

System Dynamic Model of Production Control in Indonesia's Robusta Coffee Downstream Agroindustry (A case study)

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ABSTRACT

The small-scale downstream agroindustry of Argopuro robusta coffee often faces problems related to suboptimal production management. The Kahyangan Robusta Coffee Processing Unit (called UPH) produces roasted and ground coffee and has the same problem, often being unable to meet market demand, having excess product and raw material inventory, and quite high production costs. The purpose of this study is to design a system dynamic model for production control that can guarantee the fulfillment of market demand for roasted and ground coffee, reduce excess inventory, and lower production costs. The research results show that until 2025, UPH is still unable to meet market demand (stockout occurs) of 66,25 kg (roasted coffee) and 57,04 kg (ground coffee), product stock volume of 24,6 tons, and total production costs of Rp. 1,34 billion. A policy scenario was developed to handle this unsatisfactory situation by regulating the production rate of roasted and ground coffee through variable settings for the amount of downstream product safety stock, 'inventory adjustment time', and 'time to update demand'. The results of the model simulation show that monthly demand has been met without stockouts. There were savings in production costs of up to 14% and stock reductions for raw materials of 42%, roasted coffee of 14%, and ground coffee of 27,36%. The model has proven to be useful for inventory optimization and cost management. UPH can follow up by controlling the production rate according to the level of downstream product stock so that it can increase its competitiveness.

Key words: Model system dynamic; simulation; inventory optimization; cost management; stockout.

1 INTRODUCTION

Indonesia is one of the second largest coffee producing countries in Asia and Oceania after Vietnam (International Coffee Organization - ICO, 2023). The planted area and coffee production volume in 2022 will be 1.265.930 ha and 774.961 tonnes respectively. Compared to 2019, the area of coffee plantations increased by 1.65%, while production increased by 2.98%. The area of smallholder coffee plantations reaches 1.246.352 ha or 98,45% of the entire coffee cultivation area in Indonesia (BPS, 2023). The coffee commodity is considered attractive, apart from the high demand for coffee, for developing countries coffee is also an influential source of non-oil and gas income for the country (Cen; Faisal, 2021). The development of coffee consumption in Indonesia is increasingly prospective, as shown by the increasing consumption of processed coffee. In 2022, per capita consumption of instant coffee will reach 0,861 kg/capita/year (Kementerian Pertanian Republik Indonesia, 2023). The downstream coffee agroindustry in Indonesia over the last 10 years has continued to be enthusiastic with

the increasing production of processed coffee produced, and the growing development of coffee shops and coffee shops in various cities. Currently, processed coffee products are not only roasted coffee and ground coffee but there are various types of processed coffee products such as instant coffee and sugared instant coffee in three-in-one packaging. In various coffee shops, coffee drinks of various flavors are also served with various brewing techniques which are known as espresso coffee, latte, cappuccino, flat white, and others (AEKI, 2023).

The fast-growing downstream coffee agro-industry is both an opportunity and a challenge for local brand coffee agro-industry so that they can compete in terms of product quality, service, and price. Large-scale downstream coffee agro-industry has a higher competitive advantage in terms of technology and production management, so they can sell their products at lower prices compared to small-scale downstream agro-industry. As a result, this type of agro-industry dominates the market. If this is not anticipated, in the long term it will kill the potential of small-scale downstream coffee agro-industry businesses (Aklmawati; Soemarno; Mawardi, 2016).

One effort to increase the competitiveness of small-scale downstream coffee agro-industry is to improve the production control system. This system has a wide scope, starting from raw material management, and production scheduling, to inventory control. Production control aims to increase production efficiency and effectiveness with main indicators including minimizing production and inventory costs, reducing shortages and excess inventory, and speeding up the production cycle (Amrifan, 2019; Lefta; Gozali; Marie, 2020).

Implementing this system in the downstream coffee agro-industry will be able to increase production and inventory efficiency which in turn can reduce production costs (Sunday et al., 2021). Research topics on production control in small-scale industries are generally still carried out partially with a static approach. For example, research to reduce the cost of coffee bean inventory in small-scale coffee processing industries was conducted by Sukosyah et al. (2023) using the Economic Order Quantity method. The results of this study did indeed save inventory costs by up to 33%, but it is not known whether demand can always be met because this method is static using very strict demand assumptions.

More advanced research was conducted by Riyani Indah, Pongrekun and Setiawan (2024) on production planning in the coffee beverage industry by designing production capacity using the rough cut capacity planning technique to ensure a match between needs and capacity availability. However, this study assumes that the supply of green beans is always available and does not consider inventory costs. Research to increase the efficiency of coffee bean production in Thailand has also been carried out by Kittichotsatsawat; Tippayawong; Tippayawong (2023) using the value stream mapping method. This method is able to plan the production process flow efficiently by eliminating wasted time and unnecessary activities. This research is able to reduce processing time and production profits significantly. These studies show that production control in the downstream coffee industry is indeed very urgent, especially for small-scale industries, to produce more efficiently and competitively.

Jember regency is one of the coffee-producing areas in East Java Province. In 2023, the area of coffee cultivation and production of coffee beans in this region will be 18,318 ha or 38,17% of the area of cultivation in East Java Province. Meanwhile, the production volume reached 12,361 tons of coffee beans, or 25,70% of the production of East Java Province (BPS, 2023). Most of the coffee produced is robusta coffee comes from community-owned plantations on the slopes of the Argopuro mountains which called Argopuro robusta coffee. The coffee harvest has been processed into coffee beans and ground coffee by small and medium-scale coffee processing industries owned by private companies and local governments (Purnomo; Ni'maturrakhmat; Wibowo, 2024).

One of the coffee processing units in this region is UPH Kahyangan. This processing unit has a production capacity of 94 – 100 kg/coffee beans per day and produces 14 kg of ground coffee and 61,7 – 65 kg of roasted coffee per day. Processed coffee products are sold in several outlets in Jember regency, and others are sold via e-commerce. Market demand for this product fluctuates, so the company has a policy to stock products (make-to-stock strategy) in order to anticipate market uncertainty. This causes the average product stock to be considered too high for this processing unit. In 2023, the average stock volume of downstream products will almost reach 3,12 tons/month. High stock volumes cause high production costs (Rahansyah; Kusrini, 2023). However, processing units often lack product stock at other times, and as a result market demand is not met. This is certainly very unsatisfactory because it will cause a decrease in profits (Moon; Shugan, 2022). If this situation occurs continuously, it will reduce production costs and the company's competitiveness.

Production and inventory control is one of the practices that can significantly improve production efficiency and effectiveness to maintain operational continuity and competitive advantage of small-scale processing units or home industries (Gimena; Sayson; Victoria, 2022) This confirms that research on production control at UPH Kahyangan is indeed very relevant and needs to be carried out.

Production control is a fairly complex system because it includes cross-divisions, namely production, storage and warehousing, receiving raw materials, and shipping (Zhang et al., 2021; Silfiani; Kuncoro; Sitania, 2021). Therefore, a model is needed that can handle the complexity of a system like this. One model that has such characteristics is the system dynamic model.

The system dynamic models are a methodology for understanding the dynamic behavior of a complex system where the system structure consists of elements that are interrelated and have feedback. This model can help decision-makers make the right decisions when dealing with complex and dynamic systems. Systems dynamic provides methods and tools for modeling systems with these characteristics. It is a quantitative model developed by Jay W Forrester using typical symbols known as the Forrester model or Stock Flow Diagram. This model consists of several symbols, including level/stock, auxiliary, rate, constant, and information link (Azar, 2012; Eidin et al., 2024). The systems dynamic model is an evolution of the systems approach which has cybernetic, holistic, and dynamic characteristics for effective goal achievement for complex and feedback systems (Schwaninger, 2016).

