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System Dynamics Modeling for Safety Stock Optimization Under Lead Time Uncertainty in Fertilizer Distribution: A Case Study in South Sulawesi

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A R T I C L E I N F O

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A B S T R A C T

This study develops a System Dynamics model to evaluate safety stock and reorder point policies under lead time uncertainty in fertilizer distribution in Sulawesi, Indonesia. The model integrates statistical inventory control with dynamic simulation using Vensim to capture the effects of vessel delays, port congestion, and extreme weather disruptions. Three service-level scenarios were tested using different Z-factors: 2.33 (99%), 1.645 (95%), and 1.28 (90%). Results show that safety stock increases significantly across scenarios (approximately +28% and +42%), while reorder point values remain relatively stable (below 3% variation), indicating demand dominance. Holding cost increases modestly, ranging from 0.98% to 2.93% across scenarios. The balanced policy provides the most feasible trade-off between service reliability and inventory cost

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INTRODUCTION

Sulawesi, as Indonesia's fourth-largest island, plays a crucial role in the national economy, particularly in the eastern region. With its unique geographic configuration, characterized by dominant mountains and a long coastline, this region presents complex and multidimensional logistics challenges. Previous studies have shown that logistics integration in the archipelago relies heavily on efficient intermodal connectivity, where even a small disruption at one distribution point can trigger a domino effect on the availability of goods downstream (Popov, 2024). In this context, reliance on maritime transportation makes the distribution system highly vulnerable to lead-time uncertainty, particularly due to ship delays influenced by weather factors and shipping frequency restrictions.

In the modern supply chain ecosystem, product availability is a key indicator of distribution system performance (Dai & Tang, 2022; Kurniawan & Suseno, 2023). Contrary to the classical assumption that emphasizes demand, in the context of fertilizer distribution in Sulawesi, variability is predominantly driven by lead times. Research Model (2022) shows that lead time variability has a significant impact on increasing safety stock requirements in distribution systems. This finding is reinforced by Park (2021) has stated that lead time is often a major factor causing imbalances between inventory levels and service levels.

In these conditions, safety stock serves as a crucial buffer mechanism to anticipate untimely supply. Studies by Nambiar et al. (2019) emphasize that determining optimal safety stock must consider lead time variability in addition to demand variability. In Sulawesi, fertilizer distribution from logistics hubs like Makassar to remote areas is often delayed due to maritime transport disruptions, rendering conventional statistical approaches inadequate. During the 2021–2026 period, Sulawesi's economic dynamics underwent significant changes due to industrial growth and infrastructure development. However, increased infrastructure capacity has not fully addressed the distribution challenges, particularly along the sea routes that serve as the backbone of subsidized fertilizer distribution.

In this context, a System Dynamics-based approach is relevant because it can capture the complex interactions between variables in a distribution system, including the relationship between shipping delays, inventory levels, and stockout risk. According to Jay W. Forrester, System Dynamics enables dynamic analysis of system behavior through simulation of feedback loops and stock-flow structures, making it particularly suitable for modeling complex and nonlinear logistics systems. Various international studies have demonstrated the advantages of this approach in supply chain management. Chen et al. (2022) emphasize that System Dynamics-based simulations can be used to implement inventory policies under conditions of sales and distribution disruptions. Specifically, Ivanov & Dolgui (2021) shows that transportation disruptions such as delivery delays can amplify variability in the inventory system, known as the bullwhip effect, necessitating an adaptive, simulation-based safety stock strategy.

In this study, the initial quantitative approach using safety stock calculations based on standard deviation and safety factors (Z-scores) remains the baseline, utilizing historical fertilizer distribution data. However, this approach combines a System Dynamics integration model to dynamically broadcast the impact of lead time on safety stock requirements. Therefore, this study not only stops the statistical calculation of ships, but also introduces various delay scenarios and their impact on the level of fertilizer distribution service. Based on the complexity of this problem, this study aims to develop a System Dynamics model to determine the optimal safety stock policy in the fertilizer distribution system in Sulawesi. The main focus of this study is on the effect of lead time due to ship delays on inventory stability. The contribution of this study lies in the integrated approach of statistics and dynamic simulation to produce a more adaptive inventory policy, thereby minimizing logistics costs without sacrificing service levels for the agricultural sector. Therefore, the results of this study are expected to form the basis for strategic decision-making in the fertilizer distribution system.

