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Gasoline Policy Simulation to Increase Responsiveness Using System Dynamics: A Case Study of Indonesia's Gasoline Downstream Supply Chain

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ABSTRACT

In the supply chain, inventory planning plays a crucial role in achieving a balance between supply and demand. This study aims to investigate a supply chain policy that can achieve an impressive level of responsiveness, reaching close to 100%. Additionally, by focusing on the supply chain of RON 92 gasoline in Indonesia, the research aims to identify the key factors influencing responsiveness instability. To achieve these objectives, a simulation model was used to analyze the inventory policy, considering various factors such as demand, production, safety stock coverage, transportation delays, production capacity, and importation due to insufficient production capacity. The results showed that forecasting accuracy is the main determinant of the responsiveness rate. Moreover, maintaining a minimum inventory level of 28 days yielded an impressive 99% responsiveness rate, provided that the deviation in demand does not exceed 5% of the forecast. The analytical tool used in the system dynamics framework was a simulation, which significantly contributed to the research findings. However, it is important to note that this research has limitations, specifically in its inability to analyze crude oil supply. Therefore, further research is necessary to thoroughly examine this aspect and gain a more comprehensive understanding of the overall supply chain dynamics.

Keywords: Policy Simulation, Inventory, Responsiveness, System Dynamics, Petroleum Supply Chain
JEL Classifications: C6, M110

1. INTRODUCTION

The availability of gasoline, a crucial petroleum product, holds paramount importance for the economies of all countries. Its significance extends to numerous businesses and citizens who rely on it in their daily lives. Being intricately linked with various sectors, including electricity and transportation, the petroleum supply chain serves as a vital backbone of the economy (Kumar and Barua, 2022). Distortions in the gasoline supply can have far-reaching consequences, including disruptions in manufacturing processes (Tarei et al., 2021). Additionally, the availability of petroleum plays a significant role in ensuring energy security for a country (Rose et al., 2018; Long et al., 2022).

The petroleum supply chain presents a complex and uncertain environment (Freen et al., 2023). These uncertainties can arise from demand fluctuations, supply delays, or production disruptions caused by machinery breakdowns (Kumar and Barua, 2022). To effectively navigate this intricacy, maintaining an appropriate inventory level becomes crucial (Lücker et al., 2019).

Efficient supply chain performance is a primary goal for every company, and it is evaluated through various criteria, such as responsiveness, which refers to promptly fulfilling customer demands (Holweg, 2005; Richey et al., 2021). According to Kristianto et al. (2017), achieving a high level of responsiveness is critical to gaining a competitive advantage in the global market.

Well-established supply chain policies play a pivotal role in guiding decision-making processes, particularly in determining the suitable level of safety stock to ensure product availability

amidst uncertainty. This is of paramount importance as both responsiveness and inventory policies significantly impact overall supply chain performance (Cannella et al., 2018). Thus, assessing the effectiveness of safety stock levels in meeting demand becomes crucial for determining responsiveness (Chopra and Meindl, 2015), given the close relationship between inventory management and responsiveness (Kim et al., 2023). Inadequate responsiveness in gasoline supply can indicate insufficient inventory to meet demand, leading to potential economic disruptions. Therefore, striking the right balance between responsiveness and cost considerations is vital (Yin et al., 2017). However, conducting research on the downstream petroleum supply chain, specifically in relation to gasoline supply, has been limited due to the scarcity of detailed information (Fernandes et al., 2013).

In modern society, transportation plays a crucial role, accounting for approximately 20% of energy consumption (Sarathy et al., 2018). In Indonesia, gasoline scarcity is a recurring problem in several regions (Mardiana et al., 2020). As an indicator of gasoline quality, RON is essential, with higher RON numbers denoting higher quality. Consequently, RON 92 gasoline has become a focus of research due to its environmental friendliness compared to lower RON grades, which the government encourages its use over.

The supply chain is characterized by inherent uncertainty, necessitating planning for various scenarios involving changes in demand, transportation patterns, and production levels. According to Langroodi and Amiri (2016), a systems perspective is crucial to address these uncertainties, and the system dynamics method is a practical approach. This method allows for mapping the structure of the system and behavior patterns, facilitating simulations across multiple scenarios (Li et al., 2016) to understand better complex problems (Demczuk and Padula, 2017) and policy resistance (Kelly et al., 2019).

As a critical criterion for evaluating supply chain performance, responsiveness has been widely researched (Acquah et al., 2023). However, achieving high responsiveness through increased inventory levels can lead to elevated costs. Despite Indonesia's RON 92 gasoline supply level standing at 17.2 days (Tempo.com, 2022), specific details regarding the responsiveness rate, influential factors, and key sources of instability remain undisclosed.