The system dynamic methodology is rooted in the system thinking methodology, a way of thinking that can describe and understand the interactions, causality, and reciprocal relationships between variables in a system being

studied. Meanwhile, the system dynamic model will measure the impact of these interactions (Karga; Ceyhan, 2024). The main strength of the system dynamic is its ability to simplify complex systems into easy-to-understand systems. Initially, system the dynamic was applied to business management, but now it has been used in various fields, such as the environment, society, health, automotive industry, and urban area studies (Stermann, 2019; Ghamarimajd et al., 2024).

Systems dynamics begin with identifying the system to be studied, including identifying the objectives, scope, elements, and their interactions. This stage aims to understand the system and the interventions needed to suit the system's needs. System elements can be causal factors that will later be framed into the mechanisms of the system being studied. This is a key step that determines the success of building a model. The next stage is to map system elements into a structure that represents a real situation. This activity is also called system conceptualization which produces a causal loop diagram. This diagram explains the relationship between model variables, both positive and negative relationships, including system feedback that occurs.

The next step is to create a quantitative model known as a stock-flow diagram. This is followed by model verification and validation, conducting model simulations, and ultimately using a validated model for policy analysis. The process of building a system dynamic model is cyclical and requires a thorough understanding of the system. Modelers should not skip any stages without sufficient comprehension, as this can impact the accuracy of the resulting model (Barbrook; Penn, 2022; Kang et al., 2020; Ricciardi et al., 2020; Sterman, 2000).

The production control model using a system dynamic has been used to improve the efficiency of production management but has not been widely applied in the coffee agroindustry. The system dynamic model of raw material planning in a veneer company has been studied by (Purnomo; Izza, 2020). Veneer is a thin sheet of wood as a raw material for plywood. This study succeeded in building a raw material planning model that can minimize stockouts and excess raw materials. The limitation of this study is that the resulting model only determines an efficient raw material requirement plan without being accompanied by inventory cost variables and production cost efficiency.

Another study was conducted by Morales and Arenas (2021) by building a system dynamic model of inventory management for a goods distribution company. The main variables of the model are demand, product inventory, and material orders. The model can describe the behavior of product inventory in various demand conditions until the ideal amount of product stock is obtained that can meet demand. However, the model developed has not investigated inventory costs. In addition, the development of policy scenarios is only limited to adjusting inventory levels.

Satori, Renosori and Fauzan (2020) have developed a dynamic inventory system model in a pharmaceutical distribution company with the aim of minimizing the amount and cost of inventory. The scenario was developed by setting the amount of safety stock and the lead time for delivery from distributor to retail. Although the model is quite complex, the variables are deterministic so they are less able to describe the actual reality. Naderi et al. (2021) released the results of a study on a production control model for large-scale companies that aims to minimize transportation costs and determine ideal production and inventory levels. The model can regulate the rate of production based on inventory levels and production costs but has not investigated how the level of product demand is fulfilled. Research on inventory control in home coffee shops in the Philippines was conducted by Gimena, Sayson and Victoria (2022) The system dynamic model was developed using the EOQ (Economic Order Quantity) technique to minimize the amount of stock, but the model did not investigate the level of demand fulfillment and production costs.

The production control model in a small-scale tofu factory was developed by Talitha and Berliyana (2022) which aims to increase production through a scenario of additional labor or overtime. The system dynamic model developed is still very simple, the variables are still deterministic and do not have demand feedback on production rates. Narassima et al. (2023) built a dynamic system model by applying a lean approach to the yarn manufacturing industry to see the level of work in process (WIP), process time, waiting time, and idle time without investigating production costs.

Recent research results that focus on system dynamic models for production and inventory control for small-scale agro-industry are very rare. In general, dynamic system modeling research takes topics related to supply chain performance, which is a topic that covers a broader field from upstream to downstream by involving more complex and broader performance indicators or variables. The use of dynamic systems in this study is considered very satisfying because it provides a deep exploration space for various aspects that affect business performance and the organizational environment (Chaudhuri et al., 2023). For example, research conducted by Brilliantina et al. (2018) on the performance of tea agro-industry production where the production performance indicators only focus on increasing tea leaf harvest productivity, production volume, and quality, without involving costs.

Amiri (2023) designed a large-scale mining industry production chain model to find government policies that can drive the rate of production, profits, and growth of mining companies. However, the model built still has limitations because it does not contain inventory variables to control production. The latest research on measuring the performance of the Argopuro Robusta coffee green supply chain conducted by Purnomo, Ni'maturrakhmat and Wibowo (2024) is

more comprehensive than previous research because it has integrated indicators in environmental and economic aspects, such as measuring the amount of product stock, stockout, and production costs. Similar research but with a broader scope was conducted by Khakdaman et al. (2024) who built a sustainable supply chain model for the European aluminum industry for large-scale factories. The indicators in the economic aspect are costs, production volume, and a number of environmental aspect indicators.

Kaur and Kander (2024) also built a hemp polymer composite production model for the purpose of providing resources efficiently where these conditions are observed through a stable amount of product stock. The green supply chain is an interesting issue along with the development of the sustainable development paradigm and environmental issues. Moreover, the supply chain framework offers a more integrated and holistic approach and can be aligned with the performance measurement needs of the organization being studied Raman et al. (2023). Meanwhile, Noto and Cosenz (2021) took the initiative to build a system dynamic model based on lean production to minimize production lead time and reduce inventory. This model can be used as a reference to be developed in various types of industries at various scales. However, the system dynamic model of the supply chain and lean production are not sufficient to explore production control activities because they generally do not include inventory cost variables and exogenous variables as regulators of production rates.

The results of those study indicate that the study of production control models for small-scale downstream coffee agroindustry has never been conducted. The exploration space for production control models is still wide open to be developed, especially by adding exogenous variables that have feedback as regulators of production rates. To address this gap, this study is very urgent to be carried out so that small-scale agroindustry can operate more efficiently, profitably, and competitively. The purpose of this study is to create policies in production control to be able to meet demand, reduce inventory, and save production costs. This study will contribute to enriching the literature by proposing a system dynamic model for small-scale coffee production planning. The resulting model has novelty because it can be used to explore the dynamic behavior of the system through the intervention of important variables that are directly related to the production rate in the production and inventory control system.

2 MATERIAL AND METHODS

The research was carried out at UPH Kahyangan, a small-scale Argopuro coffee processing unit in Jember Regency. The type of data used in this research consists of primary data and secondary data. Primary data was collected through surveys, observations, interviews, and focus group

discussions, while secondary data was obtained from journals, company documents, books, and other scientific sources.

The design of the system dynamic model follows the Forrester stages consisting of five stages as explained by Sterman (2019). The first is to identify the production control system in the object being studied, including determining the objectives, types of variables, relationships between variables, and system mechanisms. The second is to design a conceptual model as a causal loop. The third stage is to build a quantitative model using a model simulator. The next stage is to simulate and validate the model, while the last stage is to formulate scenarios through policy analysis. These stages have also been adopted by many researchers to build a dynamic supply chain system model (Hakim et al., 2020; Wu; Abourizk; Li, 2022).

