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A Soft System Dynamic Approach for Designing Palm Kernel Shell Supply Chain

Handaya
School of Business,
IPB University, Bogor, Indonesia
Email: ir.handaya@gmail.com (*Corresponding Author*)

Herri Susanto
Faculty of Industrial Technology,
Bandung Institute of Technology, Bandung, Indonesia
Email: herri@che.itb.ac.id

Dikky Indrawan
School of Business, IPB University, Bogor, Indonesia
Email: rdikky@apps.ipb.ac.id

Marimin
Faculty of Agricultural Engineering and Technology
IPB University, Bogor, Indonesia
Email: marimin@ipc.ac.id

ABSTRACT

Palm kernel shell (PKS) is a waste of palm oil processing, that has enormous potential to become a green energy resource for industries with thermal conversion. To realize PKS potential as biomass fuel, it is important to build an effective, efficient, and sustainable supply chain model. As with other biomass, PKS supply chain involves collection processes, storage facilities, and a transportation network, which is dynamic and optimizable. Soft systems dynamics methodology (SSDM) has been implemented in this study, by which its key feature of system dynamics is recognized as one of the most ideal modeling techniques for studying such complex and multivariate system. We demonstrate how to apply SSDM in analyzing and designing a sustainable supply system of PKS through mathematical modeling and simulations, which capture the long-term effect of and the interactions among supply chain design variables and parameters. The simulation results show that the proposed supply chain model would be able to deliver continuous availability of PKS at the end customer side by achieving the goal of minimum 95% customer production level despite decreasing PKS generation rate from the source and increasing other consumption rate. Furthermore, decision makers can identify and implement necessary changes and recommendations to improve the existing supply chain system. The application of soft systems dynamics approach in biomass supply chain will enable greater use of green energy for continuous industrial purposes.

Keywords: *green energy, palm kernel shell, soft system dynamics, sustainable supply chain*

1. INTRODUCTION

Biomass is becoming one of green energy solutions to countermeasure global sustainability problems such as depleting of fossil fuels stockpile and rising global temperature due to greenhouse gases effect (Cheng, 2018). Accordingly, palm kernel shell (PKS) is considered as one of plausible alternative biomass fuel to be used by industries. PKS is a biomass generated as waste of palm oil processing with high lignocellulosic content, which gives high heat of combustion within the range of 4,000-5,000 kkal/kg with relatively low level of ash and minimum SOx and NOx emission (Okoroigwe and Saffron, 2012; Febriansyah *et al.*, 2014; Ikumapayi and Akinlabi, 2018). Industries will commercially use PKS as biomass fuel, if PKS supports industries' processing requirements, and as an input, PKS supply chain is integrated with industries' operation management system. Therefore, it is important to design an effective and efficient supply chain model from the source of generation up to the point of consumption along with optimal inventory levels, which will ensure timely product availability, with the right quality, at the least cost possible, and in sustainable manner leading to value-added improvements (Trisna *et al.*, 2016; Duc and Nananukul, 2019; Marimin *et al.*, 2020; Ohmori and Yoshimoto, 2020).

The application of PKS as the renewable energy fuel has been studied vastly for various purposes (Oti *et al.*, 2015; Ikumapayi and Akinlabi, 2018; Kruzcek *et al.*, 2019). In Indonesia, palm kernel shell is currently utilized in a small portion as fuel for the boiler to generate power in the palm oil mill (POM) (Febriansyah et al., 2014; Susanto *et al.*, 2018), while a large amount is exported to Japan, South

Korea, several European countries and the United States for fuelling power plants (Rachmadea, 2017; Prasetyo, 2020). To our knowledge, there are very limited references that discussing about the supply chain of palm kernel shell in Indonesia for industrial uses, such as for steam generation and drying process, in comparison with other biomass products originated from the palm oil industry (Harahap *et al*., 2019). Consequently, it warrants further research in this area to explore an alternative supply chain design, which fulfils continuous industrial requirements.

Thus far, there is no research specifically studying on PKS supply chain despite there are stacks of prior research in biomass supply chain that adopt various modeling techniques, which some by nature are multi criteria, including the most common one (Mujkić *et al*., 2018), mixed integer linear programming (MILP) (Lin *et al*., 2014; Ba *et al*., 2015; Akhtari *et al*., 2018), discrete event simulation (Pinho *et al*., 2016; Akhtari *et al*., 2019; Sharma *et al*., 2018), system dynamics (SD) (Vimmerstedt *et al*., 2012; Saavedra *et al*., 2018), and various hybrid methods, such as geographic information system (GIS) and hierarchical decision-making method (Iakovou *et al*., 2010), demand-resources value targeting (DRVT) and life cycle analysis (LCA) (Lim and Lam, 2015), stochastic and simulation modeling (Duc and Nananukul, 2019), and most recently GIS, LCA, and agent based modeling (ABM) (Raghu *et al*., 2020). Furthermore, studies on the application of system dynamics in the biomass supply chain are still mainly conceptual and strategic (Saavedra *et al*., 2018) with emphasizing on economic analysis (Zhang *et al*., 2017; Arrumaisho and Sunitiyoso, 2019), which do not distinctly facilitate strategic and operational planning purposes for a particular biomass. This fact indicates a research gap and brings curiousity given the nature of uncertainties and dynamic behaviour of a supply chain system.

Despite the advantage of analytical simplicity, multi criteria techniques generally have limitations on the aspect of time dimensional, by which SD suits better in analyzing dynamic problems such in designing a supply chain system (Wang and Gunasekaran, 2017; Fauzi, 2019). SD was introduced by Forrester during 1960s, a quantitative methodology originally known as Industrial Dynamics that applies theory of information feedback and control in analyzing how a business process structure and its variables interact as a function of time (Forrester, 1965; Ulloa and Caceres, 2005; Campuzano and Mula, 2011; Bala, *et al*., 2017). An SD model inherent with the real-world supply chain can then be solved and emulated using simulation techniques, which usually require sufficient amount of replications to develop meaningful insights into the model behaviour (Magableh, *et al*., 2005; Magableh and Mason, 2009). Beyond understanding the dynamic behavior in time dimension (An and Jeng, 2005), a combination of SD modeling and simulation techniques can also be useful in exploring viable designs and optimization opportunities, including in energy supply chains (Campuzano and Mula, 2011; Chen *et al*., 2021).

PKS supply chain involves collection systems, storage facilities, and a transportation network, as for common biomass (Veal, 2018). The main challenge is to optimize the process of collection, inventory levels throughout the storage points, and the transportation of PKS, so that the whole supply chain becomes more effective, more efficient, and sustainable for industrial applications (Iakovou *et al*., 2010, Akhtari *et al*., 2019). In this study, we propose to answer the key question, which is how to apply soft systems dynamics methodology (SSDM), a hybrid methodology of soft systems methodology (SSM) and system dynamics (SD), in designing a supply chain model of PKS for strategic and operational planning purposes. The main objective is to construct a supply chain model with SSDM, which will result more robust supply chain design to ensure PKS availability for continuous industrial green energy applications.

Following SSDM steps, we built the PKS supply chain deterministic model using a systematic approach including mathematical formulations with conservation equations, transfer equations, and boundary conditions in refer to a set of empirical data from practical experience.

The stock and flow models for each stock point were solved and simulated by using Simulink™ modul from MATLAB™. In this paper, we demonstrate that a soft systems dynamics approach is helpful in facilitating PKS supply chain design and optimization works effectively and efficiently.

The remainder of this paper is structured as follows. Section 2 provides a review on palm kernel shell potential as biomass fuel and how its current supply chain is structured. Section 3 briefly discusses the use of SSDM with SD modeling in supply chain management in refer to combination of landmark and up-to-date studies in the subject. In Section 4, we describe the methodology used in this study taken from the 10 steps of SSDM, followed by Section 5 presenting the results and discussions of each SSDM step, which are linked with the proposed operating model of an improved PKS supply chain design and some managerial implications. Finally, conclusions and recommended further research are presented in Section 6.

2. PALM KERNEL SHELL AS BIOMASS FUEL AND ITS SUPPLY CHAIN

Beyond conversion of CPO into biodiesel as liquid fuel, the massive amount and high variety of biomass from palm oil processing waste can also be the source of fuel or energy, both in liquid and solid forms (Setiadi, 2011; Hambali and Rivai, 2017; Harahap *et al*., 2019). For each 100 tonnes of CPO produced, the production process generates 429 tonnes or more than 4 times amount of waste with potentially convertible into energy, by which 27 tonnes of those are palm kernel shells (Hambali and Rivai, 2017).

PKS is a source of green energy, which can be utilized by direct combustion or as feedstock for thermochemical conversion, which is the thermal decomposition of its lignocellulosic component (Okoroigwe *et al*., 2011; Okoroigwe and Saffron, 2012). Thermophysical properties and chemical composition of PKS are shown in **Table 1** (Okoroigwe and Saffron, 2012; Febriansyah *et al*., 2014; Ikumapayi and Akinlabi, 2018).