Despite the widespread use of system dynamics in various supply chain research, including the energy sector (Freeman, 2021.), a specific examination of modeling the inventory policy for gasoline in Indonesia with regard to responsiveness is lacking. This research aims to bridge this gap by employing system dynamics to model and simulate the downstream gasoline supply chain, encompassing inventory policies and other critical factors impacting responsiveness.

2. LITERATURE REVIEW

2.1. Supply Chain

The supply chain comprises a complex network of multiple entities, organizations, or individuals directly involved in the flow of products, services, finances, and information from a source to a customer (Mentzer et al., 2001, p.4). Within this intricate network, inventory-related challenges are among the prominent issues in supply chain management, encompassing supply, production, and distribution networks (Ryu et al., 2013). Supply chain management is crucial in integrating business operations, adding value to raw materials by transforming them into goods for end users (Brandenburg et al., 2019; Cooper et al., 1997).

Efficient supply chain performance positively impacts organizational performance (Gunasekaran et al., 2017), leading to the development of various measurement systems. For instance, Lai et al. (2002) identified four performance indicators, namely, responsiveness, reliability, costs, and assets. Similarly, Aramyan et al. (2007) emphasized efficiency, flexibility, responsiveness, and quality as key dimensions. Responsiveness is a critical factor in assessing supply chain performance.

The supply chain of the petroleum industry is highly complex and comprises several subsystems (Moradi Nasab et al., 2016). It involves processes like crude oil exploration, transportation, and production, ultimately delivering multiple products to consumers (Abdussalam et al., 2023). The upstream supply chain encompasses crude oil exploration, while the downstream supply chain includes refinery, transportation, and distribution activities (Ahmad et al., 2017). Due to its capital-intensive nature, the petroleum industry significantly emphasizes supply chain planning, using various analytical tools (Kazemi and Szmerekovsky, 2015; Oliveira et al., 2014). While keeping inventory value at a minimum, responsiveness remains a crucial consideration. However, determining the appropriate inventory quantity poses challenges involving demand forecasting, procurement planning, production scheduling, and delivery management (Saghafian and Tomlin, 2016).

2.2. System Dynamics

All business and social systems involve multiple resources, with their input and output flow often likened to stock movements (Morecroft, 2015). The system dynamics method is a widely used simulation modeling approach across various industries, serving diverse purposes such as policy design, economic behavior analysis, optimization, and supply-chain management. In the field of supply chain management, system dynamics has been extensively applied in various industries such as the natural gas (Yunna et al., 2015), cement (Ansari and Seifi, 2013), and petroleum (Pan et al., 2017) industries.

The energy sector has also extensively adopted the system dynamics method. For instance, Mendoza et al. (2014) simulated production planning optimization, Tan et al. (2014) developed the latest energy model of Malaysia, and Rendon-Sagardi et al. (2014) analyzed the feasibility of the ethanol supply chain for biofuel production in Mexico. Additionally, Shafiei et al. (2016) examined strategies for transitioning to biofuel vehicles, and Pan et al. (2017) investigated how the petroleum industry supply chain responds to disruptions in crude oil imports. Sani et al. (2018) predicted Indonesia's energy mix model production from various sources, and Kuo et al. (2019) analyzed the acceptability of price differences between biofuel and fuel oil in Taiwan. Mayasari et al. (2019) forecasted biodiesel production in Indonesia, Shao and Jin

(2020) developed a model of Lithium supply chain resilience in China under the impact of supply interruptions and new energy vehicles and Becerra-Fernandez et al. (2020) modeled natural gas supply chains for sustainable growth. Sheel et al. (2020) explored the impact of marketing and supply chain orientation on petroleum supply chain agility in India, Weidner et al. (2021) simulated climate control strategies to minimize energy consumption, and Chen et al. (2023) studied the resilience of the energy sector of China under the shortage of imported oil in the long run.

Despite the widespread application of system dynamics in supply chain analysis across various industries, research in the petroleum sector remains relatively unexplored, particularly in the context of logistics planning for the downstream gasoline sector in Indonesia. This research focuses on scenarios involving functional disturbances, demand deviations, and the measurement of response rates.

3. METHODOLOGY

This research used the system dynamics (SD) method for modeling and simulation based on system thinking principles. SD enables the development of simulation models, analysis of factor relationships, and holistic problem-solving within complex systems (Demczuk and Padula, 2017). SD translates the situation into quantitative formulas and conducts simulations (Poles, 2013), making it an effective tool for understanding nonlinear behavior in complex systems (Sani et al., 2018). The method combines decision-making, feedback information, simulation, and policy to form a holistic system model, allowing the examination of interrelationships between variables. This method is ideal for modeling supply chain networks (Özbayrak et al., 2007) and allows for factor modeling to evaluate supply chain effectiveness.