2.1 System Identification

System identification is done through observation and interviews with employees and production managers at UPH Kahyangan to understand the system. At this stage, the system objectives must first be determined, namely the system performance that will be observed as a solution to the problems that arise (Hafner et al., 2024). The purpose of designing this system dynamic model is to produce a production control system model that can reduce excessive product inventory, meet all market demands, and save production costs. The next step is to determine the scope of the system to be modeled to confirm the observed system entity so that its complexity is in accordance with the system objectives (Khakdaman et al., 2024).

In this paper, scoping is done by observing the actual system, discussing with business actors, and examining references to obtain adequate comparative materials. Furthermore, system variables are identified. Variables can be system elements that influence the achievement of system objectives (Zhou et al., 2024). Expert meeting and journal review techniques are used to determine key variables. Some of the identified variables include raw material inventory, final product inventory, production volume, product demand, and production costs (Purnomo; Izza, 2020; Talitha; Berliyana, 2022). The selected variables are then adjusted to the observed real world to explore the possibility of new variables emerging. This process is carried out while continuing to discuss with expert sources from UPH. The data was collected, and then some of the key variables were statistically tested using the Pearson Bivariate correlation method to see if there was a relationship between the variables (Table 1) (Toumeh, 2020).

For instance, the table illustrates that there is a moderate correlation between “raw material supply” and “green beans demand.” This indicates a connection between the two variables, which should be accounted for in the model’s mechanism. Similarly, the variable “roasted coffee demand” shows a very strong correlation with “roasted coffee production,” highlighting their feedback relationship.

Table 1: Pearson correlation values of system variables.

Variables	A	B	C	D	E	F	G
Raw material supply (A)	1,000	,639*	,748**	-,403	-,407	-,297	-,299
Green beans demand (B)	,639*	1,000	,510	-,132	-,144	-,155	-,185
Finish product storage (C)	,748**	,510	1,000	-,260	-,213	-,020	,021
Roasted coffee demand (D)	-,403	-,132	-,260	1,000	,993**	,628*	,590*
Roasted coffee production (E)	-,407	-,144	-,213	,993**	1,000	,592*	,564
Ground coffee demand (F)	-,297	-,155	-,020	,628*	,592*	1,000	,701*
Ground coffee production (G)	-,299	-,185	,021	,590*	,564	,701*	1,000

*. Correlation is significant at the 0,05 level (2-tailed).

**. Correlation is significant at the 0,01 level (2-tailed).

2.2 Designing Conceptual Model

After the elements and their relationships have been identified, they are then constructed into a conceptual model structure called a Causal Loop Diagram (CLD). The conceptual model describes the complex and holistic relationship of all system elements and their interrelationships to form a systemic qualitative logic in achieving system goals or performance. The conceptual model explains the system mechanism and is useful as a diagnostic tool if the system fails to achieve its goals, as well as exploring why problems arise in achieving system goals (Yang et al., 2019; Yan et al., 2023; Purnomo; Ni'maturrahmat; Wibowo, 2024). The CLD Kahyangan production control system can be seen in Figure 1.

Figure 1 explains the mechanism of the downstream coffee production control system which consists of several main variables. The variable "raw material stock" functions as the stock of raw materials obtained from suppliers in the form of coffee beans. The higher the supply volume, the higher the stock of coffee beans in the raw material warehouse. UPH Kahyangan already has a partner supplier, namely a coffee bean producer located on the slopes of the Argopuro mountains. Suppliers send coffee beans in uncertain volumes, depending on the quantity produced by them. However, UPH Kahyangan continues to try to control it by looking at the availability of coffee beans in the warehouse. Next, the coffee beans will be processed into roasted coffee and ground coffee at the processing facility. A small portion of coffee beans are also sold to other consumers, without going through processing.

UPH processes roasted and ground coffee regularly, according to its capacity, and then the results are stored in the final product warehouse. This is done to anticipate uncertainty in market demand. Delivery is made when there is demand for downstream products. The greater the production volume, the greater the stock volume of downstream products. If this situation is followed by low demand, it will cause product stock to become very excess, thereby increasing inventory costs. On the other hand, if the amount of production is too small because raw material stocks are low and demand is high, then UPH will suffer losses due to stock shortages.

As a result, market demand cannot be met. The volume of raw material stock, product stock, and production levels have logical consequences for production costs. The higher the stock volume and production level will increase production costs, and vice versa.

The relationships between variables cause dynamics system, where changes in the value of one variable will affect the values of other system variables. The variables relationships can be in the form of positive relationship patterns (reinforcing/R) or negative relationship patterns (balancing/B) (Sterman, 2000). For example, the relationship between the supply of raw materials and the availability of coffee beans at the CLD is reinforcing, while the relationship between the final product shipped and product stock is balancing.

2.3 Data and Analysis Methods

The data used to determine the values of the variables and model parameters consists of monthly serial data covering a period of 60 months, sourced from UPH's production records from June 2019 to May 2024 (Table 2). In cases of incomplete data, data extrapolation is performed (Song; Ayub; Shi, 2024). The data is processed using appropriate statistical techniques. For instance, to calculate the average value of the variable "raw material storage," we employ descriptive statistics, specifically the arithmetic mean and standard deviation (SD). Conversely, for predicting the amount of raw material supply (the variable "raw material supply"), we utilize random number generation (RNG) analysis. The results of the goodness of fit test, conducted using the One-Sample Kolmogorov-Smirnov (KS) method, indicated that the tested data were normally distributed (norm) with a two-tailed asymptotic significance value greater than 0.05 (Ahadi; Zain, 2023).

2.4 Building Quantitative Models

The system structure that has been built in the model conceptualization stage is then translated into a quantitative model using Forrester symbols which are called stock flow diagrams (SFD). The SFD model is one of the advantages of systems dynamic because it can describe complex, dynamic,

and non-linear mechanical models in a simple way. This model consists of several symbols. The first is the level and flow symbol which is used to describe dynamic variables, where the value can accumulate, that is, increase or decrease due to the flow which is regulated through the rate. The second is

auxiliary, namely symbols that describe model variables to form the system structure. Auxiliary is flexible because it can contain any system elements that are quantitative in nature. The last one is the arrow which functions to connect model variables and create system feedback (Schoenenberger et al., 2021).

