

INVENTORY MANAGEMENT OF GASOLINE RON 92 AND GASOIL 0,05% SULPHUR WITH MONTE CARLO SIMULATION

Satriyo Hadi Wibowo*, Niniet Indah Arvitrida
Institut Teknologi Sepuluh Nopember, Indonesia
Email: satriyo.hwibowo@gmail.com*

ABSTRACT

Fuel (*BBM*) is a strategic commodity that plays a crucial role in supporting various economic sectors. PT XYZ, one of the fuel suppliers in Timor Leste, faces significant challenges in ensuring a stable and timely supply. Issues such as demand fluctuations, lead time uncertainty, and limited storage capacity often trigger stockout risks and additional operational costs, such as demurrage. In 2023, PT XYZ recorded two stockout events and two potential demurrage occurrences, resulting in financial losses and missed sales opportunities. This study aims to analyze the current performance of inventory and supply chain management for *Gasoline RON 92* and *Gasoil 0.05% Sulphur*. This study adopts a Monte Carlo simulation approach to model the variability of daily demand and lead time more realistically. Three inventory control methods are evaluated: the Min-Max method, the (s,Q) method, and the (s,S) method, across three demand scenarios: normal, +20% increase, and -15% decrease. Key performance indicators analyzed include Economic Order Quantity (*EOQ*), Safety Stock (*SS*), Reorder Point (*ROP*), total cost, and service level. The simulation was conducted over 851 days to reflect actual operational conditions. The results show that the Min-Max method performed best under the low-demand scenario, with the lowest total cost and no stockouts. The (s,Q) method provided the best balance between ordering frequency, operational cost, and service level in the normal demand scenario. Meanwhile, the (s,S) method demonstrated less efficient performance under the high-demand scenario due to higher stockouts and increased holding costs. These findings recommend adopting inventory control strategies that are adaptive to demand dynamics and consider storage capacity limitations to enhance PT XYZ's fuel supply chain efficiency and resilience.

Keywords: *Inventory Management, Monte Carlo Simulation, Stockout Risk, Demurrage Costs*

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INTRODUCTION

One of the big challenges in the fuel supply chain is overcoming stockout. Stockouts not only have an impact on the company's operations, finances, and image, but can also cause a domino effect on the economy at large (Govindan et al., 2018). On the other hand, *demurrage* (costs incurred due to delays in the demolition process) also adds to the burden of the company's operational costs (R. , D. G. G., & C. F. Patriarca, 2020). According to the *Energy Outlook 2023* report, fuel delivery delays due to supply chain inflexibility can increase distribution costs by up to 10–15% per year, especially in regions with limited storage infrastructure (International Energy Agency (IEA), 2023). To manage fluctuating demand and ensure timely availability of fuel, careful and accurate planning is needed in the fuel supply chain. The report also mentions that improving storage infrastructure and improving accuracy in planning can reduce the risk of stockouts by up to 25%.

As one of the companies engaged in fuel supply, PT XYZ faces various significant challenges related to fuel supply chain management. Fuel supply at PT XYZ depends on supply from Singapore and Malaysia with special specifications of *Gasoline RON 92* and

Gasoil 0.05% Sulphur, which are different from the market in Indonesia (Chong, 2017). The main challenge faced is the inflexibility of fuel delivery related to changes in the *Accepted Loading Date (ALD)* and *Accepted Discharge Date (ADD)* schedules (Amico et al., n.d.; Teng, 2020). Every fuel delivery plan must be scheduled exactly one month in advance, and if there is a change in the schedule, it is not easy to do, so it can cause significant delays. The demand planning process is carried out regularly through *Demand Planning* meetings and *Master Program* simulations between the Marketing Function and the Operations Planning Function (SNOP) (Singh et al., n.d.; Verma et al., n.d.).

However, one of the obstacles that is often faced is the considerable deviation between the results of demand planning and sales realization (Jeble et al., 2018). The limited capacity of the storage tanks owned by PT XYZ also sometimes causes *demurrage* when tankers have to wait for the unloading of the entire load (Pujawan et al., 2015; Rodrigues, A., et al. (2010), n.d.). Then, the duration of delivery from Singapore to PT XYZ also takes quite a long time, which is about 7 days under normal weather conditions. Thus, when the realization of sales exceeds the plan, it has the potential to cause critical stock or even stockout, where the fuel stock runs out before the next supply tanker arrives. On the other hand, when the realization of sales is lower than planned, PT XYZ has the potential to bear the cost of *demurrage* due to the delay in the dismantling of tankers that have arrived according to schedule. In 2023, PT XYZ experienced two critical stock incidents (stockouts) and two instances of potential *demurrage* that caused company losses.