LITERATURE RIVIEW

In recent years, inventory management approaches have shifted from statistical models to systems-based adaptive approaches. Recent studies have shown that traditional models that only consider demand variability are no longer sufficient to address the dynamics of modern supply chains. Research by Huaraz & Andrade-arenas (2021) confirms that variability in distribution systems, particularly lead times, has a significant impact on inventory performance, including increasing the risk of stockouts and excess stock. This suggests that safety stock no longer serves solely as a buffer against demand but also as a mitigation mechanism for operations. Furthermore, a review of studies by Pehlivan et al. (2022) revealed that most research still focuses on stochastic demand, assuming constant lead times. However, in practice, lead times are dynamic and often a major source of disruption in inventory systems.

Lead time uncertainty is now recognized as one of the most critical factors in modern supply chain performance. This uncertainty can stem from transportation delays, port disruptions, and variability in the distribution process. According to Belhadi et al. (2024) supply chain instability stems not only from demand but also from unpredictable lead times, production capacity, and transportation schedules. This situation is further complicated in island-based distribution systems, where maritime transportation is a dominant factor. Research by Kırmızı & Ceylan (2024) also shows that increased lead time variability directly impacts: reduced service levels, increased inventory costs, and supply-demand integration. Furthermore, Zhang et al. (2024); Mehregan, (2022); Nazari-Ghanbarloo (2022) state that in modern supply chain systems, lead time is a strategic variable influencing coordination between actors in the supply chain, particularly in mitigating the bullwhip effect.

The System Dynamics approach is increasingly used in recent research to analyze complex and dynamic supply chain systems. This method is capable of capturing causal relationships (causal loops), delays, and interactions between variables in a distribution system. Research by Khakdaman et al. (2024); Khakdaman et al. (2024); Nazari-Ghanbarloo (2022) shows that System Dynamics is effective in analyzing long-term changes in supply chain system behavior, especially in the context of the demands and complexity of the distribution network. Meanwhile, Liu et al., (2023) ; Zhao et al. (2024) developed a System Dynamics-based model to examine the impact of lead time on supply chain coordination and found that reducing lead time significantly improves system stability and distribution efficiency.

This approach also allows for the simulation of various distribution scenarios, making it particularly relevant to the context of fertilizer distribution in island regions like Sulawesi. Recent research has shown the increasing use of an integrative approach between safety stock and dynamic simulation. This approach allows for the evaluation of inventory policies under more realistic, near-term conditions.

Recent research indicates that: lead time variability causes a non-linear increase in safety stock requirements; statistical inventory policies are unable to respond to system dynamics; and a simulation-based approach is needed to determine optimal policies. Khakdaman et al. (2024) asserted that model-based simulation is capable of identifying the optimal balance between inventory costs and service levels under uncertain lead times. Furthermore Amoozad Mahdiraji et al. (2024); Kırmızı & Ceylan (2024); Kumar et al. (2018), the System Dynamics approach allows for the integration of operational variables such as delivery delays, inventory levels, service levels, and order frequency within a single, comprehensive analytical framework.