Table 1 Typical physical properties and chemical composition of PKS*

Property	Parameter	UoM	Value
Physical[a]	Specific gravity	$kg.m^{-3}$	1,260
	Bulk density	$kg.m^{-3}$	560
	BET Surface Area	$m^2.kg^{-1}$	1,600
	Porosity	%	3.9
Thermal[a,b,c]	Net caloric value	$kkal.kg^{-1}$	4,000-5,000
	Specific heat	$kkal.kg^{-1}.K^{-1}$	0.47
	Thermal conductivity	$W.m^{-1}.K^{-1}$	0.68
Elementary[c]	Carbon	%	50
	Hydrogen	%	5.6
	Nitrogen	%	0.7
	Oxygen	%	35
	Sulphur	%	< 0.08
	Chlorine	ppm	0.0089
Molecular[a]	Lignin	%	56
	Cellulose	%	27
	Hemicellulose	%	7
	Ash	%	9

Sources: [a]Ikumapayi & Akinlabi 2018
[b]Febriansyah *et al* 2014
[c]Okoroigwe & Saffron 2012
*on dry basis

Given its unique physical, chemical, and thermal characteristics, PKS shows excellent combustion properties with relatively high caloric value and therefore it is a great potential of fuel for heat and power generations, which is environmentally friendly due to low content of sulphur and nitrogen (Okoroigwe and Saffron, 2012; Ninduangdee *et al.*, 2015). With these properties, PKS has humongous potential to become a major source of energy for industrial usages.

At current, PKS is mainly used in POMs as the main fuel in the in-house steam generation for fresh fruit bunch disinfection and electricity production (Kong *et al.*, 2013). For heat generation purposes, besides direct combustion method, PKS can be converted into energy through densification to form briquettes or gasification processes (Park *et al.*, 2018; Yahayu *et al.*, 2018). Becoming more common green energy technology is gasification of biomass for generating electricity (Susanto *et al.*, 2018), which is the main application for PKS export markets in Japan, South Korea, European countries, and the United States (Rachmadea, 2017).

3. SOFT SYSTEM DYNAMICS METHODOLOGY

A supply chain system is a complex dynamic system that involves many interactive feedback loops, by which to conduct its designing and analyzing tasks requires a modeling tool with causal feedback mechanism and overlapping with simulation models, which are useful in expressing the relationship among supply chain variables (Shapiro, 2007; Flores-Sigenza *et al.*, 2021). The system dynamics modeling coupled with simulations will fulfil such requirement as adopted from feedback control theory (Bala *et al.*, 2017). Based on simulation and optimization results, changes and recommendations can be derived and applied to improve the situation.

In the mathematical form, SD is represented by a set of ordinary differential equations (Bala *et al.*, 2017). This representation is useful in analyzing characteristic behaviours of long-term equilibrium, which is a characteristic of dynamic model outputs (Fauzi 2019). The formulation of mathematical equations in such systems is derived from the application of conservation principle on the fundamental quantities of S coupled with a transport rate equation to complete the mathematical modeling (Stephanopoulos, 1984), which is represented as equation (1).

$$\frac{\begin{bmatrix}\text{accumulation of S}\\ \text{within a system}\end{bmatrix}}{\text{time period}} = \frac{\begin{bmatrix}\text{flow of S}\\ \text{into a system}\end{bmatrix}}{\text{time period}} - \frac{\begin{bmatrix}\text{flow of S}\\ \text{out from a system}\end{bmatrix}}{\text{time period}} + \frac{\begin{bmatrix}\text{amount of S}\\ \text{generated within a system}\end{bmatrix}}{\text{time period}} - \frac{\begin{bmatrix}\text{amount of S}\\ \text{consumed within a system}\end{bmatrix}}{\text{time period}} \quad (1)$$

Generally, the transfer rate can be expressed in a function that relates flow rate of S with quantity of S at any given time.

For a multivariables system like a supply chain system, combination of conservation equations and transfer rate equations can be stated as a system of ordinary differential equations (ODEs), which takes a general form as shown in equation (2) (Hoffman 1993),

$$\frac{dy_i}{dt} = f_i(t, y_1, y_2, y_3, \ldots, y_n) \quad (i = 1, 2, 3, \ldots, n) \quad (2)$$

where: yi = quantity of S at location i, t = time.

Systems of ODEs can be solved by numerical analysis using a computational algorithm, such as the Fourth Order Runge-Kutta finite difference method (Hoffman, 1993; An and Jeng, 2005; Bala et al., 2017).

Another auxiliary tool to represent a system with system dynamics is the causal loop diagram to identify relationships among variables and feedback loops that exist in the system (Campuzano and Mula, 2011; Bala et al., 2017). A system, which forms a negative feedback loop, signifies long term stability through a self-correcting mechanism (An and Jeng, 2005).

Building upon SSM philosophical principles of system thinking introduced by Checkland (Checkland & Poulter 2006), Rodriguez-Ulloa and Paucar-Caceres (2007) instilled SD features into SSM, which provide more structural and soft approach to the aforementioned steps of SD process. SSDM principally augments the way how root definitions are built and used in SSM and elaborates further the 7 steps of SSM with the addition of system dynamics modeling, in both problematic situation and solving situation, and compiling learning points to become 10 stages (Rodriguez-Ulloa & Paucar-Caceres, 2005), as shown in **Figure 1**.

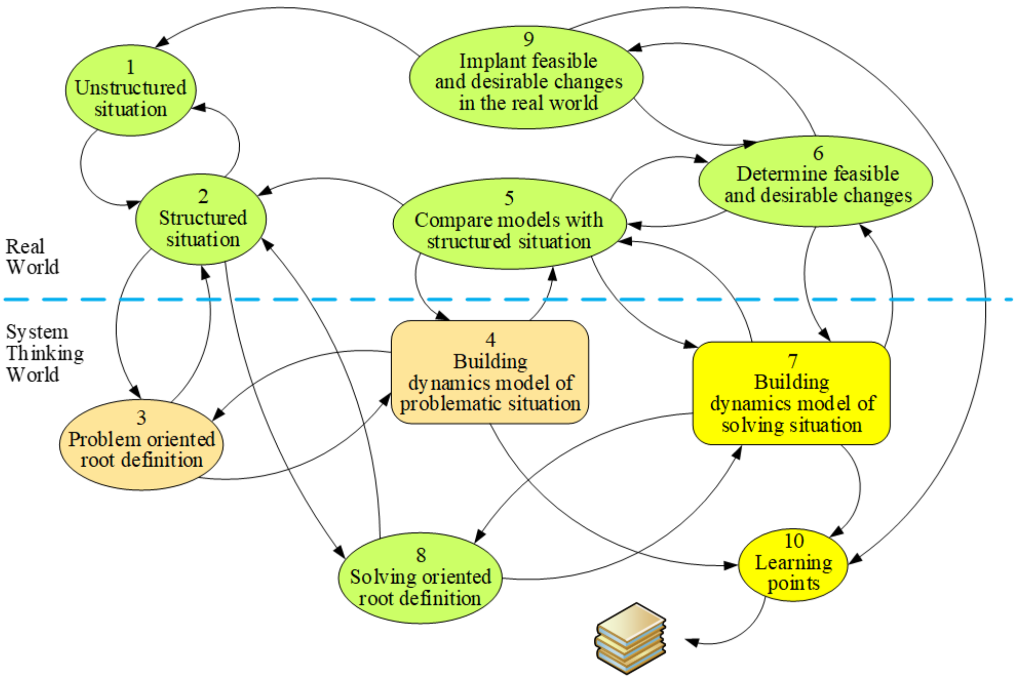

Figure 1 Soft system dynamics methodology

The dynamic features of SSDM work across three worlds, namely, to appreciate the problem in the real situation (world 1), to understand the problematic situation oriented system thinking (world 2) behaviour in a holistic manner, and systemic thinking of ways to solve the problematic situation are studied and proposed in the solving-situation system thinking (world 3) (Paucar-Caceres & Rodriguez-Ulloa, 2007).

The first step of SSDM is about identifying unstructured problematic situation as it happens in the real world, followed by Step 2, which is to express the problem in structured manner in the form of rich picture. In Step 3, in order to define problem-oriented root definitions one needs to capture all relevant elements of the system, which are the customer (C), the actors (A), the transformation (T), the world view (W), the owner (O), and the environmental constraints (E), known as CATWOE mnemonic (Checkland and Poulter, 2006). These first three steps of SSDM are the same with SSM. Whilst Step 4 builds system dynamics models of the problematic situation and characterizes the dynamic feature of SSDM in capturing the problematic situation to be resolved. Furthermore, Step 5 is about comparing models with the structured situation and Step 6 is to determine feasible and optimal changes, both mimic the same subsequent SSM steps. In Step 7, another set of system dynamics models needs to be built pertinent to the solving situation by including identified changes to the system in step 6, followed by Step 8, which is formulating solving-oriented root definitions. Lastly, Step 9 (to implement feasible and optimal changes in real world) is taken from

Step 7 of SSM, which is then supplemented by Step 10 (to draw learning points). The hybrid approach of SSDM is applied as the building block of methodology in this research as we consider it is more suitable to resolve the real-world problem in a holistic manner and to capture characteristics in dynamic modelling works of PKS supply chain compared with only using the traditional SD and SSM independently.

