

Maximizing Crude Palm Oil Production in Malaysia: A Search for an Optimal Policy Using System Dynamics and Genetic Algorithm Approach

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Abstract

Palm oil industry in Malaysia is experiencing a stagnant crude palm oil (CPO) production and has been lagging as compared to Indonesia. This situation can jeopardize Malaysia's position in world palm oil market since Malaysia needed to secure its export revenue and fulfilling increasing demand of palm oil both locally and globally in the future. The factors that influence the CPO production are many. Among others are the scarcity of plantation area, labour shortage, and demand from palm-based biodiesel industry. This study presents an integrated of system dynamics (SD) and genetic algorithm (GA) (SD-GA) model to find the optimal policy to improve CPO production in Malaysian palm oil industry. SD offers the platform to evaluate and to test policy while GA facilitate the process of searching the best solutions to achieve the maximum CPO production in 2050. The proposed model has produced five optimal values for five policy variables namely average replanting rate, mechanization adoption rate, and biodiesel mandate in transportation, industrial and other sectors respectively. The best solution suggested that CPO replanting rate need to be increased to 251743.5 hectares per year to decrease the accumulation of ageing area by optimizing all these policy variables. This study is expected to help policy makers in designing related policies and drawing the road map towards improving CPO production in Malaysian palm oil industry.

Keywords: Crude palm oil production; Genetic algorithm; System dynamics; SD-GA integrated model.



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1. Introduction

Palm oil is one of the widely used vegetable oil in and its usage spanning from a daily cooking oil, main ingredient in bakery and pastry, as well as non-food use as in cosmetics and biofuel. It is forecasted that the global palm oil consumption will greatly increase in another ten to twenty years due to high demand from rapid increase of world population as well as emerging palm-based biodiesel market (Oil World, 2017; PEMANDU, 2015). Today, Malaysia constitute of around 5.7 million hectares of oil palm plantation, with the total export value in 2016 recorded at RM41.44 billion (MATRADE, 2017). However, Malaysia palm oil production is far-fetch from its neighbouring country, Indonesia. Statistics shows that Indonesia crude palm oil (CPO) production has surpassed Malaysia in year 2004 and leaving Malaysia behind. 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 fulfilling increasing demand of palm oil both locally and globally in the future (Adnan, 2016; PEMANDU, 2015).

There are several factors contributing to this stagnant production. The first factor is the scarcity of plantation land. Since producing more palm oil requires more oil palm fruits from huge plantation area, Malaysia current plantation land bank is limited to permeate aggressive plantation expansion (Abdullah and Wahid, 2011). Another factor that influences the CPO production is the labour shortage. Palm oil is renowned as one of the most labour intensive industry, particularly involving the work like planting, nurturing, and harvesting (Abdullah *et al.*, 2011; Ismail, 2013; Ismail *et al.*, 2015). Labour shortage has hit Malaysia's palm oil industry hard as it is estimated that the industry had lost approximately RM1 billion annually from wasted and rotten uncollected fruits (Amatzin, 2006; Ismail, 2013). The third factor that influences the CPO production is the implementation of palm-based biodiesel mandate. Currently, the biodiesel mandate is enforced at 7 percent (which means 7 percent of biodiesel blended with 93 percent of petrol diesel (Adnan, 2016). The latest mandate announcement has been made in 2016, where 10 percent mandate is aimed for transportation sector with 7 percent mandate for industrial sector. The implementation of blend mandates is a part of government green campaign under the National Biofuel Policy (NBP) to increase the usage of biodiesel in all sectors that used petrol diesel, including transportation, industrial, agriculture, construction and mining, and shipping and rail (MPIC, 2006; USDA, 2015). To address the problem of stagnating CPO

production, this paper proposed a system dynamics (SD) modeling to capture the feedback process of how these factors are interrelated, integrated with genetic algorithm (GA) to help the model in maximizing CPO production.

This paper is organized as follows. The next section presents the various modeling approaches in past studies related to palm oil industry. The following section continues with the explanation on the SD model of Malaysian palm oil industry. Afterwards, detail explanation on the problem formulation and the developed approach is presented. It continues with the demonstration on the findings related to the best policy options to maximize CPO production. Finally, the conclusions and future works recommendations are presented.