Based on a recent literature review, several significant studies have identified: Dominant focus on demand uncertainty. Most research still focuses on demand variability, while long lead times have not been explored in depth. Limitations of statistical approaches. Conventional models such as EOQ and classic safety stock are unable to capture the dynamics of real distribution systems. Studies in the context of island regions are scarce. Research related to distribution in complex geographic regions such as Sulawesi is still very limited (Aldito Hermawan & Siti Muhimatul Khoiroh, 2023). Lack of integration of statistical methods and dynamic simulations. Most studies use only one approach, not integrating both

METHODOLOGY

1 Research Design

The system dynamics methodology applied in this study is explained through modeling stages using Vensim software. The approach begins with the development of a causal loop diagram, followed by the development of a Forrester diagram (stock and flow diagram), and the study of mathematical equations representing the relationships between variables in the system. These stages are carried out systematically to achieve the stated modeling objectives.
The model was developed using Vensim, a simulation software capable of modeling complex systems. Models, based on real-world system conditions as the basis for simulation, are able to represent system dynamics more accurately. This system dynamics approach is crucial because it allows for a deeper understanding of the processes occurring in real systems.

In its implementation, Vensim is used to listen to system behavior by inputting mathematical equations into the Forrester diagram. Through this process, the model can produce various outputs such as cause-and-effect diagrams, variable behavior graphs, and simulation result tables based on selected variables. Thus, the model is able to provide an overview or prediction of system behavior over a specific time period.

2. Causal Diagram or Dynamic Hypothesis

A causal loop diagram is essentially constructed from a number of variables connected by arrows, which represent the cause-and-effect relationship between those variables. Each arrow is marked with a positive (+) or negative (-) sign to indicate the direction of the independent variable's influence on the dependent variable. A positive (+) sign indicates that a change in the independent variable will be followed by a change in the dependent variable in the same direction, while a negative (-) sign indicates a relationship in the opposite direction. As an illustration, Figure 1 shows the causal relationship between the independent variable "Purchase Orders" and the dependent variable "Supply Channels." A positive relationship means that an increase in the number of purchase orders will lead to an increase in the supply channel, and conversely, a decrease in purchase orders will lead to a decrease in the supply channel. However, if the relationship is in the opposite direction, the arrow is marked with a negative (-) sign to indicate that an increase in the independent variable actually causes a decrease in the dependent variable.

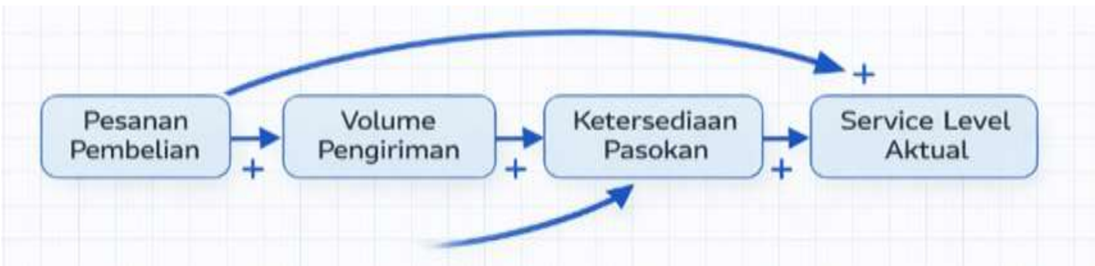

Figure 1. Causal Diagram

It can also be said that the causal loop diagram, within each loop, has a type of circle that rotates in the same direction as the loop in which it is located, this direction of rotation can be clockwise or counterclockwise; Similarly, this type of loop is divided into two types, the first is known as "Snowball or Reinforcement Feedback Loop (positive)" which is a process in which "variable a" reinforces "variable b", and in turn, "variable b" reinforces "variable a", doing this indefinitely, we can see this in Figure 2 and the second is known as "Balanced or Compensation Feedback Loop (negative)" which is a process that tries to achieve the figure, this can be observed in Figure 3, it is worth mentioning that a correctly applied causal loop diagram allows the creation of useful models for studying real systems, since it can decisively help in the planning and operation processes of the intended system, this will later be used to develop the Forrester diagram. One point that needs to be made is that, to complete this paper, the causal diagram from reference (Huaraz & Andrade-arenas (2021); Nazari-Ghanbarloo, (2022) will be used, which we can see in Figure 2.