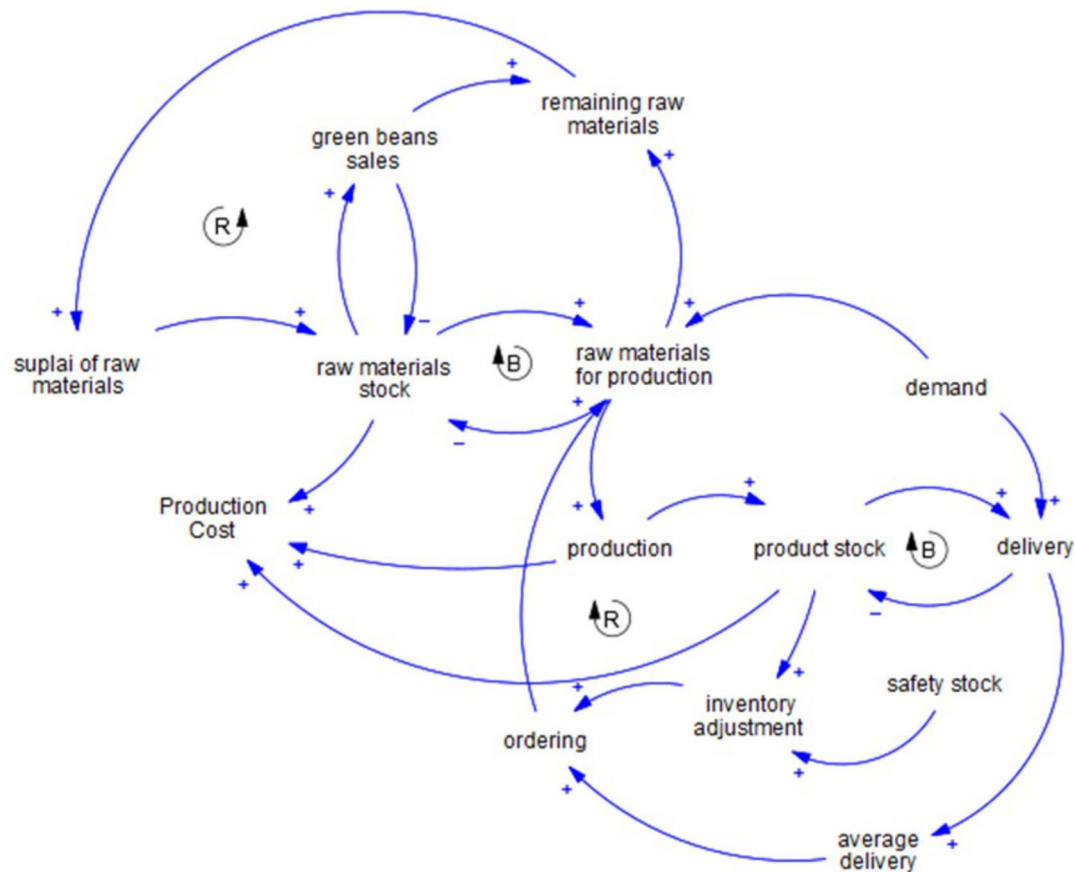


Figure 1: CLD of production control model at UPH Kahyangan.

Table 2: Required data and analysis methods.

Variabels model	Data requirements	Data source	Analysis methods	Analysis results
1 Raw material storage	Average value	Green beans inventory	Arithmetic mean, and SD	(4.254,63 ; 447) kg/mo
2 Finish product storage	Average value	Roasted and ground coffee inventory	Arithmetic mean, and SD	(32.410,5 ; 2.811,6) kg/mo
Product demand:				
3 Ground coffee	RNG	Ground coffee demand	KS	Norm (1.738,2 ; 116,8)kg/mo*
Roasted coffee	RNG	Roasted coffee demand	KS	Norm (520,6 ; 143,2)kg/mo*
4 Raw material supply	RNG	Green beans supply:	KS	Norm (2.999,02 ; 397,44) kg/mo*
5 Green beans demand	RNG	Green beans demand:	KS	Norm (626,75 ; 86,57)kg/mo*
6 Raw material cost	RNG	Prices of green beans	KS	Norm (28.500 ; 2.000)Rp/kg*
7 Holding cost	Average value	Holding cost for final product	Arithmetic mean, and SD	Means (55 ;15) kg/mo
8 Odering cost	Average value	Ordering cost for green beans	Arithmetic mean, and SD	Means (22.000 ; 1500) kg/mo
9 Product yield of roasted coffee	RNG	Ratio between roasted coffee and green beans	KS	*Norm (82,07 ; 0,27)% *
10 Product yield of ground coffee	RNG	Ratio between roasted coffee and green beans	KS	Norm (626,75 ; 86,57)% *

The SFD model can be seen in Figure 2. The model was built using the Powersim Studio Enterprise 2005 simulator. The model consists of two unit levels, namely for the variables 'raw material stock' and 'product stock'. Each stock is connected by inflow and stock flow, causing the model behavior to be dynamic and observable over time. The value of the variable 'raw material stock' is determined based on the difference between the variable supply of raw materials entering the raw material warehouse minus the volume leaving to be processed into downstream products, plus the value of 'raw material stock' in the previous period (Equation 1). The value of the variable 'rate of raw material supply' is random and follows a normal distribution with a mean of 2.999,02 kg/mo and a standard deviation of 397 kg/mo (Equation 2). The same mechanism also occurs in the 'product stock' variable (Equation 3).

$$\text{Raw material stock (t+1)} = \int_0^{t+1} [\text{rate of raw material supply} - \text{rate of raw materials for production}]dt + \text{raw material stock (t0)} \quad (1)$$

$$\text{Rate of raw material supply (t)} = \text{norm distribution (2.999,02; 397,44)kg/mo} + \text{addition of raw materials (t)} \quad (2)$$

$$\text{Product stock (t+1)} = \int_0^{t+1} [\text{production rate} - \text{product delivery rate}]dt + \text{product stock (t0)} \quad (3)$$

The double-lined symbol in Figure 2 shows an array variable, namely a variable consisting of two types of products, namely roasted coffee first and ground coffee second. For example, the variable "product yield" consists of two values. The first value is the yield for roasted coffee which adheres to a normal distribution with a mean of 82,07% and a standard deviation of 0,27%. Meanwhile, the second value is the yield of ground coffee with an average of 81,45% and a standard deviation of 0,5% (Equation 4, 5 and 6).

$$\text{Product yield (t)} = \{\text{norm distribution (82,07;0,27)\%; norm distribution (81,45;0,5)\%}\} \quad (4)$$

$$\text{Green beans demand (t)} = \text{normal distribution (626,75; 86,57) kg/mo} \quad (5)$$

$$\text{Product demand (t)} = \{\text{norm distribution (1.738,2;116,8) kg/mo; norm distribution (520.6,143.2) kg/mo}\} \quad (6)$$

The "rate" variable shows the rate at which stock increases or decreases over time. For example, the "rate" symbol in the "rate of raw material supply" variable shows that the supply of coffee beans to UPH Kahyangan adheres to a normal distribution with an average of 2.999,2 kg/month and a standard deviation of 397,44 kg/mo (Equation 7). The variable value of the rate of raw materials used for production (the variable 'rate of raw materials for production')

is determined according to if ... then logic which is influenced by the variables of orders for coffee beans, demand for downstream products, and availability of raw material stock. The model will choose one of the 3 possible conditions. If the product demand is less than the order size, then the model will choose the volume of the order size (condition 1). Conversely, if product demand is greater than orders, then the model will choose based on demand volume (condition 2). However, this condition only applies if the value is less than the raw material stock. If the value exceeds the raw material stock, the model will choose condition 3, namely the value of the variable 'rate of raw material for production' is the same as the value of the raw material stock (Equation 8).

$$\text{Rate of raw material supply (t)} = \text{normal distribution (2.999,02; 397,44) kg/mo} \quad (7)$$

$$\text{Rate of raw material for production (t)} = \text{IF (IF (product demand (t) < ordering (t), ordering (t), product demand (t)) / product yield (t) > Raw material stock (t), Raw material stock (t), IF (product demand (t) < ordering (t), ordering (t), product demand (t)) / product yield (t))} \quad (8)$$

The volume of downstream products sent to the market depends on product stock availability. If the volume of product demand is smaller than product stock, then the volume of product sent will follow product demand. Conversely, if the volume of product demand is greater than the product stock, then the volume sent follows the product stock (Equation 9). Production capacity is represented as a rate whose value is the conversion of the value of the rate of raw materials for production to production yield (Equation 10). Meanwhile, production costs are the accumulation of processing costs, raw material inventory costs, and downstream product inventory costs (Equation 11).

$$\text{Product delivery rate (t)} = \text{IF (product demand(t) < product stock(t), product demand(t), product stock(t))} \quad (9)$$

$$\text{Production rate (t)} = \text{rate of raw materials for production (t) x product yield (t)} \quad (10)$$

$$\text{Production cost (t)} = ((\text{production rate(t)} \times \text{cost standart}) + (\text{raw material stock (t)} \times \text{cost standart}) + (\text{product stock (t)} \times \text{cost standart})) \quad (11)$$

The development of the model structure is designed to enhance the systemic mechanism of the real system using systematic qualitative logic. The goal is to create a robust and reliable model (Jonsdottir; Johannsdottir; Davidsdottir, 2024). Several important variables have been incorporated, including a variable for safety stock of the final product. This safety stock will help regulate the level of final product inventory

and provide feedback on the production rate. The value of the safety stock is determined based on the average product demand.