In system dynamics theory, two primary concepts are stock and flow, which involve variables. Stock represents the accumulation of differences in inflow and outflow, while feedback denotes loops in the SD structure where the output in a node is influenced by the input (Sterman, 2000). Stocks can increase or decrease with inflows, outflows, and delays, being the source of dynamic imbalances in a system. Examples of stock, inflow, and outflow include inventory, receipt of goods, and usage of goods. In system dynamics diagrams, stocks, inflows, and outflows are represented by rectangles, arrows, and faucets controlling the flow (Sterman, 2000). Figure 1 shows an example of a stock and flow diagram.

The descriptive relationship of stock and flow is established by quantitative relationships represented through differential equations in the following formula:

$$Stock_t = \int_{t_0}^{t} (\inf low - outflow) d_t + Stockt_0 \quad (1)$$

Figure 1: Stock and flow diagram

Source: Sterman, 2000, p. 193

The process of creating an SD model involves several sequential steps. First, the problem is defined, and then the system is conceptualized and represented through a causal loop diagram (CLD). The CLD includes key variables, their interrelationships, and feedback structure (Ghadge et al., 2020; Bala et al., 2017). Subsequently, the SD model is developed, validated, and subjected to simulations with various scenarios to understand its behavior and performance. The development process may undergo iterations to refine the SD model until it reaches a satisfactory design.

To ensure the reliability of the built SD model, it undergoes validation and measurement using the mean absolute percentage error (MAPE), calculated with the following formula:

$$MAPE = \frac{1}{N} \times \sum \left[\frac{F_t - Y_t}{Y_t} \right] \times 100 \quad (2)$$

Description:
Y_t = actual value in period t
F_t = simulation value in period t
N = number of observation data
(Chase, 2013: 113)
MAPE values below 20% are considered good (Melikoglue, 2014).

4. ANALYSIS

The initial step to constructing a system dynamic is understanding the material flow and developing a closed-loop diagram. Subsequently, a system dynamics model is constructed, incorporating formulas for each variable, and the model is validated to ensure its accuracy. Finally, the system dynamics model undergoes simulation with several scenarios.

4.1. Gasoline Flow in the Downstream Supply Chain

The downstream sector encompasses crude oil processing into finished products, storage, and distribution transportation. The processing unit converts crude oil into various petroleum products, including gasoline, diesel, aviation turbine fuel, LPG, and petrochemicals which are then transported to storage areas. However, domestic production is insufficient to meet Indonesia's gasoline demand, necessitating imports stored in depots. Furthermore, gasoline is distributed from these fuel depots to customers. Figure 2 shows the gasoline flow diagram in the downstream supply chain of Indonesia.

4.2. Close-loop Diagram

The causal loop diagram for gasoline supply and demand is shown in Figure 3. Increased distribution relies on a corresponding supply from production and imports to replenish inventory. An increase in production and imports is directly proportional to the overall supply. Additionally, higher capacity can lead to increased production and reduced imports, while disruptions can lead to decreased output. High demand can create a backlog, which, in turn, decreases distribution capability.

4.3. System Dynamics Model Building

The causal loop diagram has been developed and converted into stock and flow diagrams using Powersim software. Figure 4 shows the system dynamics downstream gasoline supply-chain model.

Figure 2: Gasoline flow diagram

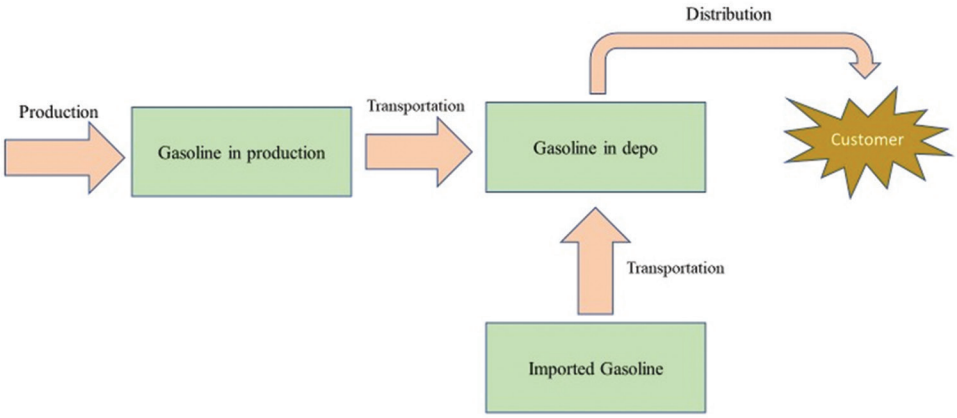
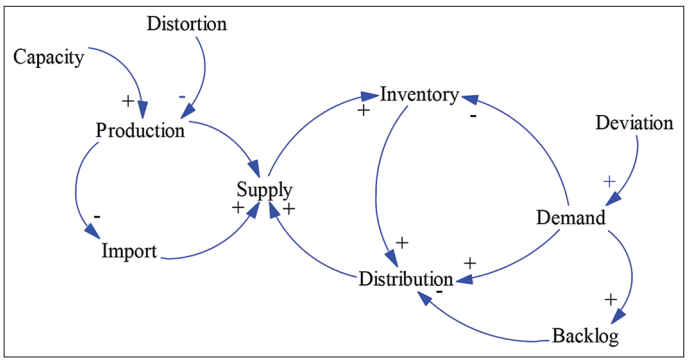