In 2023, PT XYZ faced several major challenges related to mismatches between plans and fuel sales realization, which had a direct impact on stock availability and *demurrage* risk. Based on the data of Plan vs. Realization of *Gasoil 0.05% Sulphur* and *Gasoline RON 92* products as shown in the Figure above, there are significant fluctuations in the fulfillment of fuel demand throughout the year. During 2023, there were two critical stock conditions that occurred in May and September. In May, the realization of *Gasoline RON 92* reached 120% of the planned amount, which caused critical stocks. The same thing also happened in September, when sales realization reached 145% of the plan, so at that time there was also a critical stock situation where the realization of fuel sales far exceeded the supply. As a result, PT XYZ experienced distribution disruptions, namely not being able to meet customer needs and losing sales opportunities to achieve revenue targets. This led to significant losses, because the potential income that should have been obtained at that time could not be realized, amounting to USD 242,000 (Mahendra et al., n.d.).

In addition to stockout problems, PT XYZ also faced two potential *demurrage* incidents in the same year. This happened in June 2023 and July 2023, where the realization of fuel sales was under plan. In June 2023, sales realization only reached 89% of the plan, and in July 2023 it only reached 92% of the plan. When the realization of sales is lower than planned, the tanker that has been scheduled to arrive has to wait longer for unloading because the stock in the storage tank is still full, so *demurrage* arises due to waiting ullage. This condition leads to increased operational costs and losses for the company. This imbalance between sales realization and sales planning shows that improvements in the planning process are urgently needed. Improvements in planning methods, stock management, and increased flexibility in the fuel supply chain will be key in reducing the risk of stockouts and *demurrage* in the future.

One of the main challenges faced by PT XYZ in managing the fuel supply chain is the inability to maintain sufficient inventory to meet demand at various distribution points. When there is insufficient inventory, there is a stockout that hinders the smooth distribution of fuel and has an impact on the cessation of energy supply that is urgently needed by vital sectors such as transportation and industry. This condition not only causes financial losses for PT XYZ but also has an impact on the wider community who are highly dependent on the availability of fuel to support daily economic activities. The following are the inventory conditions from the company for *Gasoil 0.05% Sulphur* and *Gasoline RON 92* products. Weaknesses in inventory management have led to two critical stock shortages in 2023, namely in May and September. This condition emphasizes the importance of implementing a more effective inventory control strategy to avoid repeated stock shortages.

In addition to stockout challenges, PT XYZ also faces significant *demurrage* costs due to delays in the fuel loading and unloading process. The company's loss costs arising from *demurrage* claims for the incident amounted to USD 19,825. Mismatches between planned inventory volumes and actual requirements often lead to delays, where tankers have to wait at the dock until ullage is available in the stockpile tank. This problem is caused by a lack of flexibility in storage capacity and suboptimal scheduling in the supply process. Whenever there is a delay in dismantling, the company has to bear additional costs in the form of *demurrage* claims from suppliers, which ultimately increases the overall operational cost burden.

The application of Monte Carlo simulations in this study is essential because it is able to overcome the inherent uncertainty in the management of fuel inventories and distribution processes. With this simulation method, the company can model various scenarios with fluctuating operational variable conditions, thus helping PT XYZ in anticipating and managing stockout and *demurrage* risks more effectively. Monte Carlo simulations provide a probabilistic picture of events that could affect fuel availability, allowing companies to design proactive supply chain strategies to reduce costs and ensure operational efficiency.