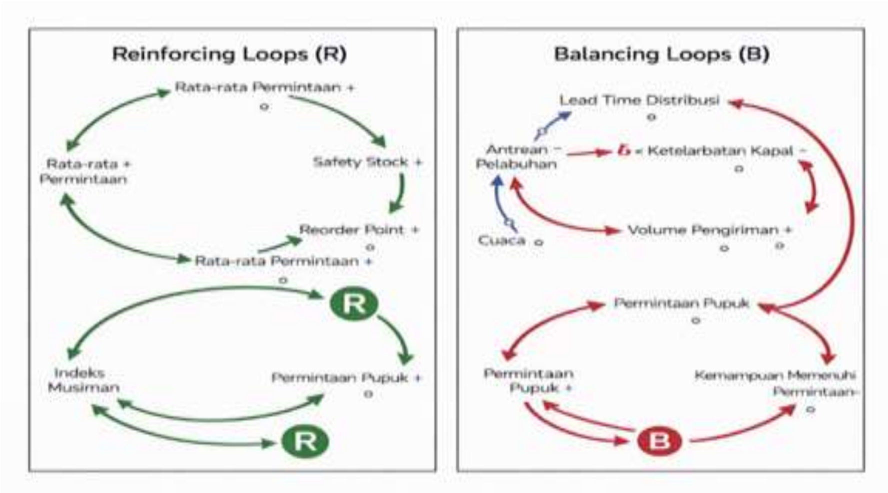

Figure 2. Reinforching Loops and Balancing Loops

3. Model Development (System Dynamics)

The transformation of the Causal Loop Diagram in Figure 4 into the Forrester Diagram form is carried out by adopting all variables and causal relationships identically to maintain the consistency of the system logic. In this modeling, each variable is classified into three main categories, namely stock variables (stock/level) which represent dynamic accumulations whose values change over time based on the difference between inflows and outflows, flow variables which are responsible for regulating the rate of replenishment or reduction in the stock variable, and auxiliary variables (auxiliary/converter) which function as supporting elements to facilitate understanding of the model structure. Determining the type of this variable is very crucial because the stock level can only be modified through the interaction of flow variables, while auxiliary variables play a role in converting information so that the system mechanism is easier to interpret. The development of the Forrester Diagram in this study specifically refers to the framework from reference [12] as illustrated in Figure 5.

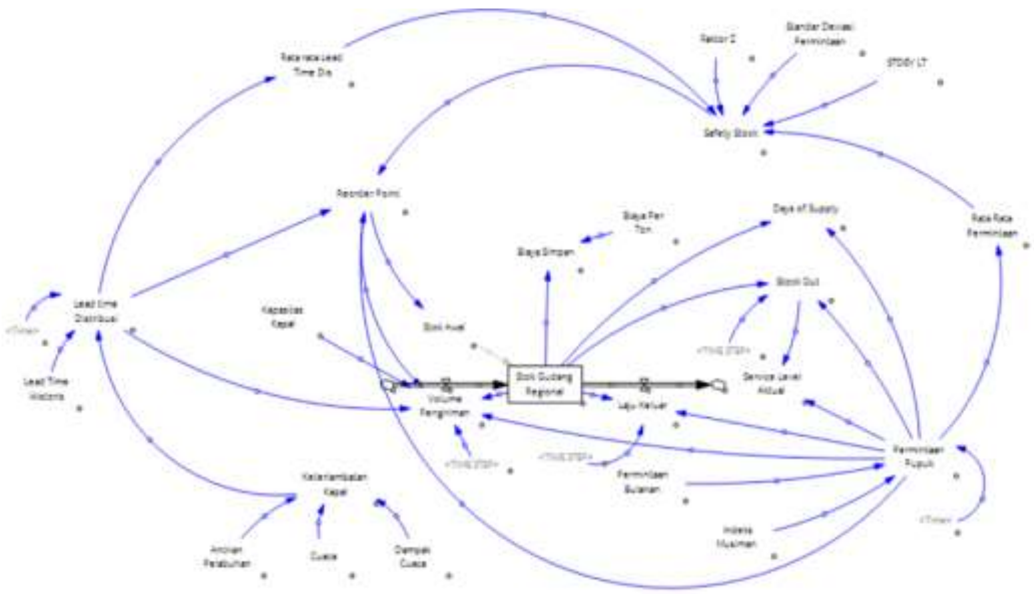

Figure 3. Stock and Flow diagram

4. Mathematical Equations

This section outlines the primary mathematical equations governing the regional fertilizer stock management system dynamics model. The equations are categorized into inventory, logistics, demand, and performance metrics.

