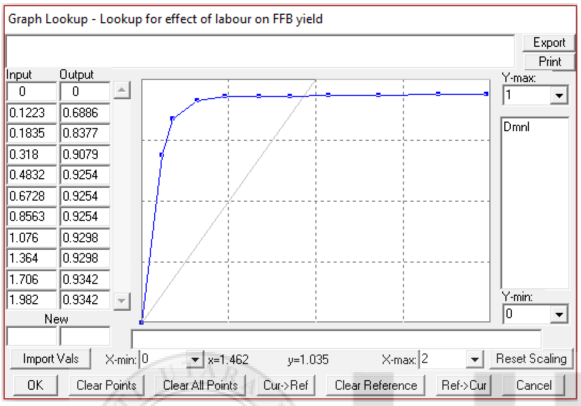
Indonesia wage rate growth= 0.04
Units: 1/Year

Labour off rate=
Factor affecting labour off rate*Labour stock/Contract duration*Year of contract duration change
Units: Labour/Year

Labour stock= INTEG (Labour taking rate-Labour off rate, 250000)
Units: Labour

Labour taking rate= Fraction of labour taking*Gap of labour
Units: Labour/Year

Lookup for effect of labour on FFB yield (
[(0,0)-(2,1),(0,0),(1,1),(2,1)],(0,0),(0.122324,0.688596),(0.183486,0.837719),(0.318043,0.907895),(0.48318,0.925439),(0.672783,0.925439),(0.856269,0.925439),(1.07645,0.929825),(1.36391,0.929825),(1.70642,0.934211),(1.98165,0.934211))
Units: Dmnl



Malaysia palm oil industry growth= 0.8
Units: Dmnl

Malaysia wage= INTEG (Malaysia wage change, 600)
Units: RM

Malaysia wage change= Malaysia wage*Malaysia wage rate growth
Units: RM/Year

Malaysia wage rate growth= 0.028
Units: 1/Year

Mechanization adoption rate= 0.2
Units: Dmnl

Optimal labour land ratio= 0.167
Units: Labour/Hectare

Relative Indonesia palm oil growth=
Indonesia palm oil industry growth/Malaysia palm oil industry growth
Units: Dmnl

Relative labour land ratio=
Actual labour land ratio/(Optimal labour land ratio/(1+Effect of mechanization on labour))
Units: Dmnl

Relative wage rate= Indonesia wage/Malaysia wage
Units: Dmnl

Total plantation area= Premature area + Mature area + Ageing area
Units: Hectare

Year of contract duration change= 1
Units: Dmnl

Year of mechanization use change=2017
Units: Year