In the context of fuel inventory management, especially for *RON 92* and *Gasoil* products, the Monte Carlo simulation method has an important role because it can handle uncertainties in stock control caused by demand variability and shipping constraints. Monte Carlo simulations allow companies to simulate a variety of scenarios with random variables, such as sudden changes in stock requirements or delays in the delivery process. With this approach, companies can gain a deeper understanding of the probability of stockouts or *demurrage*, as well as test various strategies to minimize these risks. In addition, this method supports data-driven decision-making, which can improve inventory efficiency and reduce reliance on excessive safety stocks, thus saving PT XYZ's operational costs overall. Not only that, but the use of Monte Carlo can enable researchers to model broader uncertainties, both in terms of demand variation and wait times, resulting in more accurate estimates of total costs and service levels. R. Patriarca et al. (2022) revealed that Monte Carlo simulations can identify the probability distribution of lead time, so that companies can plan more accurate safety stocks based on the uncertainty of that shipment. Weraikat et al. (2019) stated that the use of Monte Carlo for lead time variability can help reduce the risk of overstock or understock by providing more adaptive predictions of demand fluctuations.

A previous study by R. Patriarca et al. (2022) demonstrated the use of Monte Carlo simulations in identifying the probability distribution of lead time in inventory management. They suggested that these simulations could be used to improve safety stock planning by accounting for uncertainties in shipment times. While their research highlights the potential of Monte Carlo simulations for managing lead time variability, it does not specifically address how these simulations can be used to reduce stockout risks in industries with highly volatile demand, such as fuel supply chains. This gap is addressed by the present study, which applies Monte Carlo simulations to model fuel stockouts and *demurrage* risks, offering more tailored solutions for managing uncertainties in fuel inventory and distribution, where demand fluctuation and supply delays are more pronounced (Castano & Amengual, 2020).

The primary goal of this research is to analyze the current performance of inventory and supply chain management for *Gasoline RON 92* and *Gasoil 0.05% Sulphur*, and to develop an optimal inventory policy to reduce stockout and *demurrage* risks. The study's practical benefits include providing PT XYZ with strategies to minimize operational costs and enhance the fuel supply's efficiency and stability. Academically, it contributes to the literature by integrating Monte Carlo simulations into fuel supply chain management, offering new insights for improving inventory control in energy logistics

METHOD

This study adopts a Monte Carlo simulation approach to model the variability of daily demand and lead time more realistically. The research flowchart in Figure 1 provides a comprehensive overview of the stages involved in the fuel supply chain management analysis process at PT XYZ. This diagram integrates the Monte Carlo simulation approach with inventory management methods—Economic Order Quantity (*EOQ*), Safety Stock (*SS*), and Reorder Point (*ROP*)—to address demand fluctuations that often trigger stockout risks and *demurrage* costs (Banthao et al., n.d.).

The methodology begins by quantifying historical demand patterns and lead time variability for *Gasoline RON 92* and *Gasoil 0.05% Sulphur*. Using probabilistic distributions derived from real-world data, the Monte Carlo simulation generates thousands of potential scenarios to evaluate the performance of three inventory control strategies: the Min-Max method, the (s,Q) method, and the (s,S) method (Waller et al., 2013). These strategies are tested under three demand scenarios: normal, +20% increase, and -15% decrease. Key metrics such as total costs (holding, ordering, and *demurrage*), service levels, and stockout frequencies are analyzed to identify optimal policies.

The flowchart emphasizes iterative refinement, where simulation outcomes inform adjustments to safety stock levels, reorder points, and order quantities. By aligning inventory decisions with probabilistic demand and supply forecasts (Cedolin et al., n.d.), PT XYZ can mitigate risks associated with storage limitations and volatile market conditions. This approach not only enhances operational resilience but also supports data-driven decision-making to balance cost efficiency and service reliability in Timor Leste's fuel supply chain (Kurniawan et al., 2022).

The stages in the diagram begin with identifying the company's challenges and culminate in implementing an optimal inventory management strategy. Each stage addresses specific fuel

supply chain constraints, from resolving mismatches between planning and demand realization to adjusting storage capacity to prevent excessive operational costs.

During the data collection stage, relevant information—including monthly demand, lead time, storage costs, and booking costs—is gathered to establish an accurate foundation for calculating *Economic Order Quantity (EOQ)*, *Safety Stock (SS)*, and *Reorder Point (ROP)*. These calculations are then tested via Monte Carlo simulations to model various demand fluctuation scenarios. This simulation phase evaluates the sensitivity of forecasting and stock management to demand variability, ensuring strategies are robustly prepared for uncertainty. The final stage involves implementing and evaluating the derived strategy, enabling PT XYZ to achieve efficient fuel stock management and distribution.