Another variable introduced is the “inventory adjustment time,” which refers to the period required to adjust or correct the volume of downstream product stock. This variable will affect the value of the variable “Stock adjustment” (Equation 12). Additionally, a variable for “time to update demand” has been added, which will help in refining the average product delivery (Equation 13). The model structure also includes a mechanism to regulate the rate of raw material supply, adjusted according to the production rate, through the “remaining raw materials” variable. The volume this variable is adjusted according to the needs of ground coffee production, the sale of coffee beans, and the availability in storage warehouses. (Equation 14). The mathematical equation for this structure is as follows:

$$\text{Stock adjustment (t)} = (\text{safety stock (t)} - \text{finish product storage(t)}) / \text{inventory adjustment time} \quad (11)$$

$$\text{Average delivery(t)} = (\text{product delivery rate (t)} / \text{time to update demand}) \quad (12)$$

$$\text{Remaining raw materials (t)} = \text{Raw material storage(t)} - (\text{rate of raw materials for production (t)} + \text{green beans sale rate(t)}) \quad (13)$$

2.5 Model Assumptions

a) The model assumes that the UPH will fulfill product demand according to the amount of inventory it has as soon as possible. If the amount of inventory is less than the demand for the final product, then the available inventory will be sent. Inventory shortages are called stockouts. Thus, the model does not adopt a backorder and backlog system (Jalali; Ghomi; Rabbani, 2020).

b) The demand for the final product and product inventory will provide feedback on the production rate. Adjustments to the demand for the final product will directly affect the level of raw material provision or “rate of raw materials for production” and “production rate” without any time delay Naderi et al. (2021).

c) The quality standards for green beans do not change during the simulation period. These beans are produced by the wet process, dried in the sun to a water content of 20%, and have had their horns removed through a hulling process.

2.6 Model Verification and Validation

Model verification aims to ensure that the model can run correctly in computer programs according to the conceptual and quantitative models. Verification is carried out by checking whether the mathematical formulas and relationships between variables have been written correctly in the simulator. Meanwhile, model validation is carried out

to ensure the validity of the model that has been built. This research uses face validity to check whether the structure and behavior of the model accurately describe the systemic logic in order to achieve system goals. This validation requires knowledge and experience from experts in fields relevant to the context. Experts will be asked a number of questions through the instrument and then have a discussion as a form of in-depth testing (Sargent, 2020).

Validation is also carried out on the model output by comparing the model output with actual data. To validate the output, the mean absolute percentage error (MAPE) test parameter is used. The model will be considered very accurate if the parameter value is less than 5%. If the value is between 5% and 10% it is said to be quite accurate, whereas if it is more than 10% it is less accurate (Purnomo; Ni'maturrakhmat; Wibowo, 2024; Andriansyah; Rahmi; Ilyas, 2020).

2.7 Sensitivity Analysis

Sensitivity analysis is a technique used to assess how a model responds to variations in its parameters and structural changes. This analysis helps to build confidence in the model by addressing the uncertainties often associated with its parameters (Breierova, 2011; Qi; Zhang; Xu, 2022). The parameters examined are those derived from the model's structure, allowing us to observe how the model behaves under different conditions. Additionally, understanding these parameters provides valuable information for developing policy scenarios.

2.8 Policy Analysis

Policy analysis is a decision-making process to intervene in the model with in-depth consideration to improve the behavior of the model so that it has performance according to system objectives (Malbon; Parkhurst, 2023). In this research, policy analysis was carried out by building scenarios using the best - worst-case scenario method. The best or optimistic scenario is carried out by utilizing all resources to obtain maximum results, while the worst or pessimistic scenario only uses some resources (Ma; Peng, 1999). The scenario is implemented by changing the initial model structure and changing the model variable values. The first way is to provide system feedback by adding stock and order adjustment variables. Meanwhile, the second thing is done by changing the stock safety parameter values, stock adjustments, and average delivery time. The scenarios were developed into three types, namely pessimistic, moderate, and optimistic.

3 RESULT

The production control model is built in accordance with the actual mechanisms that occur at UPH Kahyangan. Currently, the production control system in this business unit is very simple. For example, the supply of coffee beans from

suppliers is not directly influenced by the volume of demand for downstream products. Adjusting the volume of raw material supply is only done simply by looking at the stock level of coffee beans. However, this is rarely done, so the supply volume is more appropriately represented using a normal distribution. The business unit also does not plan safety stock to anticipate fluctuations in market demand or uncertainty in the supply of raw materials. In fact, sales data has not been used to make corrections to the production rate of roasted and ground coffee. So far, the production rate for downstream products has only utilized 77,72% of the available capacity, or only around 2.331,83 kg/month from around 3.000 kg/month. The feedback mechanism only occurs by utilizing the previous month's demand data to regulate production rates. The resulting model structure has succeeded in representing the actual system that occurred. Next, the model is simulated on a monthly basis from

January 2021 to the end of 2025. The initial value in January 2021 for the 'raw material stock' variable is 2,68 tonnes, and the 'product stock' variable is 1.400,16 kg for roasted coffee, and 16,82 kg for ground coffee. The price of coffee beans is random between 22.200 – 34.000 Rp/kg.

The model verification results show that the model design and algorithm have been implemented correctly into the simulator so that it can be simulated. Face validity results by expert respondents from universities in the field of systems engineering and coffee agro-industry practitioners show that the model structure has been built logically and systemically. This causes the model to be able to present relevant dynamic behavior. The results of the model output validation, carried out by comparing the simulation output and actual data on the 'product delivery rate' variable, have shown high validity (Figure 3). The volume of downstream coffee products sent