4. METHODOLOGY

In conducting this research, we began with the construction of 10 steps SSDM to guide our workflow, which were completed by two subroutines of modelling and simulation processes, as outlined in **Figure 2.**

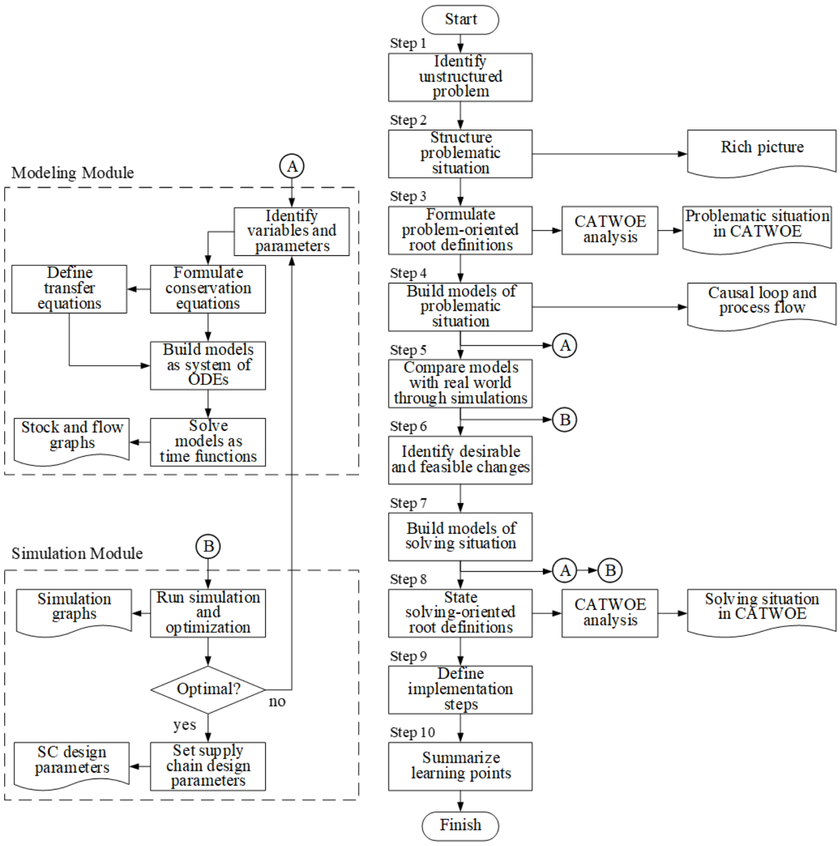

Figure 2 Research Workflow

All modeling and simulation works were done with MATLAB™ R2020a and its Simulink™ modul.

Steps 1, 2, and 3

This study is based on a typical setup of PKS supply chain currently, by which an industrial end customer buys PKS from multiple agents that each manages the inbound storages closer to POM locations, engages hauliers to conduct inter-island shipment of the material from Sumatera or Kalimantan to Java, where most industrial users are located, and usually arranges the outbound storages located closer to the end customer location. An agent may do the collection of PKS directly from POMs or alternately buys it from primary collectors, which in either case collecting PKS from POM storages and transferring it to an inbound storage, and in this study, we assume that both land and sea hauliers are always available. The main goal of the whole supply chain process is to achieve minimum 95% of PKS stock availability at the end customer within one year of continuous operations, as a chosen period for evaluating the supply chain performance by taking into account all the potential seasonal factors. In addition to this application, there are also some PKS consumptions out of the main chain, which are: (1) some reused portions of PKS for internal energy usages at POMs; (2) external power generation within the vicinity of POMs taken from POM storage; (3) export demand shipped out from inbound storage; (4) other industrial users located nearby and taking stock from outbound storage.

Besides production level variations at POM, these multiple consumptions of PKS potentially create fluctuations on material availability at the end customer under the current supply chain model. For modelling and analytical purposes in this study, we assumed a single source point of PKS collected by a single agent yet considered potential variations along the chain under some deterministic disturbance scenarios.

Having done the problem identification in getting availability of PKS continuously, we built a rich picture to capture the complexity of current supply chain. It was then followed by formulating the problem in root definitions, involving all key relevant elements within the system through a CATWOE analysis. These series of actions conclude the first three steps of SSDM as precursors to conduct a system dynamic modelling.

Steps 4 and 5

In modelling PKS supply chain with system dynamics, we commenced by building a causal loop diagram to ascertain system variables, their relationships, and feedback loops that exist within the system. Based on the causal loop, a supply chain process flow diagram was drawn, completed with all variables and parameters for modelling purposes, as listed in **Table 2**.

Table 2 Process Variables and Parameters

Independent Variables	Parameters	Dependent Variables
F_g Standard generation rate ton/day F_π Standard consumption rate ton/day	λ_β Transfer lead time day θ_β Transfer parameter day^2/ton k Stock policy constant G_β Gain factor = $1/\sqrt{\theta_\beta}$	$F_{\beta,t}$ Transfer rate at t ton/day $Q_{S\beta,t}$ Storage quantity at t ton ρ Reuse ratio %
β denotes storage units – s(0)=source, p(1)=POM, i(2)=inbound, o(3)=outbound, c(4)=customer π denotes consumption rate – c(4)=end customer, z(3)=other usage, x(2)=export, e(1)=external usage		
At steady state (pull system only): $Q_{S\beta+1,T} = k\lambda_\beta \sum_{\beta+1}^{4} F_\pi$ (β = 0,1,2,3) ≡ target stock level at downstream storage units Notes: (a) Stock policy constant (k) represents the stock day cover as a multiplier of lead time. (b) Lead time (λ) used in the model is determined by storage unit that influences the flow rate, which is dependent on the selection of push or pull system.		

In this modelling work, we defined θ_β as transfer parameters representing the flow resistance factor determined by transfer lead time (flow restriction) and quantity of material flow between storage points per time unit (dimension of conduit), which were calculated by formulae listed in **Table 3**.

Table 3 Transfer Parameters

Flow of Consumption	Lead Time	Transfer Parameter
F_c	λ_o	$\theta_o = \frac{\lambda_o}{F_c}$
F_z	λ_i	$\theta_i = \frac{\lambda_i}{F_z + F_c}$
F_x	λ_p	$\theta_p = \frac{\lambda_p}{F_x + F_z + F_c}$
F_e	λ_s	$\theta_s = \frac{\lambda_s}{F_e + F_x + F_z + F_c}$

All models built in step 4 and later in step 7 are deterministic and continuous within the range of $0 \le t \le T$. For the purpose of modelling and simulations, we used following data set of dependent variables and parameters, as shown in **Table 4**.

Table 4 Variables and Parameters Data Set

Location	All system		Push system	Pull system
Source	F_g = 200	λ_s = 1		k = 1 (all)
POM	F_e = 30	λ_p = 2	θ_p = 0.0222 $Q_{Sp,T}$ = 180	θ_s = 0.0083 $Q_{Sp,T}$ = 120
Inbound	F_x = 30	λ_i = 9	θ_i = 0.1500 $Q_{Si,T}$ = 540	θ_p = 0.0222 $Q_{Si,T}$ = 180
Outbound	F_z = 10	λ_o = 1	θ_o = 0.0020 $Q_{So,T}$ = 50	θ_i = 0.1500 $Q_{So,T}$ = 540
Customer	F_c = 50		$Q_{Sc,T}$ = 50	θ_o = 0.0020 $Q_{Sc,T}$ = 50

For problematic situation, our models are based on the assumption of push-system, shown in **Figure 3**, by which transfer shipments between storages is driven by the stock quantity at the upstream stock points, the higher the stock level, the higher quantity will be transferred, as mimic current mode of operations. For solving the situation, we propose a pull-system, a system whereby material transfer from an upstream stock point is determined by the stock level at the subsequent downstream stock point, which we will elaborate in later paragraphs.

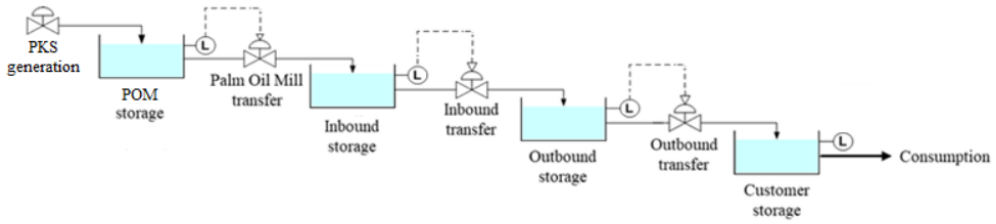

Figure 3 Supply Chain Push System

This study uses a set of empirical data based on practical experience and as well as secondary data from published reports. Parameters are either calculated or chosen arbitrarily. The data set used in the example was generated by modifying the real-world data of a typical demand and supply of PKS. This paper uses a typical problematic scenario of PKS supply for green energy purposes. There are abundant stockpiles of PKS as wastage of palm oil mill processing with the rate of generation at 200 tonnes per day (tpd) from several POMs with total daily capacity of 750 tonnes CPO per day. Under normal circumstances, the overall demand rate is 120 tpd, by which the end customer consumes 50 tpd to fuel a drying process, whilst the remaining 70 tpd are consumed by external power generator (30 tpd), exported (30 tpd), and supplied to other industry (10 tpd). All our examples use $\Delta t = 1$ day and $T = 365$ days, which represents a full year operation.

We commenced with stock modelling for each stock point (refer to **Figure 5**), which take a general form of stock (Q) and flow (F) equations, as follows:

At generation point:

$$F_{s,t} = (1-\rho)F_{g,t}\,,\ \ 0 \le \rho \le 1 \qquad (3)$$

Conservation equation:

$$\frac{dQ_{S\beta,t}}{dt} = F_{\beta-1,t} - F_{\beta,t} - F_{\pi,t}\,,\ Q_{S\beta,t} \ge 0 \qquad (4)$$

Transfer equation:

$$F_{\beta,t} = \sqrt{\frac{Q_{S\beta,t}}{\theta_\beta}} = G_\beta\sqrt{Q_{S\beta,t}} \qquad (5)$$

The transfer equation reflects a typical inventory system where demand flow is a function of time and stock level (Shah *et al.*, 2019). We choose square root function as inspired by the hydraulic metaphor in the bathtub dynamics model from Sweeney and Sterman (2001), which was derived from the Bernoulli's equation in fluid dynamics.