Figure 3: Close-loop diagram of gasoline supply and demand



4.3.1. Model description

Model descriptions, as shown in Figure 4, are as follows:

a. Stock gasoline in production

This stock variable represents the gasoline inventory in the refinery arising from the crude oil production process. It fluctuates based on input and output flow changes, including the production rate and delivery to the depot.

b. Stock gasoline in depot

This stock variable represents the amount of gasoline inventory at the depot. It increases with gasoline deliveries from refineries and imports and decreases with gasoline distribution. The gasoline inventory in the depot is expected to remain above the planned coverage level. The inventory is influenced by product and material deliveries, subject to shipping, distribution, and delivery delays described by constant variables based on planning assumptions.

c. Stock Backlog

Backlog refers to the accumulation of pending delivery requests, which grows or diminishes based on demand and distribution.

d. Flow

The inflow and outflow of gasoline are the production and delivery levels to the depot. The inflow is also the receipts from refineries, whereas the outflow is the distribution to customers. The production amount affects the flow level, which depends on the predicted demand, while the shipment is based on the rate position of the gasoline supply at the refinery or the delay in delivery to the depot. However, the level of imports depends on gasoline demand and the production level. The inflow and outflow from the backlog are the demand and distribution levels, respectively. The distribution rate is limited by the availability of gasoline at the depot.

e. Variable

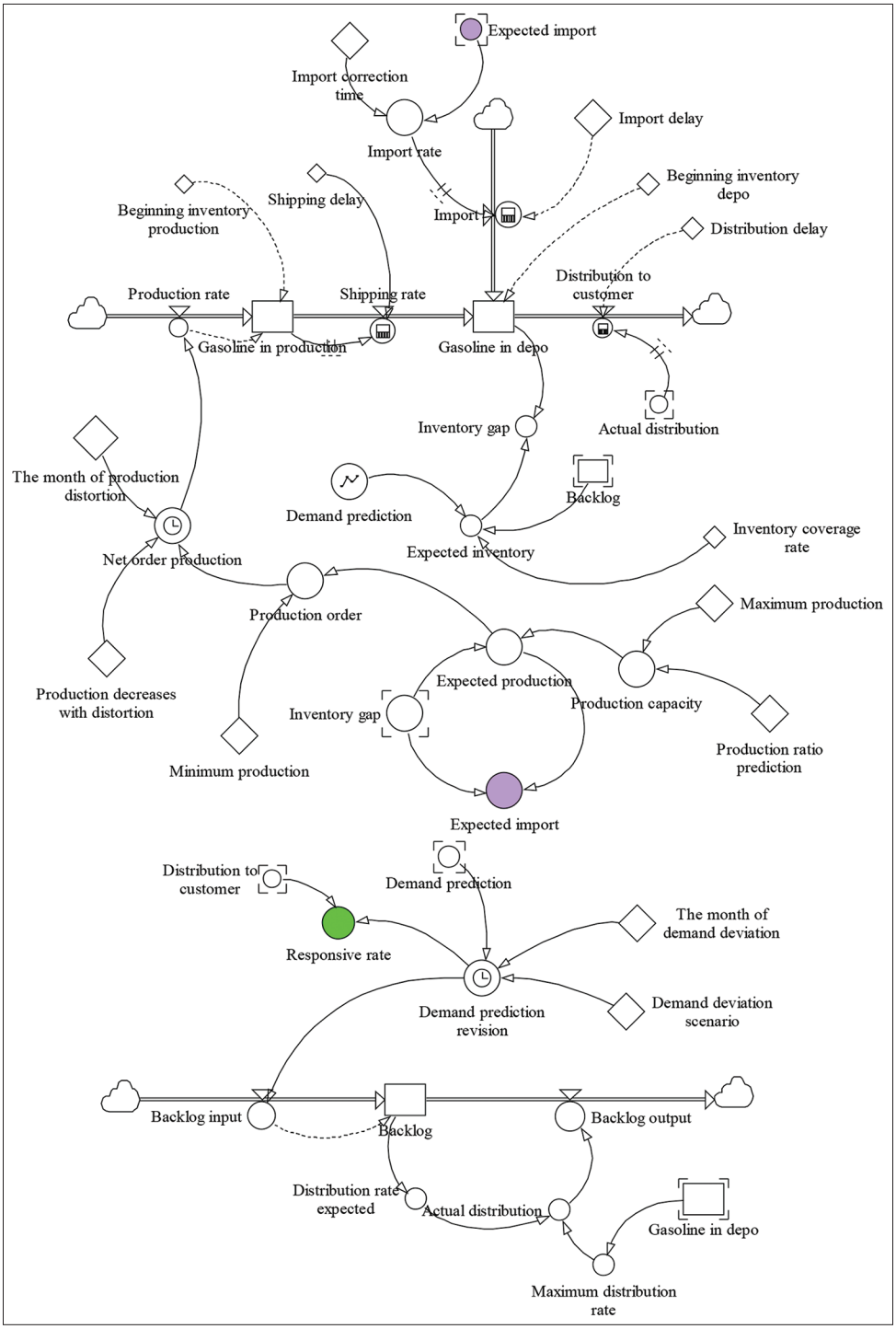
Variables are obtained from inventory, production, import, backlog, and distribution.