1. Inventory and Stock Equations

These equations manage the accumulation of stock in the warehouse and the reorder parameters:

a. **Regional Warehouse Stock (Stok Gudang Regional):** A level variable calculated as the integral of the difference between the inflow (shipment volume) and the outflow (exit rate).

$$Reigional\ warehouse\ stock = \int (shipment\ volume - exit\ rate)\ dt + initial\ St \quad (1)$$

b**. Reorder Point (ROP):** Titik pemesanan ulang dihitung berdasarkan total kebutuhan selama waktu tunggu ditambah stok pengaman

$$Reorder\ point = (Fertilizer\ demand\ x\ lead\ time\ distribution) + Safety\ stock \ (2)$$

c**. Safety Stock (SS):** Dihitung menggunakan standar deviasi permintaan dan *lead time* untuk menghadapi ketidakpastian.

$$Safety\ Stock\ = Z\ factor\ x \sqrt{Avg.\ LT\ Distiribution\ \ x\ Std\ dev\ demand^2}) \ x\ Avg\ demand\ ^2\ x\ Std\ Dev\ LT^2) \quad (3)$$

2. Logistics and Lead Time Equations

These equations model the distribution lead time influenced by external factors:

a**. Distribution Lead Time:** The total time required for distribution, combining historical data and potential vessel delays.

$$Distribution\ lead\ time = historical\ lead\ time + vessel\ delay$$

b**. Vessel Delay (Keterlambatan Kapal):** A variable determined by port queuing times and weather conditions

$$Vessel\ delay = \left(\frac{Port\ queue}{30}\right) + \left(\frac{weather\ x\ weather\ impact}{30}\right) \quad (4)$$

3. Demand and Distribution Flow Equations

These equations regulate how demand is calculated and how stock moves through the system:

a**. Fertilizer Demand (Permintaan Pupuk):** The weekly demand value adjusted by seasonal indices.

$$Fertilizer\ demand = lookup\ extrapolate\ (monthly\ demand, time) \quad (5)$$

b**. Exit Rate (Laju Keluar):** The actual sales realization, limited by the available physical stock in the warehouse.

$$Exit\ rate = min\left(\frac{Regional\ warehouse\ stock}{Time\ step}, Fertilizer\ demand\right) \quad (6)$$

c**. Shipment Volume:** The delivery logic that activates only when stock levels reach or fall below the Reorder Point (ROP).

$$Shipment\ volume =$$
$$IF\ THEN\ ELSE\ (Stock\ ROP\ min(Vessel\ capacity, Lead\ time\ requirement)\ ,0) \quad (7)$$

4. Performance and Cost Metrics

These equations are used to evaluate the effectiveness of the inventory policy:

a**. Actual Service Level:** The proportion of demand successfully met without stockouts.

$$Actual\ service\ level\ = max\ (0, min) + \left(1, 1 - (\frac{Stock\ out}{\max(0.001,\ \ fetelizer\ demand)}\right) \quad (8)$$

b**. Stock Out:** The amount of stock shortage occurring per week.

$$Stock\ out = MAX\left(0, fetelizer\ demand - (\frac{Regional\ warehouse\ stock}{TIME\ STEP}\right) \quad (9)$$

c**. Holding Cost (Biaya Simpan):** The total weekly storage cost based on the actual stock level.

$$Holding\ cost = regional\ warehouse\ stock\ x\ cost\ per\ ton \quad (10)$$

RESULT AND DISCUSSION

This section outlines the research scenario and methodology employed to develop and resolve the study, with a primary focus on the system dynamics modeling approach. An analysis of the trade-off between service level and carrying costs is explored through three different policy scenarios to determine the most effective fertilizer distribution strategy in the Sulawesi region.