To complete the model, following boundary conditions were applied:

At generation point:

$$0 \le F_{s,t} \le F_{g,t}\ ,\ \text{else}\ \ F_{s,t} = F_{g,t} \qquad (6)$$

At any intermediary point:

$$0 \le F_{\beta,t} \le F_{\beta-1,t} + \frac{Q_{S\beta,t}}{\lambda_\beta} - F_{\pi,t}\ ,\ \text{else}\ \ F_{\beta,t} = F_{\beta-1,t} + \frac{Q_{S\beta,t}}{\lambda_\beta} - F_{\pi,t} \qquad (7)$$

In these equations, β-1 denotes upstream stock point, β is downstream stock point next to β-1, β = 1,2,3,4 for 4 units of storage point and π = β+1 denotes flow of consumption out from storage point β (see **Table 2**). The assumption used in determining boundary conditions (6) and (7) is that a downstream flow will be governed by the stock level at the immediate storage unit, and if the level is sufficient, then the transfer equation (5) will be applied. Otherwise, the downstream flow will be determined directly by the upstream flow and the remaining stock level at the storage unit after deducting by the consumption rate in that particular unit.

By substituting equations (3) and (5) into (4) and applying boundary conditions (6) and (7), resulting:

At palm oil mill (β=1):

$$\frac{dQ_{Sp,t}}{dt} = (1-\rho)F_{g,t} - G_p\sqrt{Q_{Sp,t}} - F_{e,t} \qquad (8a)$$

$$F_{p,t} = G_p\sqrt{Q_{Sp,t}}\quad \forall\ \ F_{p,t} \le F_{s,t} + \frac{Q_{Sp,t}}{\lambda_p} - F_{e,t} \qquad (8b)$$

$$\text{else}\ \ F_{p,t} = F_{s,t} + \frac{Q_{Sp,t}}{\lambda_p} - F_{e,t} \qquad (8c)$$

At any intermediary point (β=2,3):

$$\frac{dQ_{S\beta,t}}{dt} = F_{\beta-1,t} - G_\beta\sqrt{Q_{S\beta,t}} - F_{\pi,t} \qquad (9a)$$

$$F_{\beta,t} = G_\beta\sqrt{Q_{S\beta,t}}\quad \forall\ \ F_{\beta,t} \le F_{\beta-1,t} + \frac{Q_{S\beta,t}}{\lambda_\beta} - F_{\pi,t} \qquad (9b)$$

$$\text{else}\ \ F_{\beta,t} = F_{\beta-1,t} + \frac{Q_{S\beta,t}}{\lambda_\beta} - F_{\pi,t} \qquad (9c)$$

At end customer (β=4):

$$\frac{dQ_{Sc,t}}{dt} = F_{o,t} - F_{c,t} \qquad (10a)$$

$$F_{o,t} = G_o\sqrt{Q_{So,t}}\quad \forall\ \ F_{o,t} \le F_{i,t} + \frac{Q_{So,t}}{\lambda_o} - F_{z,t} \qquad (10b)$$

$$\text{else}\ \ F_{o,t} = F_{i,t} + \frac{Q_{So,t}}{\lambda_o} - F_{z,t} \qquad (10c)$$

These equations were then solved by numerical integration methods to obtain Q and F.

To compare the models with the real world situation, we conducted computer simulations using various scenarios based on observed phenomena, namely PKS supply shortages at the end customer side, either due to POM production slow down (e.g.: during season when palm oil plantations do not produce as much crops as usual, known as "trek" season) or overshooting other consumptions (e.g.: excessive export when there is a short-term spike in foreign currency exchange rate). These simulations also serve as a mean for sensitivity analysis to explore how the models behave in response to system disturbances.

Steps 6, 7 and 8

Differentiated by the planning mechanism, there are two types of supply chain systems, namely forecast driven push-type system and demand driven pull-type system. In the later system, supply planning is driven by customer requirements (Zheng and Lu, 2009), whilst material inventories at each stock point can be maintained through a replenishment mechanism following certain base stock policies (Ntio and Vidalis, 2011). Under the pull system, the downstream process pulls back materials from the upstream process resulting on lower level of inventories as determined by delays in transferring materials (Zheng and Lu, 2009). Based on the nature of PKS usage, we propose a pull-type supply chain system as a desirable and feasible change to the performance of current problematic model since it is more suitable to improve system performance given demand of energy for industries is typically continuous with relatively low degree of fluctuation. Building upon the bathtub dynamics model (Sweeney and Sterman, 2001), a pull-type PKS supply chain can be illustrated as a system of stocks and flows, which is shown in **Figure 4**.

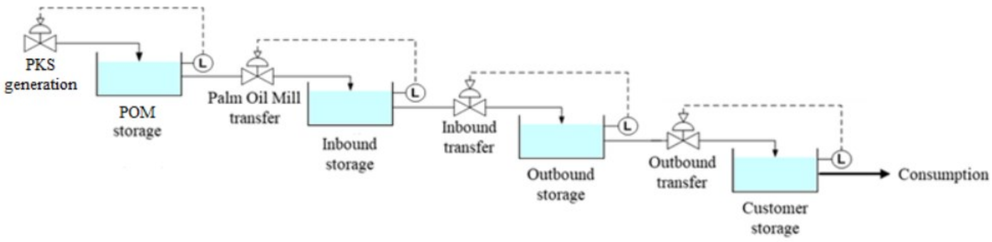

Figure 4 Supply Chain Pull System

As for problematic situation, we built stock models for each stock point, which take a general form of stock (Q) from equation (4) with modified flow (F) equation, as follows:

Transfer equation:

$$F_{\beta,t} = C_\beta - G_\beta\sqrt{Q_{S\beta+1,t}} \quad (11)$$

At steady state condition t = T → ~ :

$$\frac{dQ_{S\beta,t}}{dt} = 0 \ \rightarrow \ F_{\beta,T} = F_{\beta-1,T} - F_\pi \quad \text{and}$$

$$C_\beta = F_{\beta,T} + G_\beta\sqrt{Q_{S\beta+1,T}} \quad (12)$$

By applying formulae in **Table 2** and **Table 3** with β = 0,1,2,3, we got

$$C_\beta = F_{\beta,T} + G_\beta\sqrt{Q_{S\beta+1,T}} = (1+\sqrt{k})\textstyle\sum_{\beta+1}^{4} F_\pi \quad (13)$$

By substituting equations (13) to equation (11), following generalized function was derived

$$F_{\beta,t} = (1+\sqrt{k})\textstyle\sum_{\beta+1}^{4} F_\pi - G_\beta\sqrt{Q_{S\beta+1,t}} \quad (14)$$

which we will further explain in the result and discussion section as a characteristic function of a pull system.

By substituting equations (14) to (4) and applying boundary conditions (6) and (7), resulting:

At palm oil mill (β=1):

$$\frac{dQ_{Sp,t}}{dt} = F_{s,t} - F_{p,t} - F_{e,t} \quad (15a)$$

$$F_{s,t} = (1+\sqrt{k})\textstyle\sum_{1}^{4} F_\pi - G_s\sqrt{Q_{Sp,t}} \quad \forall \ F_{s,t} \le F_{g,t} \quad (15b)$$

$$\text{else } \ F_{s,t} = F_{g,t} \quad (15c)$$

$$F_{p,t} = (1+\sqrt{k})\textstyle\sum_{2}^{4} F_\pi - G_p\sqrt{Q_{Si,t}} \quad \forall \ F_{p,t} \le F_{s,t} + \frac{Q_{Sp,t}}{\lambda_p} - F_{e,t} \quad (15d)$$

$$\text{else } \ F_{p,t} = F_{s,t} + \frac{Q_{Sp,t}}{\lambda_p} - F_{e,t} \quad (15e)$$

At any intermediary point (β=2,3):

$$\frac{dQ_{S\beta,t}}{dt} = F_{\beta-1,t} - F_{\beta,t} - F_{\pi,t} \quad (16a)$$

$$F_{\beta-1,t} = (1+\sqrt{k})\textstyle\sum_{\beta}^{4} F_\pi - G_{\beta-1}\sqrt{Q_{S\beta,t}} \quad \forall \ F_{\beta-1,t} \le F_{\beta-2,t} + \frac{Q_{S\beta-1,t}}{\lambda_{\beta-1}} - F_{\pi-1,t} \quad (16b)$$

$$\text{else } \ F_{\beta-1,t} = F_{\beta-2,t} + \frac{Q_{S\beta-1,t}}{\lambda_{\beta-1}} - F_{\pi-1,t} \quad (16c)$$

$$F_{\beta,t} = (1+\sqrt{k})\textstyle\sum_{\beta+1}^{4} F_\pi - G_\beta\sqrt{Q_{S\beta+1,t}} \quad \forall \ F_{\beta,t} \le F_{\beta-1,t} + \frac{Q_{S\beta,t}}{\lambda_\beta} - F_{\pi,t} \quad (16d)$$

$$\text{else } \ F_{\beta,t} = F_{\beta-1,t} + \frac{Q_{S\beta,t}}{\lambda_\beta} - F_{\pi,t} \quad (16e)$$

At end customer (β=4):

$$\frac{dQ_{Sc,t}}{dt} = F_{o,t} - F_{c,t} \tag{17a}$$

$$F_{o,t} = (1+\sqrt{k})F_c - G_o\sqrt{Q_{Sc,t}} \quad \forall\ F_{o,t} \le F_{i,t} + \frac{Q_{So,t}}{\lambda_o} - F_{z,t} \tag{17b}$$

$$\text{else}\ \ F_{o,t} = F_{i,t} + \frac{Q_{So,t}}{\lambda_o} - F_{z,t} \tag{17c}$$

As with problematic situation, these equations were solved by numerical integration to obtain Q and F using MATLAB™ R2020a.

Steps 9 and 10

In Step 9, we established an operating model to setup the improved supply chain in refer to Van der Vorst's supply chain development framework (Van der Vorst, 2006). Lastly, managerial implications were drawn as key learning points from the whole SSDM steps to conclude Step 10.