The description and formula of variables, as shown in Figure 4, are as follows:

- The *shipping delay* represents the time required for fuel oil products to be transported from the refinery to the fuel depot. For this simulation, the assumed shipping delay is two days.
- *Inventory coverage rate* indicates the safety stock level in terms of days.
- The *beginning inventory depot* represents the initial quantity of inventory available at the start of the simulation in the fuel depot.
- *Beginning inventory production* denotes the starting inventory level at the refinery for the simulation.
- The *demand* variable is calculated using a formula based on a graph curve. The formula is: GRAPH CURVE (MONTH (TIME),1,1 (predicted value of month 1, predicted value of month 2…, the expected value of month 12;//min 300, max 400//) <<MB/day>>
- *Expected inventory* calculates the required inventory level to meet both safety stock coverage and backlog. This variable is dependent on the forecasted demand for the month.

  The formula is: Inventory expected = (Inventory coverage rate * demand prediction) + Backlog.
- The *inventory gap* represents the difference between the expected inventory level and the current stock in the depot. When the gap exceeds zero, it shows that additional inventory is needed to reach the expected level.
  The formula is: MAX (0<<MB>>, Inventory expected–Gasoline in depot).
- The *shipping rate* determines the amount of fuel oil delivered from the refinery to the depot per unit of time. This variable depends on the production level and the shipping delay. When there is a delay, the DELAY formula is used.
  The formula is: DELAYPPL (Gasoline in production, Shipping delay,1, Gasoline in production)/1<<Mo>>

Figure 4: System dynamics model of gasoline downstream supply chain



- *Distribution to customers* represents the amount of fuel oil delivered from the depot to the customers per unit of time. The quantity depends on the actual distribution, backlog, and distribution delay.
  The formula is: DELAYPPL (Actual distribution, Distribution delay).
- *Production rate* signifies the amount of fuel oil produced per unit of time, equal to the net order production.
- *Demand prediction revision* calculates the revised demand prediction when there is a deviation from the expected demand for a particular month.
  The formula is: IF(MONTH(TIME) = The month of demand deviation,
  Demand prediction * Demand deviation scenario, Demand prediction).
- The *month of production distortion* represents the number of months in which maintenance or disruptions occur in the production unit. It is a constant variable with its value determined based on simulation assumptions and ranges from 1 to 12.
- Production decreases with distortion indicates the percentage decrease in production caused by disturbances such as machine breakdowns, which is a constant variable.

- *Minimum production* denotes the assumed minimum quantity of production. It is a constant variable set at 2600 MB per month.
- *Maximum production* signifies the assumed maximum quantity of production. It is a constant variable set at 4200 MB per month.
- *Production ratio prediction* represents the assumed production percentage, which can vary over time. The ratio rate is set between 97%–100%.
  The formula is: GRAPH (MONTH (TIME), 1,1, (0.973, 1, 0.995, 0.97, 0.97, 0.984, 0.984, 0.97, 0.97, 0.98//Min:0; Max:1//)
- *Production capacity* depends on the maximum production and the predicted production ratio.
  The formula is: Production capacity= Maximum production * Production ratio prediction
- *Expected import* represents the number of imports required when the expected production is insufficient to fill the inventory gap. Expected imports are calculated as the difference between the inventory gap and expected production, and the value is greater than zero.
  The formula is: MAX (0<<mb>>, Inventory gap–Expected production)
- *Expected production* represents the production required to fill the inventory gap, considering the available production capacity. When the production capacity is smaller than the inventory gap, the expected production is equal to the capacity. However, when the production capacity exceeds the inventory gap, the expected production is equal to the inventory gap.
  The formula is: MIN (Inventory gap, Production capacity)
- *Production order* represents the quantity based on the minimum and expected production. The value lies between the minimum production and expected production.
  The formula is: MAX (Minimum production, Expected production)
- *Net order production* represents the amount of production when there is a decrease due to production disruptions. The value is similar to the production order when there are no disruptions.
  The formula is: IF(MONTH(TIME) = The month of production distortion,
  (Production order x Decrease in production because of distortion), Production order
- *Import correction time* represents the value used to adjust the import order quantity when there are no interruptions, and the value ranges from 0.1 to 1
- The *import rate* represents the rate at which imports occur, calculated based on the expected import and import correction time.
  The formula is: Import rate = Expected import/Import correction time
- *Import delay* represents the delay in the delivery of imported gasoline, and it is a constant variable.
- *Import* represents the imported quantity of gasoline, determined by the import rate and import delay
  The formula is: DELAYPPL (import rate, import delay)
- The *demand deviation scenario* represents the rate of increase or decrease in demand prediction.
- The *month of demand deviation* represents the specific months in which there is an increase in demand.
- *Demand prediction revision* calculates the revised demand prediction when there is a demand deviation.
  The formula is: IF(MONTH(TIME)=The month of demand deviation
  Demand prediction * Demand deviation scenario, Demand prediction)
- *Backlog input* represents the flow that contributes to the backlog stock.
  The formula is: Backlog = Demand prediction revision
- *Actual distribution* represents the rate at which the backlog is being delivered.
  The formula is: MAX (0<<MB/Mo>>; (MIN (Maximum distribution rate, Distribution rate expected))
- The *maximum distribution rate* represents the maximum amount that can be distributed from the depot to customers based on the existing inventory. It cannot exceed the amount of inventory in depo.
  The formula is: MAX (0<<MB/Mo>>, Gasoline in depo)
- *Backlog output* represents the flow that reduces the stock backlog.
  The formula is: MAX(0<<MB/Mo>>, Actual distribution)
- The *responsive rate* represents the ability of the inventory to meet the demand.
  The formula is: =Actual distribution/Demand prediction revision * 100