The study utilizes secondary data for inventory management analysis and supply chain optimization. Below is a detailed breakdown of the data types and sources:

Table 1. Data Types and Their Sources

Yes	Data Type	Data Source
1	Historical Data on Fuel Demand	Sales, distribution, internal reports of PT XYZ
2	Data Lead Time	Logistics department, transportation management system (TMS)
3	Inventory Data (Fuel Stocks)	PT XYZ INVENTORY MANAGEMENT SYSTEM (ERP, IMS)
4	Operational Cost and Demurrage Data	Financial statements, logistics and finance department of PT XYZ
5	Fuel Price and Cost Data	Procurement Department of PT XYZ

This stage involves analyzing data to optimize PT XYZ’s fuel supply chain management by reducing *stockout* risks and *demurrage* costs caused by unpredictable demand fluctuations. Key steps include calculating *Economic Order Quantity (EOQ)*, *Safety Stock (SS)*, and *Reorder Point (ROP)* to establish inventory benchmarks, followed by *Monte Carlo simulations* to test strategy resilience against demand variability. These simulations model diverse scenarios—such as sudden demand spikes or drops—to identify vulnerabilities in current protocols, enabling PT XYZ to refine order quantities, safety buffers, and replenishment schedules. By integrating probabilistic forecasting with inventory optimization, the analysis provides actionable insights to balance cost efficiency and service reliability while mitigating operational risks.

RESULTH AND DISCUSSION

Company Description

PT XYZ gets regular fuel supply from Singapore for Gasoline RON 92 and Gasoil 0.05% S products using tanker mode. However, in emergency conditions, PT XYZ gets alternative supplies from Indonesia, namely from Kupang and Atapupu using tank car mode. Fuel imported from Singapore is stored in the storage tank of the PT XYZ Fuel Terminal. From the data on the realization of fuel supply using the tanker mode above, the smallest total supply volume (Gasoline RON 92 and Gasoil 0.05% S) per shipment is 3,156,747 liters and the largest supply volume per shipment is 5,500,971 liters. The fuel is then stored in storage tanks, then then distributed to consumers, both owned petrol stations, private petrol stations and industrial consumers. The distribution of fuel to consumers is mostly carried out using tank car modes

for petrol station and small industry consumers, but for large industrial consumers it is carried out using barge modes. The distribution of Gasoline RON 92 fuel is the lowest at 1,958,000 liters per month and the highest at 3,729,880 liters per month. As for the distribution of Gasoil 0.05% S fuel, the lowest is at 1,219,200 liters per month and the highest at 3,348,890 liters per month.

Simulated Demand Scenarios

After determining the basic parameters of the inventory system such as EOQ, Safety Stock, and Reorder Point (ROP), the next stage is to conduct a monte carlo simulation of the implementation of inventory control strategies in various demand conditions. This simulation aims to evaluate the performance of three stock control methods, namely Min-Max, (s,Q), and (s,S), in maintaining the availability of RON 92 Gasoline and 0.05% S Gasoil fuel at PT XYZ's storage facility. Each method was tested in three different scenarios, namely the normal demand scenario (based on historical actual data), the high demand scenario (+20% of the average daily demand), and the low demand scenario (−15% of the average daily demand). This approach is carried out to test the sensitivity of each method to demand fluctuations that may occur in fuel distribution operations. This simulation will be carried out to project a total of 852 days based on historical data and then the results will be analyzed.

In the monte Carlo simulation, each method will be evaluated based on a number of key performance indicators, namely the number of days of stockout, the number of orders placed, the average daily stock, and the total cost, which consists of the cost of ordering and storage costs. The simulation results will be compared between methods and between scenarios for each fuel product, in order to identify the most effective and efficient method in answering the dynamics of needs in the field.

It should be emphasized that the data presented in this report, particularly in the form of daily simulation tables, are only a snapshot of the simulation results for the first 30 days as an initial representation of the inventory system's response to each scenario and control method. This view aims to provide a more concrete and easy-to-understand picture of the reorder flow, stock changes, and the potential for stockouts during daily operational periods.