2. Review of Palm Oil Models

A wide number of previous studies have been found in modeling palm oil industry. One of the approaches is econometrics modeling. This can be seen in the studies by (Shamsudin *et al.*, 1988); (Mohammad *et al.*, 1999); (Shri *et al.*, 2011); (Rahman *et al.*, 2011). However, researchers started to move to the operation-based modeling rather than observation-based modeling. Olaya (2016) argued the shortcoming of observation-based modelling are the reliant on historical data to forecast the future trend, and the limitation in capturing the feedback process. Operation-based modeling on the other hand models an operation system and incorporate the actual factor that influence the operation rather than numerical percentage of probability (Olaya, 2016). This permeates the inclusion of feedback processes that dictate the dynamics of the system.

It is well established in the literatures that previous research has been adopting the operation-based modeling using SD method in modeling palm oil industry. For instance, a study by J. *et al.* (2006) adopted SD to model the impact of biodiesel mandate implementation on the Malaysian palm oil industry. Besides, (Shri *et al.*, 2010) combined econometrics and SD to model the impact of biodiesel demand on Malaysian palm oil market which parameter from econometrics analysis were used in SD modeling. Another study on biodiesel industry by [19] investigated the impact of various biodiesel mandates on palm oil industry. Apart from biodiesel industry, a study by (Abdulla *et al.*, 2014) used SD to study the impact of export tax on palm oil market while Mohammadi *et al.* (2015) investigate the determinants of CPO prices by conducting SD model simulations using various palm oil production, soybean prices, and biodiesel mandate.

However, although these studies were able to incorporate feedback process 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, various optimization methods are available from the simplest linear programming to the complex metaheuristics such as simulated annealing (SA) and genetic algorithm (GA). For instance, (Nwawe *et al.*, 2008) used linear programming 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. Besides, (Banitalebi *et al.*, 2016) employed non-linear programming to minimize the total operational cost in palm oil plantation management.

The mentioned studies have adopted SD modeling to understand the palm oil industry and to simulate various scenarios to achieve their research objective. However, there are not many studies combined SD and GA approaches. Surprisingly, to the best of our knowledge, there is not even a study found used these combinations in palm oil modelling. The integration of SD-GA can be found in the studies in environmental pollution (Yu and Wei, 2012); education assessment (Hussein and El-Nasr, 2013); and cyclic storage system (Jahanpour *et al.*, 2013). Hence, this study extends the contribution with the used of SD modeling and GA in finding optimal policy options. The integration of SD-GA model proposed in the research functioning to complement each other. Basically, this research involves policy scenario evaluation and experimentation in a dynamic environment. Therefore, SD offers the platform to evaluate and to test policy options, integration with GA facilitate the process of searching sufficiently good solutions to achieve the maximum CPO production.