5. RESULTS AND DISCUSSION

Unstructured, Structured, and Problematic Situation in Root Definitions

Within certain period of time, there are supply shortages to the end customer due to unplanned production issues at POM and excessive export quantity beyond normal rate that happen simultaneously. These shortages cause disruptions in the production process of the end customer, which demands for a resolution to avoid such costly occurrence. The problematic supply chain situation can be drawn as a rich picture shown **in Figure 5**.

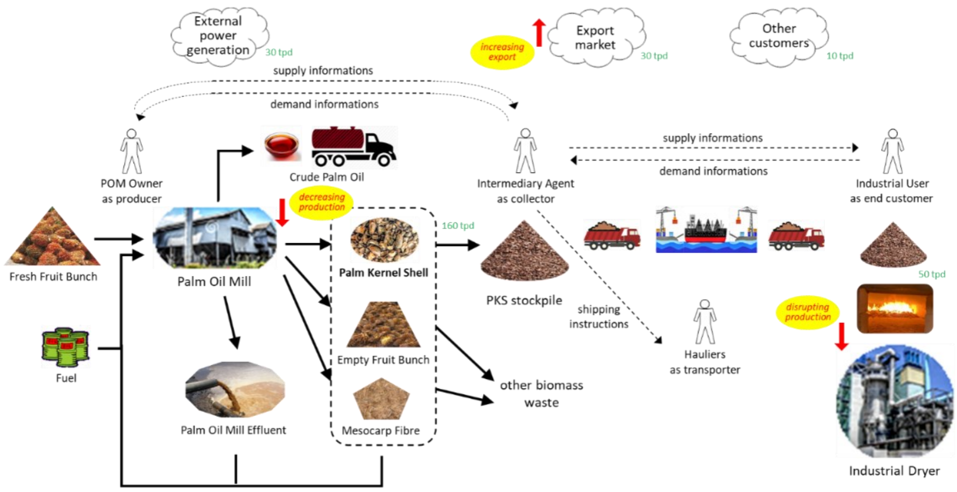

Figure 5 Rich Picture of PKS Supply Chain

To define the problematic situation in root definitions, we firstly identified CATWOE elements involved in this situation, namely:

[C] The end customer

[A] POM, intermediary agent

[T] Current supply chain design is not able to maintain stock availability of PKS at end customer

[W] Shortage of PKS stock at end customer is causing production disruption

[O] The end customer

[E] Other consumptions outside the end customer

Based on the CATWOE, this particular supply chain system can be described in a root definition as follows:

The end customer requires continuous stock availability of PKS as the source of green energy to maintain its production at least 95% level. Under current supply chain model, the intermediary agent occasionally failed to fulfil this requirement resulting on several incident of PKS shortages due to decreasing supply from POM and/or increasing usages for other consumptions, which lead to out of stock situation either at end customer or outbound storages.

Problematic Situation Modelling and Comparing with Real World

As shown by the following causal loop diagram in **Figure 6**, the whole PKS supply chain system forms a negative feedback loop, which signifies long term stability through a self-correcting mechanism (An & Jeng 2005).

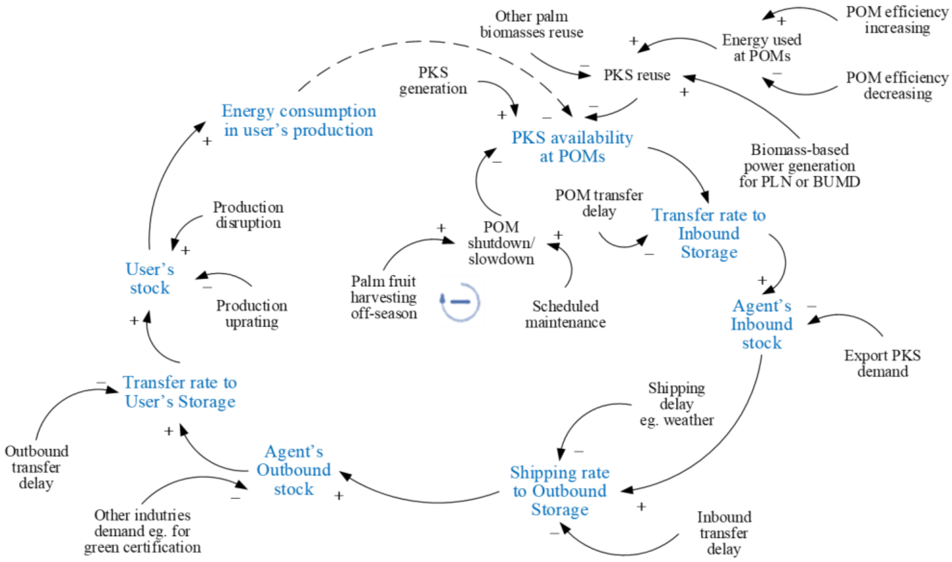

Figure 6 Causal Loop Diagram of PKS Supply Chain

Building upon the causal loop diagram, the flow process of PKS supply chain can be constructed as shown in **Figure 7**, along with all the variables and parameters for modelling purposes.

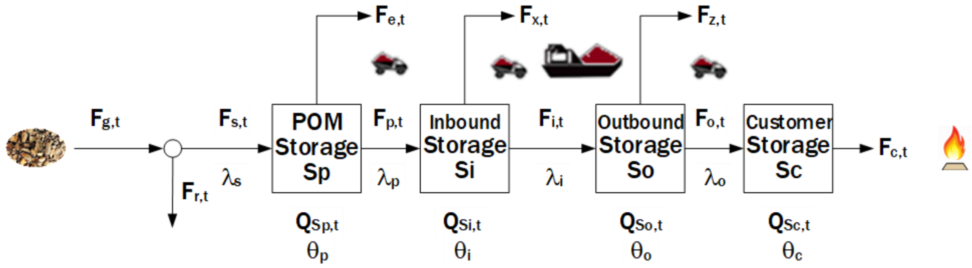

Figure 7 Flow Process of PKS Supply Chain

In refer to equations (8) to (10) and applying variables and parameters in **Table 2**, **Table 3**, and **Table 4**, we solved and simulated the models of problematic situation using Simulink™ module in MATLAB™ R2020a.

Furthermore, to test the model robustness under disturbances from decreasing generation rate and increasing other demand (e.g.: shipment to export markets), we conducted some simulations under three scenarios during the period of day 100 to day 200, started from steady state condition at t=0, namely:

- Optimistic scenario: $\Delta F_g = -10\%$ (decreasing PKS generation), all other standard rates remain as per initial conditions
- Pessimistic scenario: $\Delta F_g = -30\%$, $\Delta F_x = +200\%$ (increasing demand for export)
- Likely scenario: $\Delta F_g = -20\%$, and $\Delta F_x = +100\%$

As shown in **Figure 8**, in the optimistic scenario, the supply chain model would be quite capable to deliver continuous availability of PKS at the end customer side and to achieve the goal of minimum 95% customer production level despite decreasing PKS generation rate from the source. In comparison, the pessimistic scenario resulted only 70% of average customer consumption level, whilst the likely scenario would give 72% of average customer production level, which are both below 95% target. These results reflect problematic situation in the real world, where there are occasional shortages due to upstream disruptions, either driven by lack of supply from the source (eg. shortage of fresh fruit bunches) or increasing of other demands (eg. more export when IDR is weakening), or combination of the two.

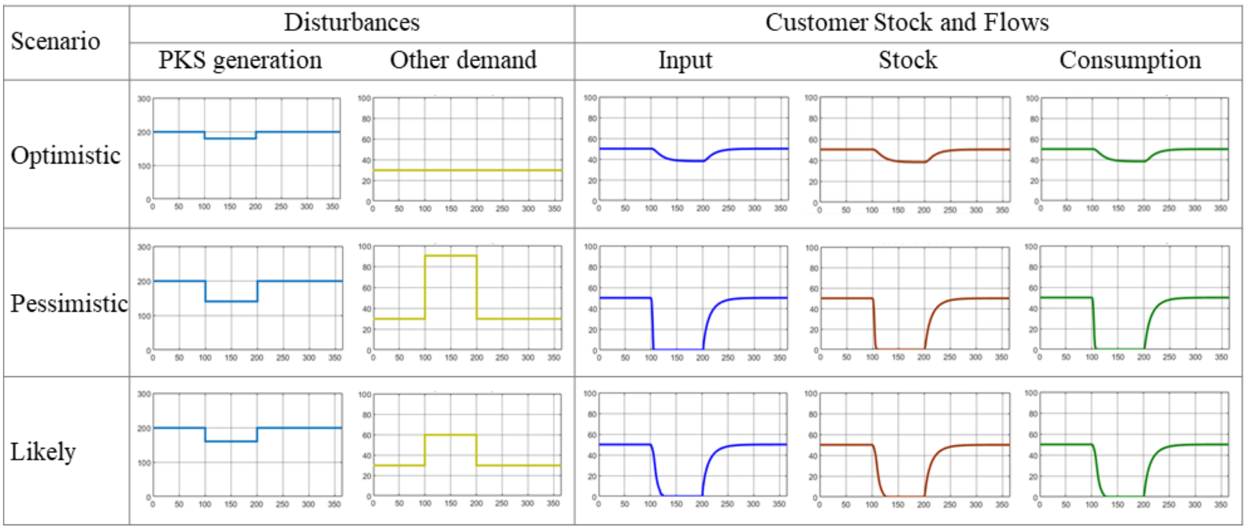

Figure 8 Problematic Situation Model Outputs

Solving Situation Modelling Based on Desirable and Feasible Changes

By introducing a pull type supply chain in replace to the current push system, we solved and simulated the solving situation models from solutions of model equations (11) to (14). This was done by incorporating the same set of variable and parameter values as for the problematic situation.