Nevertheless, in practice, a thorough inventory system simulation is carried out for a long-term projection of 852 days based on actual demand data obtained from 2022 to 2024. The entire evaluation of the method's performance—including the total number of orders, the number of stockout days, the average daily stock, and the calculation of the total cost—was generated from the full simulation process over the course of 852 days.

Scenario 1: Normal Demand

The first scenario in this simulation uses actual historical data from 2022 to 2024 as a representation of normal demand conditions. This data reflects the daily distribution pattern of Gasoline RON 92 and Gasoil 0.05% S as occurred in PT XYZ's real operations, without any modifications or projections of increasing or decreasing demand. The purpose of this scenario is to evaluate the performance of each inventory control method under stable demand conditions and reflect the day-to-day operational conditions. Simulations were carried out to determine the level of cost efficiency, frequency of orders, risk of stock shortages, and average inventory availability under basic conditions before being tested in extreme scenarios. The full

simulation results that will be shown in this report are only for Gasoline RON 92 products while Gasoil 0.05% S can be seen in Appendix 6. The results of the comparison of the two products will be presented in the next section. The following are the simulation results for scenario 1 with the min-max method.

Simulation of the Min-Max (s,S) method for 30 days under normal demand conditions shows that the stock control mechanism works dynamically based on daily demand fluctuations. At the beginning of the simulation, the initial stock of 1,401,470 liters experienced a gradual decline as daily demand was met. From day 1 to day 12, the system is still able to meet demand without experiencing stockouts. However, since the 13th day, the stock has started to touch the reorder point (ROP) level, and on the 17th day the stock has touched a critical point.

New orders do not come immediately due to lead time. This causes stockout to occur from day 17 to day 24, indicated by the Stockout column with a value of 1. This signifies that during that period the demand cannot be met due to depletion of stock or insufficient supply. The new order was finally shipped and received on the 25th day with a volume of 2,600,000 liters, which is the maximum level (S) value of the Min-Max method. Once the supply came in, the stock increased significantly and was again able to meet daily demand for the remainder of the simulation period without experiencing further stockouts.

Method simulation (s,Q) for 30 days with normal daily demand data shows the dynamics of stock management that depends on the reorder point/s trigger. At the beginning of the simulation period, the initial stock of 1,401,470 liters gradually decreased in line with the fulfillment of fluctuating daily demand.

The system uses logic (s,Q), which triggers a fixed amount of reorders (Q) whenever the stock touches or is below the limit of the Reorder Point(s). In this simulation, the order is placed on the 1st day, but because this method uses a lead time that resembles real conditions, the order does not go directly into stock. It is noted that orders placed on the first day are only received on the 30th day, as shown in the "Incoming Orders" column which is worth 2,600,000 liters, and the "Incoming Order Day" column shows the number 56 (meaning that it was previously calculated to enter after a certain lead time). Then the following are the results for scenario 1 normal with the (s,S) method.

Table 2. Si mulation of Normal Scenarios with Method (s,S)

Da y	Demand	Inco ming Orde r	Initial Stock	Final Stock	Sent order	Order Day Coming In	Active Order Status	Stockou t
1	64343,810 36	0	1401470, 436	1337126,6 26	YA	28	ACTIVE	NO
2	80970,255 19	0	1337126, 626	1256156,3 71	NO	-	ACTIVE	NO
3	39396,569 61	0	1256156, 371	1216759,8 01	NO	-	ACTIVE	NO
4	72293,127 91	0	1216759, 801	1144466,6 73	NO	-	ACTIVE	NO
5	173372,00 07	0	1144466, 673	971094,67 24	NO	-	ACTIVE	NO