4.3.2. Validation

The model and formula undergo validation by comparing the simulation with actual data on the imported variable. The validation results reveal a MAPE value of 13.77% for the imported gasoline. This shows that the developed model and formula are good as they provide results closely resembling those of the actual system. Figure 5 shows a visual representation of both the actual import value and the import value generated by the model during the simulation.

4.4. Simulation

The logistics planning simulation is conducted to assess how changes in variables and the scope of safety stock impact the required distribution response level to meet demand. The simulation in the gasoline supply logistics model involves modifying parameters such as safety stock coverage, deviation from predicted demand levels, transportation lead time, production disruption, and their influence on inventory response.

The simulation is based on certain assumptions, including an initial inventory of 8000 mb at the depot and 2000 mb at the refinery. The minimum monthly production is set at 2650 mb, while the maximum production is capped at 4200 mb. Delivery delays from the refinery and depot are 2 days and 4 days, respectively, with an additional 3-day (0.1 months) delay for import deliveries.

Demand assumptions were derived from the prediction analysis of Mardiana et al. (2020). The demand prediction for RON 92 in 2022 was calculated by combining the pure needs of RON 92 with 55% of the needs for RON 90. This is because RON 90 comprises a mixture of 45% RON 88 and 55% RON 92. Figure 6 shows the predicted RON 92 demand for the year 2022.

The simulation encompasses multiple scenarios to evaluate the effects of different factors on logistics planning. The scenarios explored are as follows:

1. Safety stock coverage: Assumptions are made for four coverage periods, namely, 17, 21, 25, and 28 days.
2. Deviation needs: Scenarios are considered for no deviation, deviations occurring in specific months, and deviations persisting throughout the year
3. Import delay: Two import delay durations are specified, namely, 0.1 months (equivalent to 3 days) and 0.2 months (equivalent to 6 days)
4. Production: Disruptions in specific months lead to an 80% reduction in production levels during those periods
5. Import correction time: The simulation assumes import correction times of 0.9 and 0.75 months. A correction time of 0.9 months means that the monthly need can be fulfilled within 0.9 months, while a correction time of 0.75 months indicates completion of the monthly need within 0.75 months. The number of corrections is directly proportional to a higher volume of imports.

5. RESULTS AND DISCUSSION

Simulations are conducted for each scenario, and the results are shown in Table 1.

- Scenario 1: The average response rate is 96.04% when using a 17-day safety stock with no deviations in demand or production disruptions.
- Scenario 2: With a 21-day safety stock and no interruptions or deviations, the average response rate is 96.45%.