The key difference between solving situation and problematic situation models is the introduction of function $f(u) = F_{\beta,t} = \left(1+\sqrt{k}\right)\sum_{\beta+1}^{4} F_{\pi} - u$, where $u = G_{\beta}\sqrt{Q_{S\beta+1,T}}$ with $\beta = 0,1,2,3$, which we call the *pull* function. This function characterizes a supply chain pull system that signifies the influence of downstream stock level on the transfer quantity from the upstream storage. This feedback mechanism of stock movement is in contrast with the push system, which is solely determined by the upstream stock level without any feedback from the downstream processes. We argue that this mechanism provides more stability in the entire supply chain due to self-regulating nature of a negative feedback system, namely increasing the inflow when the stock is less than the target and decreasing it when the stock is reaching the target (Sweeney & Sterman, 2001), which in turn ensures better stock availability at any downstream stock points. The output graphs of modelling and simulation works from the solving situation are shown in **Figure 9**.

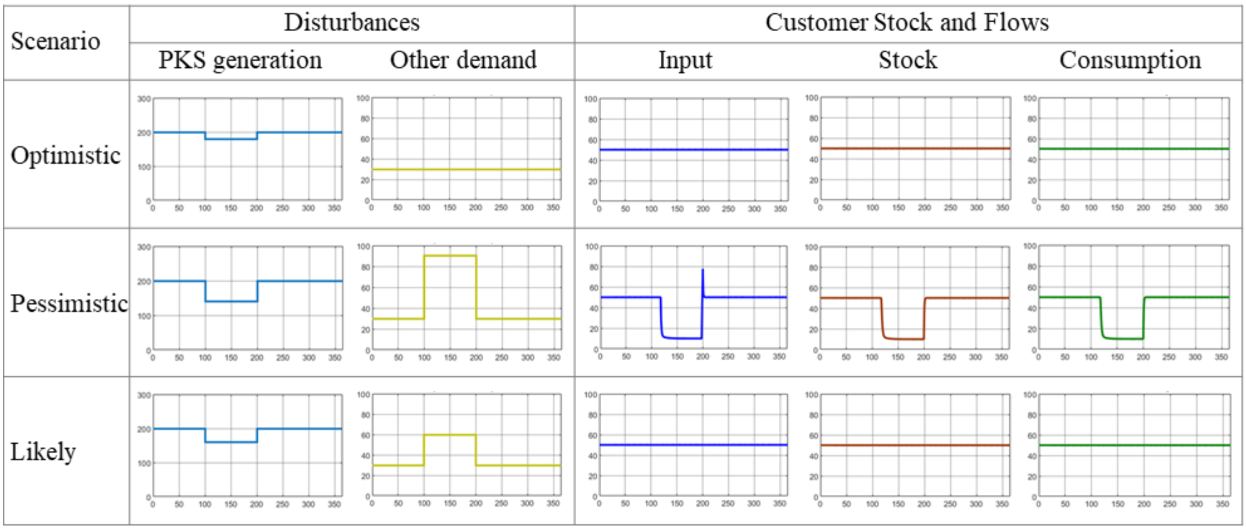

Figure 9 Solving Situation Model Outputs

Under the same three scenarios, the solving situation model demonstrates more robust supply chain in handling disruptive events compared to the problematic situation model during the same 100 days period with disturbances. Despite both decrease in generation rate and increase in other consumption rate, the solving situation model gives better response in delivering higher customer production level compared to current problematic situation model. The simulations also suggest that in response to such disturbances an agent needs to source from other POMs to obtain more quantity of PKS to minimize shortages at the end customer storage. This simulation also shows that a pull system is capable to mitigate effects from such supply and demand fluctuations helped by pre-setting buffer stocks along the chain with only slightly higher overall inventory level at steady state condition ($\Sigma Q_{S\beta,T}$ = 890 tonnes in solving situation vs $\Sigma Q_{S\beta,T}$ = 820 tonnes in problematic situation). In this case, the incremental working capital within the system outweighs the benefit of continuous availability at end customer. **Table 5** summarizes simulation results on customer production level in both problematic situation and solving situation.

Table 5 Simulation Results – Customer Production Level

Scenario	PKS Generation	Export Demand	Production Level	
			Problematic Situation	Solving Situation
Optimistic	90%	100%	93%	100%
Pessimistic	70%	300%	70%	82%
Likely	80%	200%	72%	100%

These results can also be shown as 3D graphs in **Figure 10**, which illustrates how changes in two independent variables (F_g and F_x) affect production level at the end customer (F_c) in both problematic situation and solving situation models.

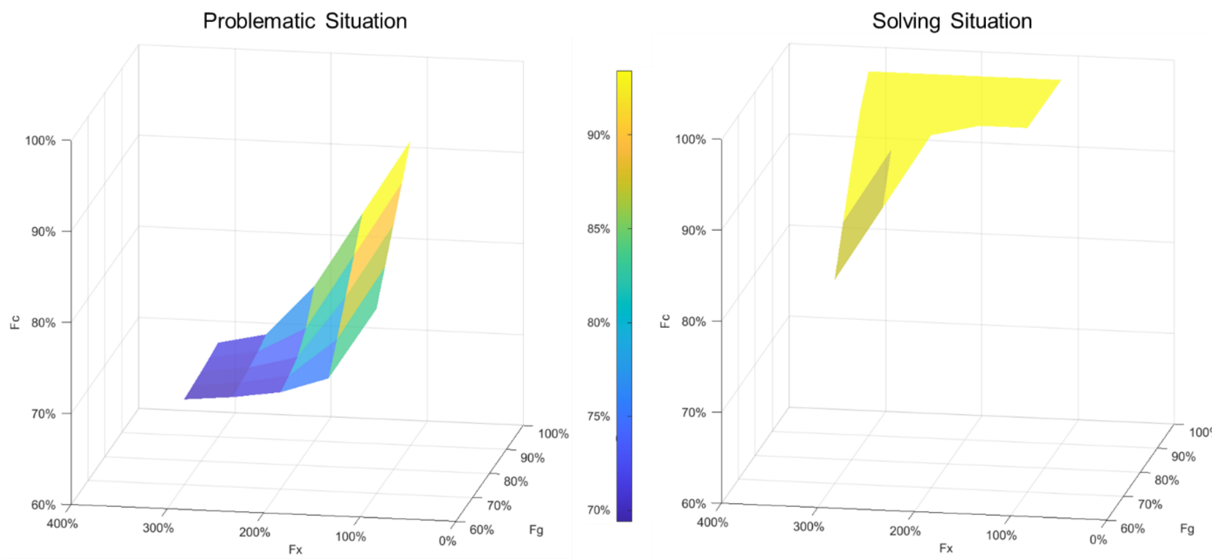

Figure 10 Problematic Situation and Solving Situation Simulation Outputs

As shown in the graphs, the problematic simulation model gives only 70% to 90% stock availability at the end customer within the range of simulated disturbances, whilst the solving situation model by far provides higher level of stock availability at 85 to 100% throughout 365 days period.

By the same simulations, the pull model also provides lower stock variabilities in the customer side throughout the period of simulation in refer to coefficient of variance as an indicator. The pull model yields lower coefficient of variances compared to the push model in all three scenarios as revealed from the results of statistical calculation in **Table 6**. This implies that deploying pull model will give more stability in inventory planning.

Table 6 Simulation Results – Customer Stock Variability

Scenario	Mean		Coefficient of Variance	
	Problematic Situation	Solving Situation	Problematic Situation	Solving Situation
Optimistic	47	50	10.1%	0.0%
Pessimistic	34	38	63.8%	57.2%
Likely	35	46	62.2%	17.0%

The improvements on stock availability and variability demonstrate the robustness of suggested supply chain model.

Root Definitions of Solving Situation

Based on the results of modeling, we defined the solving situation in root definitions referring to the same CATWOE elements, as follows:

The end customer requires continuous stock availability of PKS as the source of green energy to maintain its production at least 95% level. This can be achieved more robustly by deploying pull supply chain system that ensuring the intermediary agent to fulfil this requirement despite temporary disruptions along the chain. From time to time, other sources of PKS need to be sought in order to suit with either changing generation rate or other consumption rates.

Comparing to the root definition in the problematic situation, this modified definition introduces the deployment of pull model as the remedy to PKS supply shortage problems in the current supply chain system. The new definition also stipulates a requirement to have some alternatives of PKS source, which will help securing supply continuity in order to maintain inventory level throughout the supply chain.

Implementations in Real World

For the implementation of solving situation, we constructed an operating model that was adopted from the framework developed by Van der Vorst, consisting of four elements, namely the network structure, chain business processes, network and chain management, and chain resources (Van der Vorst, 2006), as shown in **Figure 11**.