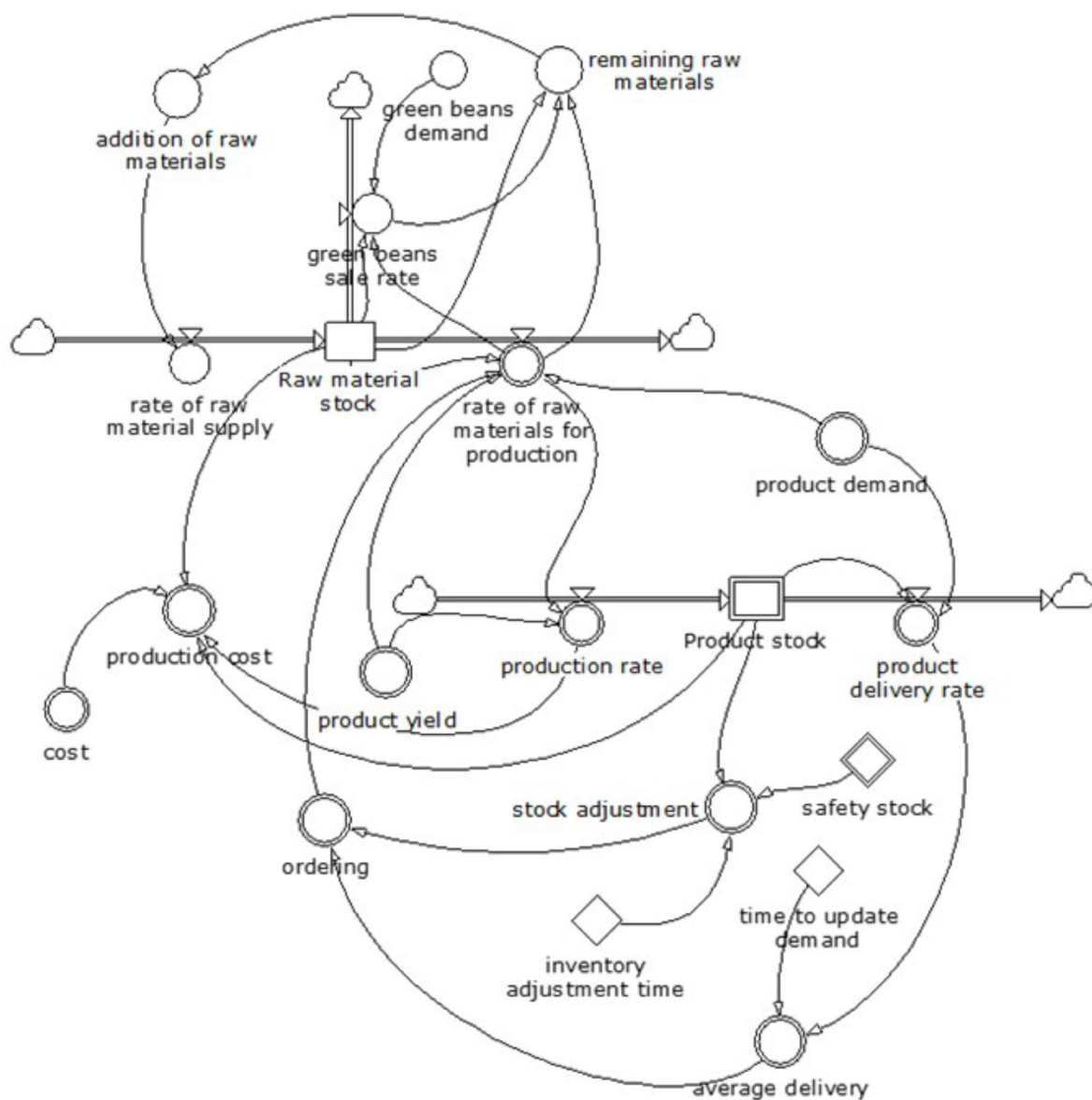


Figure 2: SFD model of production control.

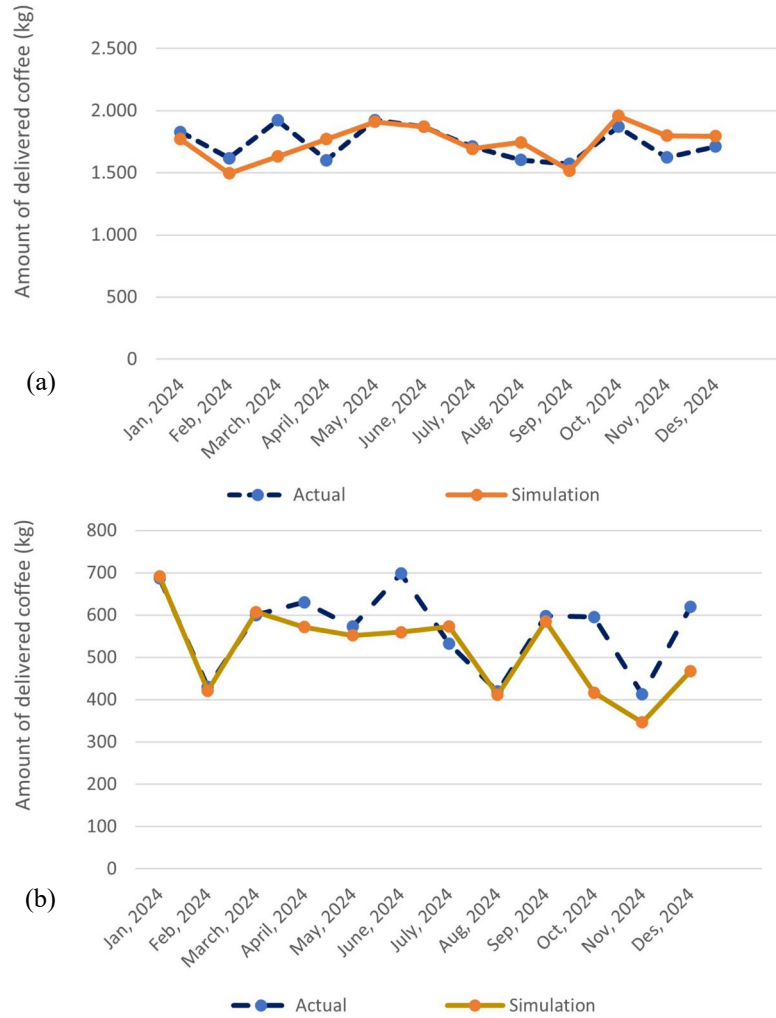


Figure 3: Variable behavior of delivery roasted coffee (a), and ground coffee (b).

to the market shows randomness from time to time without showing any specific pattern. Delivery of ground coffee has higher uncertainty in terms of volume, compared to roasted coffee. The MAPE test parameter value is only around 7,27% for roasted coffee and 9,91% for ground coffee. If the results below 10% indicate that the simulation model described is accurate in describing actual conditions (Kim; Kim, 2016).

Model reliability testing is conducted through sensitivity analysis. Table 3 shows the types and levels of parameter changes utilized in this analysis. The range of parameter change levels is determined based on the modeler's justification, which is adjusted to fit the characteristics of the system being studied. In this analysis, there are three parameters, each with five levels of change. For example, the safety stock value for roasted coffee is varied from 1.200 kg to 1.886 kg. The average monthly demand for roasted coffee, which is 1.715 kg, serves as a reference for determining the levels of change. In this case, Level A (1.200 kg) represents 70% of the demand; Level B represents 80%; Level C represents 90%; Level D is 100%; and Level E corresponds

to 110%. Similarly, the reference value for the safety stock of ground coffee is 677 kg per month and is varied according to the following percentages: 40% (Level A), 60% (Level B), 80% (Level C), 100% (Level D), and 110% (Level E).

Table 3: Parameters for Sensitivity Analysis.

Variables	Variable change level				
	A	B	C	D	E
Safety stock:					
Roasted coffee (kg)	1.200	1.372	1.543	1.715	1.886
Ground coffee (kg)	271	406	542	677	813
Time to update demand (mo)	1	2	3	4	5
Inventory adjusmen time (mo)	1	2	3	4	5

Figure 4 shows the changes in the behavior of the variables “finish product stock” and “finish product production” in the sensitivity analysis. If observed in depth, the increase in the safety stock value that is getting bigger

will increase the amount of final product stock with an increasing pattern, but this does not happen to the amount of production. This variable pattern shows fluctuations where the increase in safety stock slightly increases the production rate. Meanwhile, the increase in the value of “time to update demand” actually decreases the amount of product stock and

the amount of production. On the other hand, the increase in the value of “inventory adjustment time” will increase the amount of stock and decrease the amount of production. The behavior of the variables shows similarities at various levels of parameter changes which indicates that the model is reliable and convincing (Ford; Flynn, 2005).