Figure 5: Model validation graph

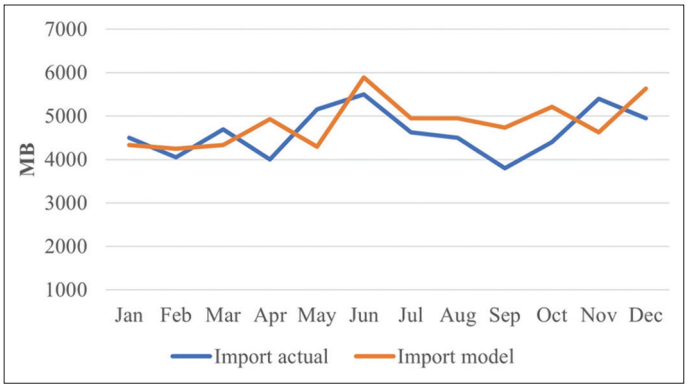
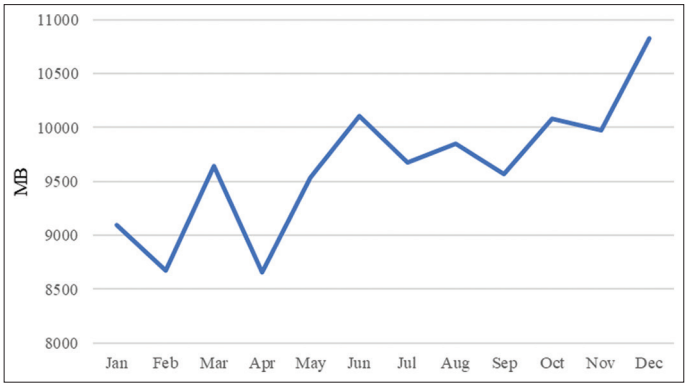


Figure 6: RON 92 gasoline demand prediction in 2022



- Scenario 3: The average response rate is 96.29% when using a 21-day safety stock with an 80% decrease in production and a 10% demand deviation.
- Scenario 4: The average response rate is 96.13% with a 21-day safety stock, an 80% reduction in production, and a 5% demand deviation.
- Scenario 5: With a 25-day safety stock, an 80% reduction in production, and a 10% demand deviation, the average response rate is 97.48%. This response rate is higher than that of Scenario 4 with 21-day safety stock.
- Scenario 6: With the same 25-day safety stock as Scenario 5, but with import delays and a 5% demand deviation, the response rate slightly decreases to 97.27% compared to Scenario 5.
- The deviation of the import delay from 2 to 6 days does not affect the response rate, which means that the 28-day safety stock can still overcome the delay.
- Scenario 7: With a 28-day safety stock, production deviations, a 5% demand deviation, and import delay deviations, the response rate is 98.12%. This response rate is higher than that of Scenario 6, which has a lower safety stock.
- Scenario 8: With the same 28-day safety stock as Scenario 7 but with a 10% demand deviation occurring in the 10th month, the average response rate is 98.37%. However, the response rate drops to 89.96%, specifically for the 10th month.
- Scenario 9: The average response rate is 98.58% with a 28-day safety stock, an 80% reduction in production, a 5% demand deviation, and a 6-day import delay deviation.

Inaccurate demand predictions with a 10% deviation lead to a sharp decline in the response rate, reaching approximately 89%, for safety stocks of 21, 25, and 28 days, as shown in Scenarios 2, 4, and 6. The response rate increases when the demand deviation is low, such as 5% every month. In Scenarios 7 and 8, where the safety stock and production disturbances are the same, the response rate differs due to the variance in demand prediction deviation. Scenario 7, with a lower deviation, yields a response rate of 98.19%, while Scenario 8 records a response rate of 89.96%, as shown in Figures 7 and 8. Therefore, forecasting accuracy significantly influences the response rate in comparison to production decrease. The decrease in production can be mitigated by augmenting imports to bridge the supply gap.

This research makes a valuable contribution to the field of system dynamics modeling, specifically within the downstream petroleum industry. The stocks and variables used in the model represent key components of the downstream supply chain. Consequently, the developed system dynamics model can be readily applied to other product types by adjusting the variable values accordingly.

The findings of the system dynamic model strongly emphasize the importance of accurate demand forecasting and its significant impact on responsiveness. It is evident that the effect of demand forecasting accuracy surpasses the impact of shipping delays. This finding aligns with the conclusions drawn by Kourentzes et al. (2020) through their use of a parametrized forecasting model, where they concluded that the accuracy of demand forecasts greatly influences inventory performance. Additionally, precise demand

Table 1: Summary of RON 92 simulation result

Scenario	Safety stock level	Distortion/deviation	The average response rate (%)
1	17 days	No production distortion or demand deviation	94.97
2	21 days	Production disruption in month 10 with an 80% reduction in production	96.45
3	21 days	Production disruption in month 10 with an 80% reduction in production and a 10% demand deviation in month 10	96.29
4	21 days	Production disruption in month 10 with an 80% reduction in production, a 5% demand deviation every month, and a 0.2-month import *delay* deviation in month 10	96.13
5	25 days	Production disruption in month 10 with an 80% reduction in production and a 10% demand deviation in month 10	97.48
6	25 days	Production disruption in month 10 with an 80% reduction in production, a 5% demand deviation every month, and a 0.2-month import *delay* deviation in months 10 and 11	97.27
7	28 days	Production disruption in month 10 with an 80% reduction in production, a 5% demand deviation every month, and a 0.2-month import *delay* deviation in months 10 and 11	98.12 Month 10: 98.19
8	28 days	Production disruption in month 10 with an 80% reduction in production and a 10% demand deviation in month 10	98.37 Month 10: 89.96
9	28 days	Production disruption in month 10 with an 80% reduction in production, a 5% demand deviation every month, and a 0.2-month import delay deviation in months 10 and 11	98.58