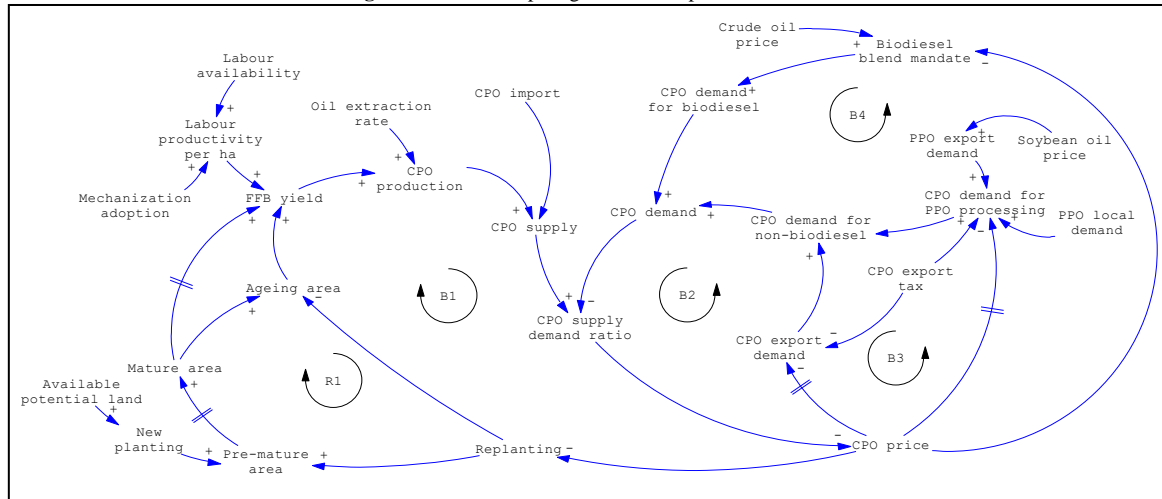
3. Methodology

3.1. Causal Loop Diagram of Palm Oil Model

SD evolves from the invention of industrial dynamics to model and to simulate the long term behaviour of complex systems (Forrester, 1961). The complexity of palm oil industry displays some characteristics that turns SD as an adequate method to model its long-term behaviour. Causal loop diagram (CLD) in SD captures the mental model in a system in non-technical fashion (Sterman, 2000). CLD highlights the interrelationship between variables and basic mechanism in the system. Further, CLD shows the positive and negative feedback loops derived from these interrelationships. Positive feedback loop act as reinforcing force where any changes of variable in the loops increase the total output, whilst any changes in negative feedback loops will balance out the total output (Sterman, 2000). Positive and negative feedback loops are sometimes named as 'R' and 'B' respectively.

The application of SD model in the Malaysian palm oil study was developed through the construction of CLD as the conceptual model that consist of several sub-models. The interrelationship between supply and demand of CPO, the oil palm plantation sector, the labour, and the palm-based biodiesel sector in the Malaysian palm oil industry is shown in Figure 1. The CLD diagram consists of one reinforcing loop and four balancing loops.

Fig-1. The causal loop diagram of CPO production



On the supply side, loop R1 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 replaced and lead to smaller ageing area but wider mature area, subsequently ensure higher 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 contrary, low CPO price will increase the motivation in replanting.

On the demand side, loop B2 represent the negative relationship of CPO price with CPO export demand, whereas loop B3 represent the negative relationship between the CPO prices with CPO local demand. It is understandable when CPO price is high, both overseas and local demand becomes low albeit some delay. Note that the role of CPO export tax that influence both export and local demand are also incorporated in these loops. CPO export tax is one of the means for the government to control the CPO export (The Star, 2015;2016a). In addition, soybean oil has been incorporated as one of the influencing factors of PPO export demand. As supported by (Shri et al., 2011); (Senteri, 1988); (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 the increase in biodiesel blend mandate there will be more CPO demand for biodiesel production, disrupting the CPO supply ratio thus increasing the prices. The relationship of crude oil and CPO price on biodiesel blend mandate incorporated in this loop. This relationship is 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 2017 by taking into the consideration the difference between CPO and crude oil prices in the current volatile market (The Star, 2016b).

3.2. Genetic Algorithm Process

A metaheuristic optimization method, namely Genetic Algorithm (GA) was used to assist the SD model in finding optimal policies to maximize CPO production. GA basically depicts the biological evolution process, in which the solutions in GA undergo reproduction loop through the series of selection, crossover and mutation process (Mitchell, 1996). The policy variables which is optimized during optimization process were taken from each sub-models based on the aforementioned factors explained in Introduction Section. These include the average replanting rate, mechanization optimization rate, and biodiesel mandates in transportation, industrial and other sectors. These factors serve as the inputs in the model while the output is CPO production.

3.3. Mechanism of System Dynamics and Genetic Algorithm Approaches Integration

In this study, GA was developed to assist SD model in finding optimal value for the five policy variables (see Table 1) to obtain maximum CPO production. The simulation period is set from 2000 until 2050 due to the long delay involves in the oil palm plantation planting phases. The model's objective function is to maximize the CPO production in year 2050 as represented by Equation 1 with consideration of five policy variables (constraints) listed in column 1 in Table 1.

$$Objective\ function = Max\ CPO_P(t=2050) \tag{1}$$

The solutions (or chromosomes) consist of an array of five values representing the five policy variables. Further, all changes in policy variables are set to begin in year 2020. The general idea is to have the algorithm to generate potential solutions from the search space and export it to SD model for simulation, where the output from the model will be imported back by the algorithm for ranking process. This involves several iterations as the algorithm improve the solution in every iteration until the stopping criteria is met. The concept of integration of SD and GA has been demonstrated by the works of Grossman (2002); Duggan (2008); Alborzi (2008); and Eksin (2008).