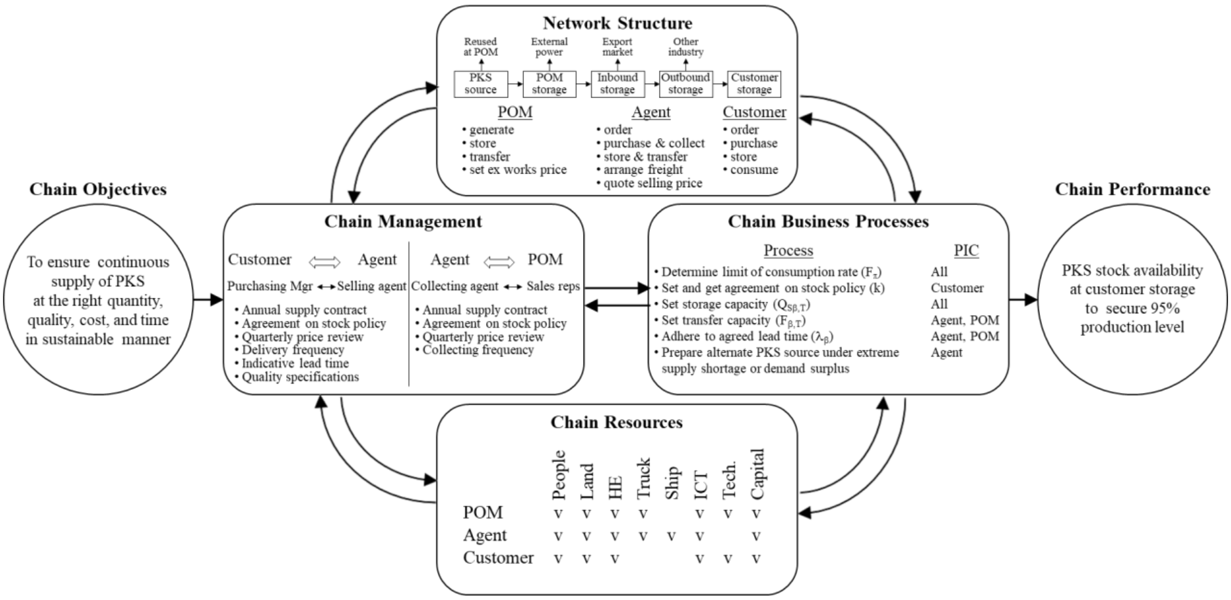

Figure 11 Solving Situation Operating Model

As shown by SD models earlier, the operating model captures elements that need to be in place prior to implement the solving situation model. For instance, supply contracts must be agreed upon to ensure each party fulfiling the preset contractual terms (eg. stock policy, supply and demand quantities, price, quality specifications, etc.). Moreover, the model also suggests supply chain design features that need to be determined beforehand (eg. storage space, transfer capacity, lead time, etc.), including the contingency plan in the case of under supply or over demand conditions, such as to find alternatives of PKS source by the agent. Applying this model will ensure the robustness of PKS supply chain in fulfiling the chain objective and satisfying each customer within the chain.

Managerial Implications as Learning Points

Some managerial implications that can be drawn from the whole SSDM steps are as follows:

- Building system dynamics models of the problematic and solving situations helps to identify opportunity for improvements that uplifting performance of the supply chain system.
- Prior to setup a supply chain operation for utilizing PKS as source of green energy, it is advisable to firstly determine a suitable supply chain system along with the appropriate process parameters to achieve the main objective of its continuous availability.
- A system thinking approach, as in the application of SSDM, enables the process of redesigning supply chain in a comprehensive way, which optimizes performance of the entire chain rather than focusing only on certain chain elements and processes.
- These implications also bring some insights to learn how a supply chain system behaves under certain practical situations.

6. CONCLUSIONS AND RECOMMENDATIONS

In conclusion, we have shown that PKS has great potential to become the source of green energy for industrial purposes, yet it needs to be supported by a well-designed supply chain to maximise the value creation by switching from fossil fuels to biomass. In this study, we demonstrated that SSDM can be applied in designing a more robust supply chain model of PKS, which is more effective, more efficient, and sustainable for industrial applications. Findings from this study are expected to motivate decision makers for utilizing PKS as a green energy source, which helps overcoming growing issues in depleting fossil fuels and GHG emissions.

Even though this study is limited to the PKS supply chain, it enables further explorations on similar problems with other biomass under more complex supply chains. We recommend future studies in deploying the same methodology with different approaches of modelling and simulation, for instance by building stochastic models and comparing the results with deterministic models built in this study. In addition, it will be useful to develop a control model in managing day-to-day disturbances, which can be adopted from studies in the area of dynamic process control system, such as for multiple tanks interacting system (Changela and Kumar, 2015).

Beyond modelling, how to streamline PKS supply chain through better cooperation among stakeholders may warrant further studies by using recent methods, such as fair profit allocation (Asrol *et al*., 2020) and collaborative planning (Acevedo-Urquiaga *et al*., 2021). By using such approach, it is expected that future modelers will be able to generate more robust supply chain solution in solving similar problems of biomass supply chain.

REFERENCES

Acevedo-Urquiaga, A. J., Sablón-Cossío, N., Acevedo-Suárez, J. A., Urquiaga-Rodríguez, A. J. (2021), A Model with a Collaborative Approach for the Operational Management of the Supply Chain. *International Journal of Industrial Engineering and Management*, 12(1), pp. 49-62.

Akhtari, S., Sowlati, T., Griess, V. (2018), Integrated strategic and tactical optimization of forest-based biomass supply chains to consider medium-term supply and demand variations. *Applied Energy*, 213, pp. 626-638.

Akhtari, S., Sowlati T., Benitez D.G.S., Roeser, D. (2019), Impact of inventory management on demand fulfilment, cost and emission of forest-based biomass supply chains using simulation modeling. *Biosystems Engineering*, 178, pp. 184-199.

An, L., Jeng, J. J.. (2005), On Developing System Dynamics Model for Business Process Simulation. *Proceedings of the 37th Winter Simulation Conference, The Institute for Operations Research and the Management Sciences*, Orlando (US), pp. 2068-2077.

Arrumaisho, U. S. and Sunitiyoso, Y. (2019), A System Dynamics Model for Biodiesel Industry in Indonesia. *The Asian Journal of Technology Management*, 12(2), pp. 149-162.

Asrol, M., Marimin, Machfud, Yani, M., Taira, E. (2020), Supply Chain Fair Profit Allocation Based on Risk and Value Added for Sugarcane Agro-industry. *Operations and Supply Chain Management*, 13(2), pp. 150–165.

Ba, B. H., Prins, C., Prodhon, C. (2015), Models for Optimization and Performance Evaluation of Biomass Supply Chains: An Operations Research Perspective. *Renewable Energy*, 2015, pp. 1-13.

Bala, B. K., Arshad, F. M., Noh. K. M. (2017), *System Dynamics: Modeliling and Simulation*, Springer Science+Business Media, Singapore (SG).

Campuzano, F., Mula. J. (2011), *Supply Chain Simulation: A System Dynamics Approach for Improving Performance*, Springer-Verlag Ltd., London (UK).

Changela, M., Kumar, A. (2015), Designing a Controller for Two Tank Interacting System. *International Journal of Science and Research*, 4(5), pp. 589-593.

Checkland, P., Poulter, J. (2006), *Learning for Action*, John Wiley & Sons Ltd., Chichester (UK)

Chen, S., Wang, W., Zio, E. (2021), A Simulation-Based Multi-Objective Optimization Framework for the Production Planning in Energy Supply Chains. *Energies*, 14, 2684. https://doi.org/10.3390/en14092684

Cheng JJ. (2018), *Biomass to Renewable Energy Processes 2nd ed.*, CRC Press, New York (US).

Duc, D. N., Nananukul. N. (2019), Advanced Methodologies for Biomass Supply Chain Planning. *Processes*, 7(659), pp. 1-19.

Fauzi, A. (2019), *Teknik Analisis Keberlanjutan*, PT Gramedia Pustaka Utama, Jakarta (ID).

Febriansyah, H., Setiawan, A. A., Suryopratomo, K., Setiawan, A. (2014), Gama Stove: Biomass Stove for Palm Kernel Shells in Indonesia. *Energy Procedia*, 47, pp. 123-132.

Flores-Sigenza, P., Marmolejo-Saucedo, J. A., Niembro-Garcia, J., Lopez-Sanchez, V. M. (2021), A Systematic Literature Review of Quantitative Models for Sustainable Supply Chain Management. *Mathematical Biosciences and Engineering*, 18(3), pp. 2206–2229.

Forrester, J. W. (1965), *Industrial Dynamics*, The M.I.T. Press, Cambridge (US).

Hambali, E., Rivai, M. (2017), The Potential of Palm Oil Waste Biomass in Indonesia in 2020 and 2030. *Proceeding of International Conference on Biomass: Technology, Application, and Sustainable Development - Surfactant and Bioenergy Research Center (SBRC) IPB*, Bogor (ID), pp. 1-9.

Harahap, H., Leduc, S., Mesfun, S., Khatiwada, D., Kraxner, F., Silveira, S. (2019), Opportunities to Optimize the Palm Oil Supply Chain in Sumatra, Indonesia. *Energies*, 420(12), pp. 1-24.

Hoffman, J. D. (1993), *Numerical Methods for Engineers and Scientist*, McGraw-Hill, Pte Ltd., Singapore (SG).

Iakovou E., Karagiannidis A., Vlachos, D., Toka, A., Malamakis, A. (2010), Waste biomass-to-energy Supply Chain Management: A Critical Synthesis. *Waste Management*, 30, pp. 1860–1870.

Ikumapayi, O. M., Akinlabi, E. T. (2018), Composition, Characteristics and Socioeconomic Benefits of Palm Kernel Shell Exploitation - An Overview. *Journal of Environmental Science and Technology*, 11(5), pp. 220-232.

Kong, S. H., Loh, S. K., Bachmann, R. T., Choo, Y.M., Salimon, J., Rahim, S. A. (2013), Production and Physico-Chemical Characterization of Biochar form Palm Kernel Shell. *Proceedings of the Universiti Kebangsaan Malaysia, Faculty of Science and Technology 2013 Postgraduate Colloquium*, Selangor (MY), pp. 749-752.

Kruzcek, H. P., Arora, A., Mościckic, K., Krochmalny, K., Sharma, S., Niedzwiecki L. (2019), A Transition of a Domestic Boiler from Coal to Biomass – Emissions from Combustion of Raw and Torrefied Palm Kernel Shells (PKS). *Fuel*, 263, pp. 1-9.

Lim C. H., Lam, H. L. (2015), Functionality of Element Targeting Approach in Dynamic Biomass Resources Supply Chain System. *Chemical Engineering Transactions*, 45, pp. 1855-1860.