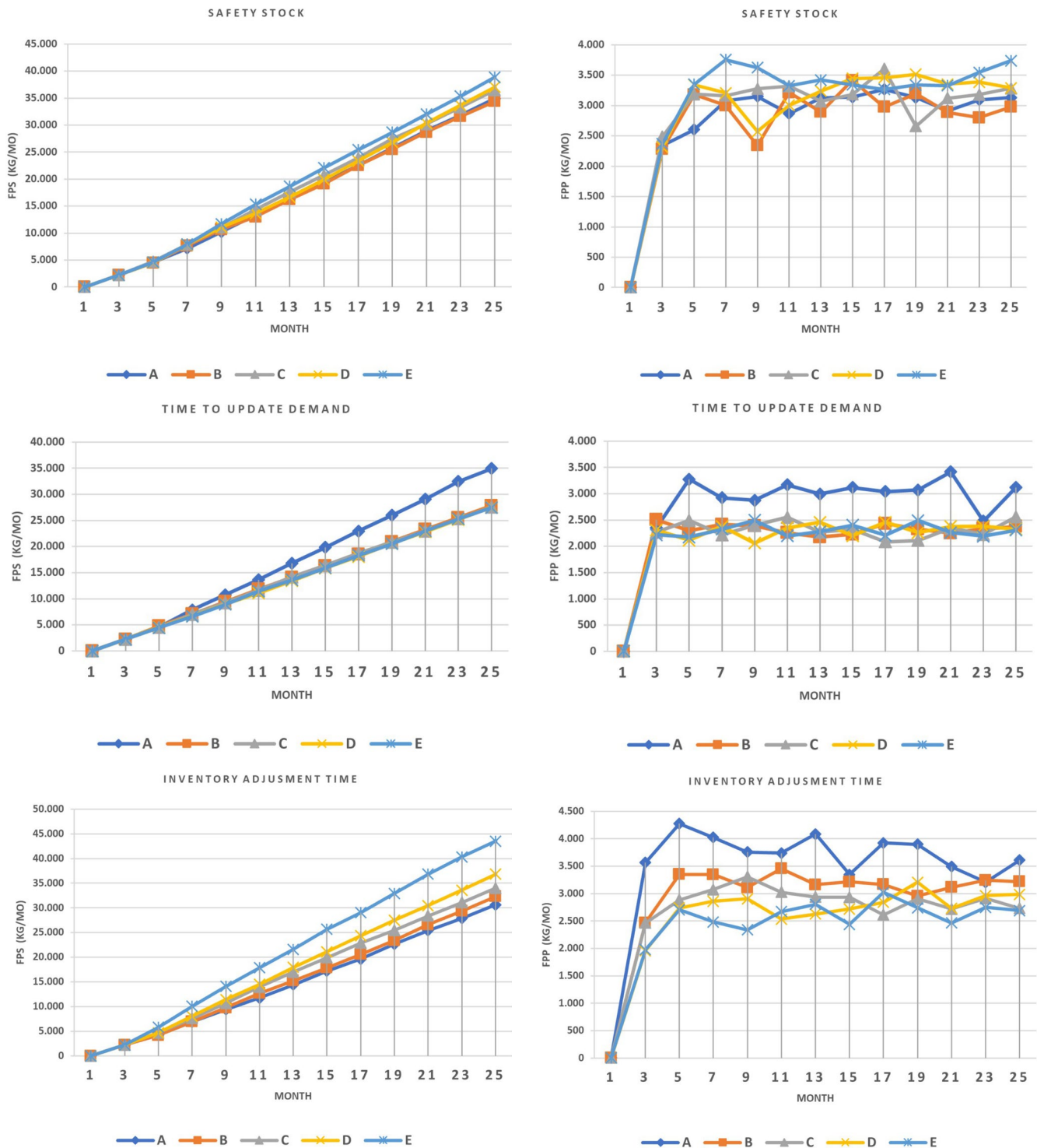


Figure 4: Results of sensitivity analysis on the values of the variables “finish product stock” (FPS) (left image) and “finish product production” (FPP) (right image).

The basic model simulation until 2025 for several important variable values can be seen in Table 4. The average production for roasted coffee is 2.307,9 kg/month, and ground coffee is 380,31 kg/month, or if converted to raw materials is around 2.318 kg coffee beans/month or around 77,25% of production capacity. The stock volume of roasted coffee products is 2,3 times greater than ground coffee because the production rate is greater. However, there are still stockouts of downstream products. The prediction in 2025, UPH will still be unable to meet market demand for roasted coffee (stockout frequency 3 times a year), which occurs in April, May, and July with a total shortage of 66,25 kg. Meanwhile, stockouts occur twice a year for ground coffee with a total shortage of 57,04 kg. Even though the volume doesn't seem that big, it will have a negative effect on consumer confidence (Helm; Hegenbart; Endres, 2013). Total production costs, which include raw material stock costs, final product stock, and processing costs, will be Rp. 1,34 billion in 2025. As a result of interviews with UPH Kahyangan, information was obtained that current production costs are still considered too high. The processing unit wants the final product stock volume to be reduced, but still able to avoid stockouts. Therefore, scenarios were developed to achieve these goals.

The simulation results of the model in Table 4 provide more complete information for production control in the coffee industry and other small-scale industries compared to inventory control models that only present the results of the number of stocks, production, and inventory costs (Satori; Renosori; Fauzan, 2020). The advantage of the proposed model is its ability to detect the frequency, number, and time of stockouts. A model that calculates the number of stockouts

was once developed by Purnomo and Izza (2020) but without calculating production costs, while the research of Purnomo et al. (2024) also calculates the number of stockouts but in the context of a supply chain model. Thus, this model has an important contribution to building a more detailed production control model that has never existed in much literature.

Next, scenario development is carried out to improve the values in Table 5. Scenario development is carried out by changing the parameter values through trial and error in such a way that satisfactory simulation results are obtained (Liu; Qin; Zhang, 2022). Policy scenarios were developed into three types, namely pessimistic (worst), moderate, and optimistic (best). The optimistic scenario is an attempt to mobilize resources ideally, whereas the pessimistic scenario only uses normative resources. The moderate scenario is between the two (Yuzaria et al., 2022). The safety stock value and two scenario variables were determined by trial and error based on the results of interviews with UPH owners and managers. For roasted coffee, the safety stock value in the optimistic scenario is equal to the average demand per month, while in the moderate and pessimistic scenarios, it is 90% and 80% of the demand volume, respectively. Meanwhile, for ground coffee, the proportions are 75% (moderate) and 50% (pessimistic). Alternative scenarios for increasing production control efficiency are shown in Table 5.

4 DISCUSSIONS

The system dynamic model for controlling coffee production at UPH Kahyangan has succeeded in accurately simulating system behavior as indicated by a MAPE value of

Table 4: Simulation results from the basic model until 2025.

Variables	Roasted coffee	Ground coffee
Total production cost (Rp/year)	1.344.766.437,96	
Volume of product stock (kg/year)	24.654,80	10.660,00
Average of production rate (kg/month)	2.307,90	380,31
Frequency of stockout	3 times a year with a total of 66,25 kg: a. -28,75 (April) b. -18,75 (May) c. -18,75 (July)	2 times a year with a total 57,04 kg: a. -54,36 kg (June) b. -2,68 kg (October)

Table 5: Alternatives scenarios developed.