The process starts with the generation of initial population of solution based on the pre-defined lower and upper bound on the interface panel. Then, each chromosome generated are exported to SD software for the simulation process. Each corresponding simulation output (the CPO production) are imported back to the interface so GA can compute the fitness score. The fitness score determines the fitness of the chromosomes where the fittest are selected using roulette wheel selection process and undergo mating, crossover and mutation as the process to generate new generation. This loop continues until the stopping criteria met. The stopping criteria is met when the pre-defined number of generations is reached. Finally, the process is repeated for 50 runs and GA compiles the best-so-far solutions where the best solution is chosen for policy interpretation.

The SD model was developed using *Vensim* while GA code was developed using *Visual Basic* in Microsoft Excel. Microsoft Excel acts as the interface to integrate between SD and GA, as well as to specify data, to receive results, and to prepare graphs and output in tables.

3.4. Data and Main Assumptions

The data is collected from year 2000-2017. In the base run, the implementation of biodiesel mandate starts in year 2011, with 5 percent blending followed by 7 percent blending implemented in 2014 (Adnan, 2016). Further, it is assumed those new blend mandates (10 percent for transportation, 7 percent for industrial sector) are implemented in 2017. The average replanting rate is assumed at 70,000 hectares per year, taken by averaging the replanting rate from 2000 to 2017 (MPOB, 2017). Finally, mechanization adoption rate is assumed at 20 percent (PEMANDU, 2015). These values will be used to simulate the base run scenario or business as usual scenario. Base value for the five policy variables experimented in the model are summarized in Table 1.

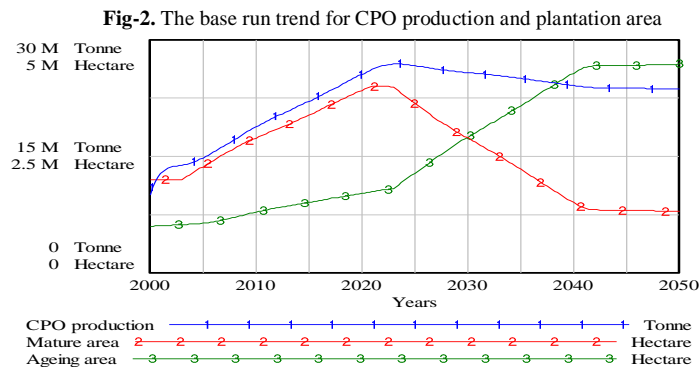
Table-1. The summary of policy variables of base run, lower and upper bound.

Policy variables/constraints	Base run	Upper bound	Lower bound
Mechanization adoption rate	0.20	1.0	0.2
Average replanting rate	70,000	400,000	70,000
Biodiesel mandates in transportation	0.10	1.0	0.10
Biodiesel mandates in industrial	0.07	1.0	0.07
Biodiesel mandates in others	0	1.0	0

The second scenario involved the optimization process. The simulation take place from 2000 until 2050. The changes in policy variables will begin in 2020. A lower and upper bound for each policy variables are defined to narrow the search space thus helping the finding of optimal values. Further, the bounded range deter any non-sensible solution beyond physical logic of the system. The upper and lower bound for each policy variables are summarized in Table 1.

4. Results and Discussions

The base run for CPO production illustrated in Figure 2 shows the CPO production is at the maximum value in 2023 before declining to equilibrium state at 12 percent lower. When the industry has reached its maximum planting area (with low replanting rate and low mechanization rate adoption for increasing labour productivity) the accumulation of ageing area relative to mature area impose significant decrease in the yield thus affecting the CPO production. Further, with the current biodiesel mandate, the CPO price has increased due to more consumption of CPO as biodiesel feedstock. High CPO price demotivate planters to replant thus the accumulation of ageing area is remained.

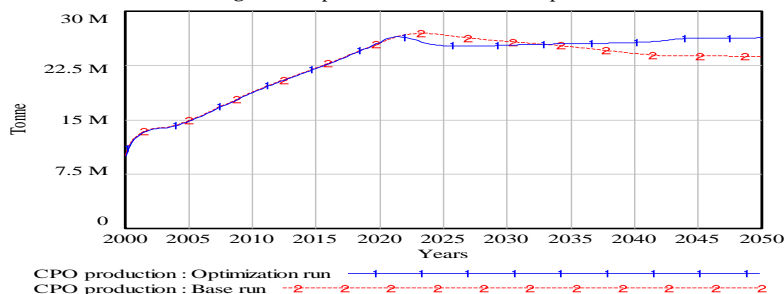


The top five results from optimization process have been tabulated in Table 2. The best solution (highlighted row) has produced higher CPO production as compared to the base run as shown in Figure 3. Although there is a disruption of supply from year 2023 to 2033, the CPO production has been successfully maximized at the end of simulation. The disruption of supply can be traced from the change of policy variables that took place as shown in Table 2.