Day	Demand	Incoming Order	Initial Stock	Final Stock	Sent order	Order Day Coming In	Active Order Status	Stockout
6	23318,667 42	0	971094,6 724	947776,00 49	NO	-	ACTIVE	NO
7	133897,13 61	0	947776,0 049	813878,86 88	NO	-	ACTIVE	NO
8	0	0	813878,8 688	813878,86 88	NO	-	ACTIVE	NO
9	94935,907 74	0	813878,8 688	718942,96 11	NO	-	ACTIVE	NO
10	129884,29 68	0	718942,9 611	589058,66 43	NO	-	ACTIVE	NO
11	128897,77 6	0	589058,6 643	460160,88 83	NO	-	ACTIVE	NO
12	122400,21 98	0	460160,8 883	337760,66 85	NO	-	ACTIVE	NO
13	39806,230 63	0	337760,6 685	297954,43 79	NO	-	ACTIVE	NO
14	85237,022 43	0	297954,4 379	212717,41 55	NO	-	ACTIVE	NO
15	643,33351 19	0	212717,4 155	212074,08 2	NO	-	ACTIVE	NO
16	123798,28 61	0	212074,0 82	88275,795 86	NO	-	ACTIVE	NO
17	106781,81 9	0	88275,79 586	0	NO	-	ACTIVE	YES
18	80352,608 86	0	0	0	NO	-	ACTIVE	YES
19	61412,299 62	0	0	0	NO	-	ACTIVE	YES
20	62678,196 52	0	0	0	NO	-	ACTIVE	YES
21	125924,05 39	0	0	0	NO	-	ACTIVE	YES
22	100977,04 02	0	0	0	NO	-	ACTIVE	YES
23	0	0	0	0	NO	-	ACTIVE	NO
24	125069,54 06	0	0	0	NO	-	ACTIVE	YES
25	113395,51 13	0	0	0	NO	-	ACTIVE	YES
26	0	0	0	0	NO	-	ACTIVE	NO
27	53029,650 17	0	0	0	NO	-	ACTIVE	YES
28	147379,41 98	2600 000	2600000	2452620,5 8	YA	49	ACTIVE	NO
29	194772,90 29	0	2452620, 58	2257847,6 77	NO	-	ACTIVE	NO
30	53026,687 59	0	2257847, 677	2204820,9 9	NO	-	ACTIVE	NO

A 30-day simulation method (s,S) illustrates how the inventory control system works when demand varies daily. In this method, orders are placed when the stock touches or is below

the reorder point (ROP), and the order volume is intended to replenish inventory until it reaches the maximum level (S). At the beginning of the simulation, the initial stock of 1,401,470 liters continued to decline in response to the meeting of daily demand. When the stock is below the ROP, the system triggers a reorder on the 1st day. However, because the system applies lead times that resemble real conditions in the field—that is, lead times that can vary due to operational and logistical factors—orders are not immediately accepted. Based on this simulation, orders sent on day 1 only come in on day 28. During the waiting period for the arrival of orders, the stock continued to decline and reached the point of exhaustion on the 17th day, which led to 11 consecutive days of stockouts (17th to 27th days). The system's inability to meet demand in that period is illustrated by the "Stockout?" column marked YES.

Scenario 2: High Demand (+20%)

The second scenario was designed to simulate operational conditions at a time of 20% increase in demand compared to the actual average daily demand. This scenario is designed to test the resilience and responsiveness of the inventory control system to significant spikes in demand, which can occur due to various factors such as seasonal increases in consumption, supply disruptions in other regions, or government policies that encourage the consumption of certain fuels. By increasing the demand parameters by 20%, this simulation is an important tool to assess how effective the Min-Max, (s,Q), and (s,S) methods are in maintaining stock availability levels and preventing stockouts under high load conditions.

Table 3. Simulation of +20% Demand Scenario with Min-Max Method

Day	Demand	Initial stock	Incoming Order	Final stock	Stockout
1	77212,57	1401470	0	1324258	0
2	97164,31	1324258	0	1227094	0
3	47275,88	1227094	0	1179818	0
4	86751,75	1179818	0	1093066	0
5	208046,4	1093066	0	885019,5	0
6	27982,4	885019,5	0	857037,1	0
7	160676,6	857037,1	0	696360,6	0
8	0	696360,6	0	696360,6	0
9	113923,1	696360,6	0	582437,5	0
10	155861,2	582437,5	0	426576,3	0
11	154677,3	426576,3	0	271899	0
12	146880,3	271899	0	125018,7	0
13	47767,48	125018,7	0	77251,24	0
14	102284,4	77251,24	0	0	1
15	772,0002	0	0	0	1
16	148557,9	0	0	0	1
17	128138,2	0	0	0	1
18	96423,13	0	0	0	1
19	73694,76	0	0	0	1
20	75213,84	0	0	0	1
21	151108,9	0	0	0	1
22	121172,4	0	0	0	1