Lin, T., Rodríguez, L. F., Shastri, Y. N., Hansen, A. C., Ting, K. C. (2014), Integrated Strategic and Tactical Biomass–biofuel Supply Chain Optimization. *Bioresource Technology*, 156, pp. 256–266.

Magableh, G.M., Rossetti, M., Mason, S. J.. (2005), Modeling and Analysis of a Generic Cross-docking Facility. *Proceedings of the 37th Winter Simulation Conference, Institute of Electrical and Electronics Engineers*, Piscataway (US), pp. 1613-1620.

Magableh, G. M., Mason, S.J. (2009), An Integrated Supply Chain Model with Dynamic Flow and Replenishment Requirements. *Journal of Simulation*, 3, pp. 84–94.

Marimin, Djatna, T., Machfud, Asrol, M., Papilo, P., Taufik, B., Darmawan, M.A., (2020), Supply chain performance measurement and improvement of palm oil agroindustry: A case study at Riau and Jambi Province. *IOP Conference Series: Earth and Environmental Science, Volume 443, International Conference on Food and Bio-industry 2019*, 012056, Bandung (ID), pp. 1-21.

Mujkić, Z., Qorri, A., Kraslawski, A. (2018), Sustainability and Optimization of Supply Chains: a Literature Review. *Operations and Supply Chain Management*, 11(4), pp. 186–199.

Ninduangdee, P., Kuprianov, V. I., Cha, E. Y., Kaewrath, R., Youngyuen, P., Atthawethworawuth, W. (2015), Thermogravimetric Studies of Oil Palm Empty Fruit Bunch and Palm Kernel Shell: TG/DTG Analysis and Modeling. *Energy Procedia*, 79, pp. 453-458.

Ntio, D.D., Vidalis, M.J. (2011), Base-Stock Policies for Two and Three Stages Serial Inventory Systems with Stochastic Demand and Replenishment. *Operations and Supply Chain Management*, 4(2), pp. 78–84.

Ohmori, S., Yoshimoto, K. (2020), A Robust Optimization for Multi-Period Lost Sales Inventory Control Problem. *Operations and Supply Chain Management*, 13(4), pp. 375-381.

Okoroigwe, E. C., Li, Z., Unachukwu, G., Stuecken, T., Saffron, C. (2011), Thermochemical Conversion of Palm Kernel Shell (PKS) to Bio-Energy. *Proceedings of the ASME 2011 5th International Conference on Energy Sustainability*. Washington DC (US), pp. 1183-1191.

Okoroigwe, E. C., Saffron, C.M. (2012), Determination of Bio-Energy Potential of Palm Kernel Shell by Physicochemical Characterization. *Nigerian Journal of Technology*, 31(3), pp. 329-335.

Oti, J. E., Kinuthia, J. M., Robinson, R., Davies P. (2015), The Use of Palm Kernel Shell and Ash for Concrete Production. *International Journal of Civil and Environmental Engineering*, 9(3), pp. 263-270.

Park, S.W., Lee, J. S., Yang, W. S., Alam, M. T., Seo, Y. C., Lee, S. Y. (2018), Gasification Characteristics of Biomass for Tar Removal by Secondary Oxidant Injection. *Journal Material Cycles Waste Management*, 20, pp. 823-831.

Paucar-Caceres, A., Rodriguez-Ulloa, R. (2007), An Application of Soft Systems Dynamics Methodology (SSDM). *Journal of the Operational Research Society*, 58, pp. 701-713.

Pinho, T. M., Coelho, J. P., Moreira, A. P., Cunha, J. B. (2016), Modeling a Biomass Supply Chain Through Discrete-Event Simulation. *IFAC-PapersOnLine*, 49(2), pp. 84-89.

Prasetyo, A. (2020), Jepang Siap Serap Cangkang Kelapa Sawit Indonesia, Jul 14, 2020. *Kompas*. (https://kompas.id/baca/ekonomi/2020/07/14/jepang-siap-serap-cangkang-kelapa-sawit-indonesia/), last access on 01/08/2020.

Rachmadea, A. (2017), Palm Kernel Shell Exports May Double in Next 3 Years, Jul 29, 2017. *The Jakarta Post*. (https://www.thejakartapost.com/news/2017/07/29/palm-kernel-shell-exports-may-double-next-3-years.html), last access on 25/07/2020.

Raghu, K. C., Aalto, M., Korpinen, O. J., Ranta, T., Proskurina, S. (2020), Lifecycle Assessment of Biomass Supply Chain with the Assistance of Agent-Based Modeling. *Sustainability*, 12(5), pp. 1964-1977.

Rodriguez-Ulloa, R., Paucar-Caceres, A. (2005), Soft System Dynamics Methodology (SSDM): Combining Soft Systems Methodology (SSM) and System Dynamics (SD). *Systems Practice and Action Research*, 18, pp. 303-334.

Saavedra, M. R. M., Fontes, C. H. O., Gaudêncio, F., Freires. (2018), Sustainable and Renewable Energy Supply Chain: A System Dynamics Overview. *Renewable and Sustainable Energy Reviews*, 82(1), pp. 247-259.

Setiadi T. (2011), Palm Oil and Palm Waste Potential in Indonesia. In: *Water and Wastewater Treatment Technologies Volume II*. Eolss Publishers Co. Ltd., Oxford (UK).

Shah, N. S., Chaudhari, U., Jani, M. Y. (2019), Inventory Control Policies for Substitutable Deteriorating Items Under Quadratic Demand. *Operations and Supply Chain Management*, 12(1), pp. 42-48.

Shapiro, J. F. (2007), *Modeling the Supply Chain*, 2nd ed., Cengage Learning, Duxbury (US).

Sharma, B., Clark, R., Hilliard, M. R., Webb, E. G. (2018), Simulation Modeling for Reliable Biomass Supply Chain Design Under Operational Disruptions. *Frontier in Energy Research*, 6(100), pp. 1-15.

Stephanopoulos, G. (1984), *Chemical Process Control: An Introduction to Theory and Practice*,. Prentice Hall, Inc., Englewood Cliffs (US).

Susanto, H., Suria, T., Pranolo, S. H. (2018), Economic Analysis of Biomass Gasification for Generating Electricity in Rural Areas in Indonesia. *IOP Conference Series: Materials Science and Engineering, Volume 334, the 3rd International Conference on Chemical Engineering Sciences and Applications 2017*, 012012, Banda Aceh (ID), pp. 1-9.

Sweeney, L. B., Sterman, J. D. (2001), Bathtub Dynamics: Initial Results of a Systems Thinking Inventory. *System Dynamics Review*, 16(4), pp. 249-286.

Trisna, T., Marimin, Djatna, T. (2016), Multi-objective Optimization for Supply Chain Management Problem: A Literature Review. *Decision Science Letter*, 5, pp. 283-316.

Veal, M. W. (2018), Biomass Logistics. In: *Biomass to Renewable Energy Processes 2nd ed.*, CRC Press, New York (US).

Vimmerstedt, L. J., Bush, B., Peterson, S. (2012), Ethanol Distribution, Dispensing, and Use: Analysis of a Portion of the Biomass-to-Biofuels Supply Chain Using System Dynamics. *PLoS ONE*, 7(5), e35082. (https://doi.org/10.1371/journal.pone.0035082)

Van der Vorst, J. G. A. J. (2006), Performance Measurement in Agri-food Supply-Chain Networks: An Overview. In: *Quantifying the Agri-food Supply Chain*. Springer, Dordrecht (NL).

Wang, G., Gunasekaran, A. (2017), Modeling and Analysis of Sustainable Supply Chain. *Annals of Operations Research*, 250, pp. 521-536.

Yahayu, M., Abas, F. Z. A., Zulkifli, S. E., Ani, F. N. (2018), Utilization of Oil Palm Fiber and Palm Kernel Shell in Various Applications. In: *Sustainable Technologies for the Management of Agricultural Wastes*, Springer Nature Singapore Ltd, Singapore (SG).

Zhang X., Luo, K., Tan, Q. (2017), A game theory analysis of China's agri-biomass-based power generation supply chain: A co-opetition strategy. *Energy Procedia*, 105, pp. 168–173.

Zheng, N., Lu, X. (2009), Comparative study on push and pull production system based on Anylogic. *Proceedings of the 2009 International Conference on Electronic Commerce and Business Intelligence*, Beijing (CN), pp. 455-458

Handaya is a PhD student at the School of Business, IPB University, Indonesia. He received his Bachelor degree in Chemical Engineering at Bandung Institute of Technology, Indonesia and Master degree in Financial Management at University of Indonesia. His research interests include Supply Chain Management, Supply Chain Modelling, Biomass Energy, and Islamic Economic.

Herri Susanto is a Professor of Chemical Engineering at Bandung Institute of Technology, Indonesia. He has a PhD degree from Bandung Institute of Technology, Indonesia. He has published several papers in various international journals and conferences. His current research interests are biomass gasification, energy conversion, and biomass to methanol and DME.

Dikky Indrawan is a lecturer at the School of Business, IPB University, Indonesia. He has a PhD degree in Business Economics from Wageningen University and Research, The Netherlands. He has published several papers in high-quality journals and conference proceedings and written three books. His research interests are marketing management, strategic management, partnership, global value chain, and competitiveness, food safety, biosecurity, environmental issue, animal health, and one health.

Marimin is a Professor of Industrial System Engineering at IPB University, Indonesia. He has a PhD degree in System Engineering from Osaka University, Japan. He has published over 200 papers in various journals and conferences. His current research interests include Intelligent System, Decision Analysis and Decision Support System, Supply Chain Management, Green, and Sustainable Industrial Development.