Table-2. Top five best optimization results

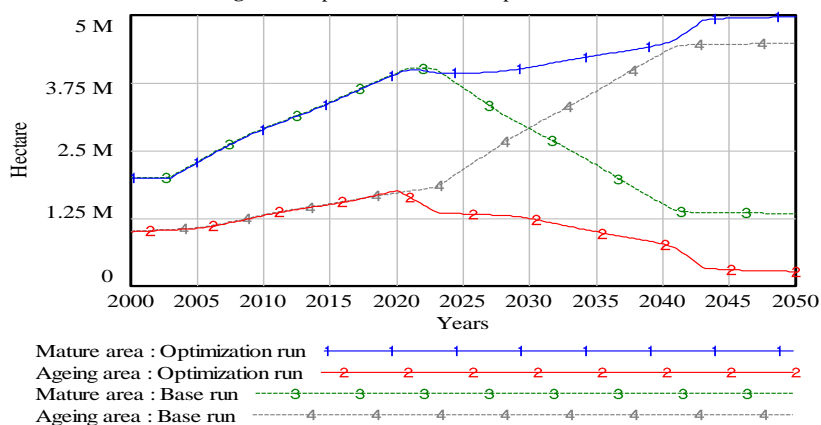
Mechanization adoption rate	Average replanting rate	Biodiesel mandate			CPO production
		Transportation	Industrial	Other	
0.73	252287.3	0.17	0.15	0.18	26,332,376
0.67	253751.8	0.19	0.17	0.18	26,334,172
0.73	251743.5	0.19	0.11	0.2	26,344,546
0.66	255771.1	0.17	0.16	0.17	26,299,462
0.98	260600.7	0.19	0.2	0.18	26,266,482

Fig-3. The optimization trend for CPO production



The best solution suggested that CPO replanting rate to be increased to 251743.5 hectares per year. The suggested replanting rate managed to decrease the accumulation of ageing area as shown in Figure 4. However, due to the aggressive replanting, it has temporarily reduced the FFB yield (from year 2023 to 2033 as compared to the base run in the same period) due to the replacement of productive (albeit lesser yield than mature tree) ageing trees with new seedlings. This required at least 3 years for the trees to become mature and capable of giving maximum yield, explaining the sudden interruption in CPO production.

Fig-4. The optimization trend for plantation area



As compared to the palm oil model in the past studies, this study has proposed five optimal values for five policy variables to improve CPO production through optimization process. Even though the CPO production has been maximized, it is still far fetch as compared to that of Indonesia. The biggest limitation that deters our CPO production to compete with Indonesia is the scarcity of plantation area. This limitation is a physical limitation to the model and only with aggressive expansion of plantation area would Malaysia CPO production present a significant increase. Nevertheless, the optimization has provided the important finding to help policy designing to maximize the CPO production with existing limitation in Malaysian palm oil industry. Through SD and GA optimization in this study, at the least level has helped in providing ideas in designing related policies and drawing the road map towards improving CPO production in Malaysian palm oil industry.

5. Conclusions and Future Works

This study proposed the used of SD and GA integration to suggest the best policy towards maximizing CPO production. The results suggested the optimal value for five policy variables namely mechanization adoption rate, average replanting rate, and biodiesel mandate in transportation, industrial and other sector are 0.73, 251743.5 hectares per year, 0.19, 0.11 and 0.20 respectively to maximize CPO production. Even though our CPO production is far fetch as compared to that of Indonesia, the model has able to increase the CPO production with current limitation in the industry. This study can help the policy maker in planning the road map of CPO production in the future, considering the limitation in plantation area, the need of progressing biodiesel industry, and addressing labour shortage. Future works include the inclusion of more policy variables in palm oil industry and solving various

objective functions including prices, supply and demand. Further, with some modification the proposed model can be used in other commodity industry like cocoa, coconut and rice.

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