1. Safety Stock and Reorder Point Dynamics under Lead Time Uncertainty

The simulation results show that safety stock requirements increase significantly across the scenarios. Scenario 1 produces the lowest safety stock values, ranging from 872.123 to 916.086 units. Scenario 2 increases safety stock to a range of 1120.81–1177.31 units, while Scenario 3 generates the highest buffer inventory between 1587.54 and 1667.56 units. This trend confirms that increasing service level targets requires higher buffer stock to absorb uncertainty caused by vessel delays and extreme weather conditions.

The average safety stock of Scenario 2 is approximately 28% higher than Scenario 1, while Scenario 3 is approximately 42% higher than Scenario 2. This finding is consistent with inventory theory that safety stock increases non-linearly as the Z-factor rises, especially under uncertain lead time conditions

(Nambiar et al., 2019; Kırmızı & Ceylan, 2024). The results also support resilience research arguing that disruption-prone distribution systems require adequate buffering to prevent service collapse (Ivanov & Dolgui, 2021).

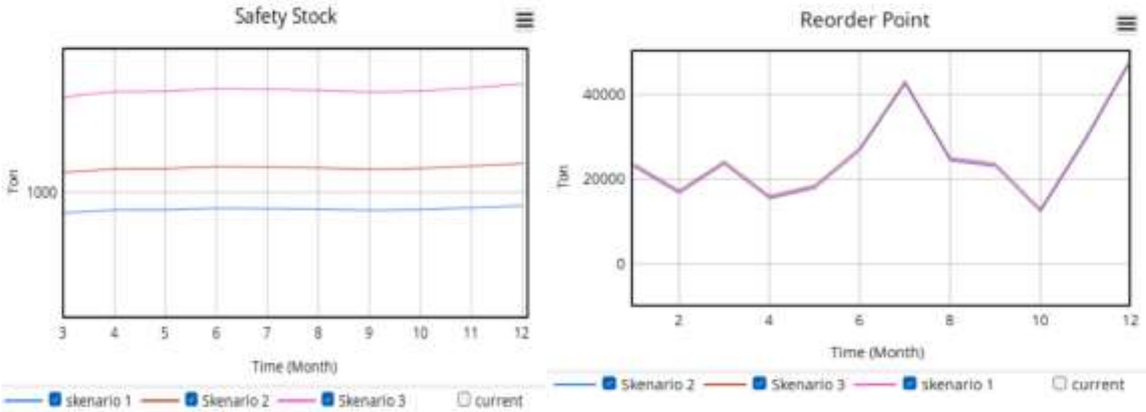

Figure 4. Safety stock and reorder point chart

Table 1. Safety Stock Scenario

Time (Month)	SS : Scenario 1	SS : Scenario 2	SS: Scenario 3
1	877.375	1127.56	1597.1
2	877.375	1127.56	1597.1
3	872.123	1120.81	1587.54
4	890.269	1144.13	1620.57
5	891.511	1145.73	1622.83
6	900.185	1156.88	1638.62
7	898.397	1154.58	1635.36
8	894.744	1149.89	1628.71
9	888.398	1141.73	1617.16
10	892.472	1146.97	1624.58
11	903.409	1161.02	1644.49
12	916.086	1177.31	1667.56

Table 2. Reorder Point Scenario

Time (Month)	RP : Scenario 1	RP : Scenario 2	RP : Scenario 3
1	22932.8	23183	23652.5
2	16633.4	16883.6	17353.1
3	23555	23803.7	24270.4
4	15375.2	15629.1	16105.5
5	17815.6	18069.8	18546.9
6	26697.4	26954.1	27435.9
7	42449.4	42705.6	43186.4
8	24334.8	24590	25068.8
9	23005	23258.4	23733.8
10	12249.8	12504.2	12981.9