Figure 7: Graph of responsive rate scenario 7

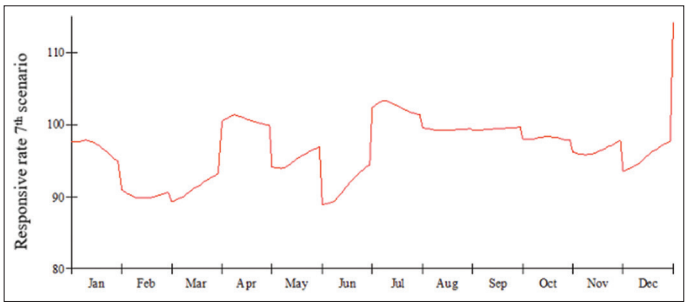
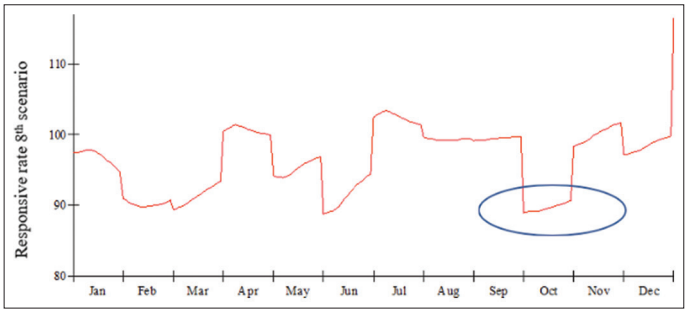


Figure 8: Graph of responsive rate scenario 8



forecasting directly impacts sales, inventory levels, and production planning (Gonçalves et al., 2021). These fi0ndings also align with the research by Rexhausen et al. (2012), which emphasized the superior influence of demand management performance on overall supply chain performance compared to other factors. It is crucial for analysts to carefully select the demand forecasting model, as it directly affects the accuracy of the results (Siddiqui et al., 2022).

Demand forecasting serves as the foundation for effective supply chain planning. Inventory planning, including safety stock management, relies heavily on accurate demand predictions. Similarly, distribution planning, particularly for shipping operations, is highly dependent on precise demand estimates. The routes of ships need to be strategically planned based on the estimated demand and inventory levels at various locations.

The importation of gasoline is necessary to overcome the insufficient production capacity in Indonesia. Therefore, companies must choose a reliable gasoline supplier. The reliability of the supplier directly affects inventory availability, leading to a higher level of responsiveness. This finding aligns with the research conducted by Qrunfleh and Tarafdar (2013), which emphasizes the influence of strategic supplier partnerships on responsiveness.

In terms of gasoline supply policy, Indonesia lags behind other countries. For example, Singapore and Japan maintain a minimum gasoline supply of 90 days and 107 days, respectively, despite having smaller populations of 4.7 million and 127 million. A simulation research showed that the oil supply of China can withstand a disruption for 180 days (Pan et al., 2017). Therefore, it is recommended that Indonesia considers setting the gasoline safety stock level at 28 days or more to account for operational disturbances and demand deviations. Meanwhile, maintaining a higher supply level for gasoline requires substantial financial resources, a low safety stock level leads to gasoline unavailability when needed, leading to economic distortions.

This research focuses solely on the gasoline supply chain and does not include the logistics of crude oil. Therefore, further research is recommended to investigate the crude oil logistics supply chain. Exploring modeling approaches that combine system dynamics with agent-based modeling or scenario planning within the scope of the petroleum industry can provide valuable insights.

6. CONCLUSION

In conclusion, this research focuses on evaluating the sufficiency of supply through an analysis of the response to demand. It

further investigates the response rates of different inventory levels when subjected to factors with a deviation of nearly 100%. The application of system dynamics to the gasoline logistics planning case provides valuable insights into the factors that contribute to the instability of the supply response.

The SD model, as shown in Figure 4, is used to simulate the responsiveness of the gasoline supply chain. The findings reveal that a 17-day safety stock is associated with a high risk of gasoline shortages, leading to a low response rate of 94.97%, even in the absence of distortions and demand deviations. Conversely, a safety stock of 28 days proves to be a relatively safe inventory level, generating a response rate of up to 99%, provided that the demand deviation does not exceed 5%. When the demand deviation reaches 10% or higher, it leads to a significant reduction in response rates. A safety stock level of 28 days or more is required to effectively accommodate operational distortions and achieve a relatively high response rate. The accuracy of demand forecasting emerges as a key lever influencing the stability of responsiveness.

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