Variables	Basic	Pessimistic (worst)	Moderate	Optimistic (best)
Safety stock (kg):				
Roasted coffee	0	1.372	1.544	1.715
Ground coffee	0	271	407	542
Time to update demand (mo)	0	2	3	4
Inventory adjustment time (mo)	0	3	2	1

less than 10%. This test parameter explains the absolute average percentage error between the actual data and the predicted data from the simulation results (Kim; Kim, 2016). This shows that the model is valid and can be used for analysis and decision-making purposes. The basic model simulation results show that UPH is still suffering from stockouts where downstream products in the warehouse are not available so market demand cannot be met. This is due to uncertainty in demand, as well as production which is very dependent on the availability of raw materials. Stockouts can reduce product demand in both the short and medium term so they need to be handled seriously (Yan; Chao; Lu, 2024). The way to avoid stockouts is by determining the right inventory level to anticipate market uncertainty (Koren et al., 2024). Safety stock is one strategy that can be implemented to prevent stockouts. Safety stock is an inventory level that is set to cover demand in several future periods. Stock values can be determined by trial and error, for example, based on the average demand for products from several previous periods (Belhajali; Hachicha, 2013).

The results of model simulations using pessimistic, moderate, and optimistic scenarios can be seen in Table 6. The application of all scenarios has a positive impact, namely that stockouts can be avoided, meaning that all demand can be met without shortages during the simulation period. This is due to the existence of a model feedback structure that regulates production rates based on the specified safety stock volume. Downstream products will always be available in storage warehouses so they can handle uncertain demand (Koren et al., 2024).

The presence of safety stock typically leads to an increase in the volume of product stock in storage warehouses. However, the results from our model simulation reveal a contrary trend: as the safety stock value increases, the average number of product stocks in the warehouse decreases. This finding differs from the results reported by Satori, Renosori and Fauzan (2020) which indicated that increasing safety stock raises stock volume.

In contrast, Morales and Arenas (2021) illustrate that controlling production rates through feedback from demand and maintaining targeted stock levels can significantly reduce inventory levels. Our proposed model adheres to this principle,

yielding improved results compared to previous studies. It demonstrates that production rates have been effectively controlled by demand and adjusted according to the levels of downstream product stock in the warehouse. Stock levels fluctuate based on the safety stock value. If in a period t , the stock level in the warehouse is greater than the safety stock, then the adjustment value will be negative. Conversely, if the stock level in the warehouse is lower than the safety stock, then the adjustment value will be positive. The production adjustment value is the key to success in managing stock levels so that they remain in the range of safety stock values, but market demand can be met (Belhajali; Hachicha, 2013; Poles, 2013).

Production adjustments are made based on the 'inventory adjustment time' variable. This variable shows how quickly downstream product stocks are arranged. In the optimistic scenario, the value of the 'inventory adjustment time' variable is one month, meaning that production adjustments are made every month. Meanwhile, if the value is 3 as in the pessimistic scenario, then production adjustments are made every 3 months. The smaller the value of the adjustment time variable, the greater the impact will be on reducing stock levels in the storage warehouse. Meanwhile, the constant 'time to update demand' is the period used to average demand for downstream products. The greater the value of 'time to update demand', the greater the range of the smoothing period so that the demand data will better represent the uncertainty meaning that the average demand data is the last 4 months. This is certainly better than just 3 months of smoothing. This technique is also commonly referred to as Single Moving Average (Ali et al., 2015).

The simulation results show that the lowest total production cost is the optimistic (best) scenario, namely Rp. 1,15 billion or 14% lower than the cost in the actual situation. Production costs consist of processing costs, raw material storage costs, and downstream product storage costs. In the optimistic scenario, the storage volume of downstream products is the lowest compared to the other two scenarios. Through this scenario, the volume of roasted coffee stock can be reduced by 13,93% from the initial 24,65 tons to around 3 tons, while ground coffee drops by 27,36% from 10,66

Table 6: Scenario simulation results in 2025.

Variables	Basic	Pessimistic (worst)	Moderate	Optimistic (best)
Total production costs (Rp billion)	1,34	1,29	1,21	1,15
Average volume of raw material stock (kg coffee beans/month)	5.215,61	3.144,98	3.056,12	3.025,62
Total product stock (kg):				
Roasted coffee	24.654,80	21.971,32	22.754,76	21.640,52
Ground coffee	10.660,00	10.055,54	9.889,87	8.370,16
Frequency of product stockouts (kg/month):				
Roasted coffee	3 months	0	0	0
Ground coffee	2 months	0	0	0

tons to only 2,29 tons. The optimistic scenario is also able to reduce the average volume of raw material stock significantly by 42% from 5.215,61 kg of coffee beans to 3.025,62 kg of coffee beans. The application of model feedback from the raw material storage warehouse, production rate, and green beans sales rate to the raw material supply rate variable is able to control the volume of raw material entering the storage warehouse according to production needs. This is what causes the volume of raw material to be lower than the actual situation.

The optimistic (best) scenario is the chosen alternative for UPH Kahyangan to help avoid downstream product stockouts, reduce excessive stock volumes in warehouses, and reduce production costs. An optimistic scenario will have an impact on increasing processing unit profits and consumer satisfaction. This scenario is very possible to implement because it does not require too large an investment, both in the form of costs and human resources. The policy that can be taken by processing units based on an optimistic scenario is to control production rates according to stock levels of downstream products.

To support an optimistic scenario, UPH Kahyangan can manage its production rate in relation to the inventory levels of downstream products. A new Production and Inventory Control (PIC) division can be established to oversee this activity. This division will be responsible for planning and controlling production across several areas, including marketing, processing, inventory, and raw material procurement. The PIC division will implement control mechanisms in several ways: a) establishing the safety stock levels for downstream products; b) recording and monitoring the stock levels of downstream products and raw materials; c) Adjusting the stock of downstream products on a monthly basis; d) analyzing the average demand for downstream products over the last four periods; e) modifying the production rate based on the insights derived from points c and d; f) determining the required raw material supply. Employees in this division must be capable of quickly updating data and calculating production costs to facilitate continuous adjustments. This system will ultimately ensure that business units achieve higher efficiency and improved production performance (Berling; Sonntag, 2022; Dendra; Amrina; Indrapriyatna, 2023).

5 CONCLUSIONS

The resulting dynamic system model has improved UPH Kahyangan's production performance. By managing product safety stock levels and production levels, it has succeeded in avoiding stockouts by up to 100%, reducing stocks of roasted coffee (13,93%) and ground coffee (27,36%), as well as saving production costs of up to Rp. 1,15 billion (14%) compared to the actual situation. This model can be easily adapted to other agro-industries on a larger scale by changing the variable values and model paramters.

6 AUTHORS' CONTRIBUTION

Conceptual Idea: Purnomo, B.H.; Elida Novita. Methodology design: Purnomo, B.H; Hendra Andiananta; Anik Setiawati; Puji Wahono. Data collection: Mokhammad Fatoni Kurnianto; Anik Setiawati; Elida Novita; Afif Amiluddin. Data analysis and interpretation: Purnomo, B.H; Rahmat Pramulya; Devi Maulida Rahmah; Adi Sutrisno; Anik Setiawati; Afif Amiluddin. Writing and editing: Purnomo, B.H.; Hendra Andiananta; Anik Setiawati.

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