Time (Month)	RP : Scenario 1	RP : Scenario 2	RP : Scenario 3
11	29212.2	29469.9	29953.3
12	47802.5	48063.7	48554

In contrast to safety stock, reorder point values exhibit relatively small differences across scenarios. Scenario 1 produces reorder points ranging from 12,249.8 to 47,802.5 units, while Scenario 2 ranges from 12,504.2 to 48,063.7 units and Scenario 3 ranges from 12,981.9 to 48,554 units. The average reorder point differences between Scenario 1 and Scenario 3 remain below 3%, indicating that reorder point is primarily driven by demand volume during lead time rather than by safety stock adjustments.

This suggests that in fertilizer distribution, the demand component dominates reorder point magnitude, while safety stock contributes a smaller incremental portion. Similar findings are reported in supply chain modeling studies, where reorder point is largely determined by demand forecasts and replenishment cycles (Park, 2021). Therefore, the main policy leverage for managing uncertainty in this system lies in safety stock configuration rather than major reorder point restructuring (Nazari-Ghanbarloo, 2022).

2. Holding Cost Comparison Across Scenarios

The holding cost simulation output provides an important economic comparison between scenarios. Scenario 1 generates monthly holding costs ranging from 1.11E+09 to 1.36E+09 IDR, with an average of approximately 1.229E+09 IDR. Scenario 2 produces an average holding cost of around 1.241E+09 IDR, while Scenario 3 results in the highest average holding cost of approximately 1.265E+09 IDR.

Table 3. Holding Cost Point Scenario

Time (Month)	Holding Cost : Scenario 1	Holding Cost: Scenario 2	Holding Cost: Scenario 3
1	1.15E+09	1.16E+09	1.18E+09
2	1.32E+09	1.33E+09	1.35E+09
3	1.25E+09	1.27E+09	1.29E+09
4	1.20E+09	1.21E+09	1.24E+09
5	1.15E+09	1.16E+09	1.19E+09
6	1.11E+09	1.12E+09	1.14E+09
7	1.26E+09	1.28E+09	1.30E+09
8	1.36E+09	1.37E+09	1.39E+09
9	1.26E+09	1.27E+09	1.29E+09
10	1.19E+09	1.20E+09	1.23E+09
11	1.16E+09	1.17E+09	1.20E+09
12	1.34E+09	1.35E+09	1.38E+09

In percentage terms, Scenario 2 increases holding cost by only 0.98% compared to Scenario 1, while Scenario 3 increases holding cost by approximately 2.93% compared to Scenario 1. Although the increase appears relatively small, it represents a substantial cumulative cost burden when projected annually. This finding highlights that inventory policy decisions must be evaluated not only in percentage differences but also in long-term budget accumulation. Such cost-based evaluation is critical for sustainable distribution planning and aligns with supply chain cost-performance frameworks emphasizing economic sustainability (Dai & Tang, 2022; Belhadi et al., 2024).

3. Service Level and Stockout Risk under Disruption Scenarios

The scenario analysis demonstrates that service level targets significantly affect system vulnerability to stockout under lead time disruption. Scenario 1 (Aggressive Buffer) is designed to achieve a 99% service level using a Z-factor of 2.33. This scenario provides the strongest resilience against ship delays up to two weeks and extreme weather disruptions (index 0.3), thereby reducing the probability of stockouts in regional warehouses. Such buffering is consistent with resilience strategies emphasizing redundancy as a mechanism to maintain operational continuity during disruption events (Chen et al., 2022; Belhadi et al., 2024).

Scenario 2 (Balanced Policy) uses a Z-factor of 1.645, targeting a 95% service level. Simulation results indicate that this scenario maintains adequate robustness against average port queue delays of up to three weeks. However, under prolonged extreme weather conditions, service level performance may decrease slightly to around 92%, indicating that forecasting accuracy and early-warning integration become crucial.

Scenario 3 (Lean Logistics) applies a Z-factor of 1.28, targeting a minimum service level of 90%. While lean inventory policies are theoretically intended to reduce costs, the model reveals that this scenario increases vulnerability. Small disruptions in lead time can rapidly drive regional warehouse inventory into critical levels, triggering frequent shortages and emergency replenishment. This reflects disruption amplification behavior similar to the bullwhip effect, where lead time uncertainty escalates instability throughout the supply chain (Ivanov & Dolgui, 2021).

4. Trade-off Analysis: Cost Efficiency vs Distribution Resilience

The results confirm a clear trade-off between cost efficiency and distribution resilience. Scenario 1 provides maximum protection against disruptions, but it requires a larger buffer stock and higher holding cost compared to the baseline. Scenario 3 provides the highest vulnerability, despite being designed as a lean policy, due to the unstable maritime distribution environment in Sulawesi. Scenario 2 offers the most practical compromise, delivering stable service performance while keeping holding cost increases minimal.

This trade-off is consistent with supply chain resilience research, where higher service targets require redundancy and buffer capacity, while overly lean systems are exposed to higher disruption risks and recovery costs (Ivanov &

Dolgui, 2021; Khakdaman et al., 2024). Therefore, Scenario 2 emerges as the optimal strategy for balancing long-term operational sustainability.

CONCLUSIONS AND RECOMMENDATIONS

This study developed a System Dynamics model to analyze safety stock and reorder point policies under lead time uncertainty in fertilizer distribution in Sulawesi. The simulation results confirm that lead time variability caused by vessel delays, port congestion, and extreme weather conditions significantly affects inventory stability and service performance. The model shows that safety stock is highly sensitive to changes in service level targets, increasing by approximately 28% from Scenario 1 to Scenario 2 and by about 42% from Scenario 2 to Scenario 3. In contrast, reorder point values remain relatively stable with variations below 3%, indicating that demand during lead time is the dominant driver of reorder point magnitude.

The holding cost analysis reveals that the financial impact across scenarios is relatively modest, with increases ranging from 0.98% to 2.93%. However, these differences may accumulate into substantial annual costs. Overall, Scenario 2 (Balanced Policy) provides the most feasible trade-off between maintaining fertilizer availability and controlling inventory costs, making it the most suitable policy for long-term implementation in Sulawesi.

Based on the findings, it is recommended that fertilizer distribution stakeholders adopt the Balanced Policy (Scenario 2) as the default inventory strategy. Scenario 1 (Aggressive Buffer) should be applied selectively during peak planting seasons or periods of high disruption risk to ensure maximum service reliability. Scenario 3 (Lean Logistics) should be avoided as a primary policy because it increases vulnerability to stockouts under lead time shocks, potentially triggering costly emergency distribution.

Furthermore, policymakers should integrate real-time monitoring systems such as weather forecasting, port congestion indicators, and vessel schedule tracking into distribution planning. This adaptive approach would enable dynamic adjustment of safety stock levels based on disruption risk, improving supply chain resilience and reducing the probability of fertilizer shortages in rural areas.

FURTHER STUDY

Despite its contributions, this study has several limitations. First, the model assumes relatively stable demand patterns and focuses mainly on lead time uncertainty, while demand fluctuations due to planting cycles, farmer behavior, and government subsidy policies were not modeled in detail. Second, the simulation is based on aggregated regional data, meaning that variations between districts and island clusters in Sulawesi may not be fully represented. Third, the model does not explicitly include transportation capacity constraints, emergency shipment costs, or multi-echelon inventory interactions between central warehouses and local distributors.

Future research should extend this model by incorporating seasonal demand forecasting, multi-echelon inventory structures, and stochastic disruption scenarios. Further studies may also integrate optimization algorithms with System

Dynamics simulation to determine the most cost-effective adaptive safety stock policy. Additionally, combining the model with digital supply chain technologies such as IoT tracking and real-time maritime logistics data would enhance prediction accuracy and decision-making relevance.

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