Day	Demand	Initial stock	Incoming Order	Final stock	Stockout
23	0	0	0	0	1
24	150083,4	0	0	0	1
25	136074,6	0	2600000	2463925	0
26	0	2463925	0	2463925	0
27	63635,58	2463925	0	2400290	0
28	176855,3	2400290	0	2223435	0
29	233727,5	2223435	0	1989707	0
30	63632,03	1989707	0	1926075	0

A 30-day simulation using the Min-Max method (s,S) under conditions of increased demand by 20% showed that the stock control system faced greater pressure than normal conditions. At the beginning of the simulation, the initial stock of 1,401,470 liters began to dwindle rapidly due to the relatively high demand in the early days, as seen on day 5 which recorded the highest daily demand of 208,046 liters.

The Min-Max system works with a reorder mechanism when the stock touches the reorder point (Reorder Point/s), with the quantity replenished until it reaches the maximum level (S). In this simulation, the system detects that the stock has been below the order point on day 1, so the order is shipped immediately. However, because the simulation uses a lead time that resembles real conditions (i.e. variable lead time), a new order entered the system on the 25th day of 2,600,000 liters. As a result of this waiting time, there was a long stockout, namely for 13 consecutive days from the 13th day to the 25th. The period shows that the system cannot meet demand due to delays in stock fulfillment. Column "Stockout"

Table 4. Simulation of +20% Demand Scenario with Method (s,Q)

Da y	Demand	Incomi ng Order	Initial Stock	Final Stock	Sent order	Order Day Coming In	Active Order Status	Stoc kout
1	77212,57 243	0	1401470 ,436	1324257 ,864	YES	23	AKTIF	NO
2	97164,30 623	0	1324257 ,864	1227093 ,557	NO	-	AKTIF	NO
3	47275,88 353	0	1227093 ,557	1179817 ,674	NO	-	AKTIF	NO
4	86751,75 349	0	1179817 ,674	1093065 ,92	NO	-	AKTIF	NO
5	208046,4 008	0	1093065 ,92	885019, 5196	NO	-	AKTIF	NO
6	27982,40 09	0	885019, 5196	857037, 1187	NO	-	ACTIVE	NO
7	160676,5 633	0	857037, 1187	696360, 5554	NO	-	ACTIVE	NO
8	0	0	696360, 5554	696360, 5554	NO	-	ACTIVE	NO
9	113923,0 893	0	696360, 5554	582437, 4661	NO	-	ACTIVE	NO
10	155861,1 561	0	582437, 4661	426576, 31	NO	-	ACTIVE	NO

Da y	Demand	Incomi ng Order	Initial Stock	Final Stock	Sent order	Order Day Coming In	Active Order Status	Stoc kout
11	154677,3 312	0	426576, 31	271898, 9788	NO	-	ACTIVE	NO
12	146880,2 638	0	271898, 9788	125018, 715	NO	-	ACTIVE	NO
13	47767,47 676	0	125018, 715	77251,2 3826	NO	-	ACTIVE	NO
14	102284,4 269	0	77251,2 3826	0	NO	-	ACTIVE	YES
15	772,0002 143	0	0	0	NO	-	ACTIVE	YES
16	148557,9 433	0	0	0	NO	-	ACTIVE	YES
17	128138,1 828	0	0	0	NO	-	ACTIVE	YES
18	96423,13 063	0	0	0	NO	-	ACTIVE	YES
19	73694,75 955	0	0	0	NO	-	ACTIVE	YES
20	75213,83 583	0	0	0	NO	-	ACTIVE	YES
21	151108,8 646	0	0	0	NO	-	ACTIVE	YES
22	121172,4 483	0	0	0	NO	-	ACTIVE	YES
23	0	260000 0	2600000	2600000	YES	45	ACTIVE	NO
24	150083,4 488	0	2600000	2449916 ,551	NO	-	ACTIVE	NO
25	136074,6 136	0	2449916 ,551	2313841 ,938	NO	-	ACTIVE	NO
26	0	0	2313841 ,938	2313841 ,938	NO	-	ACTIVE	NO
27	63635,58 02	0	2313841 ,938	2250206 ,357	NO	-	ACTIVE	NO
28	176855,3 038	0	2250206 ,357	2073351 ,054	NO	-	ACTIVE	NO
29	233727,4 835	0	2073351 ,054	1839623 ,57	NO	-	ACTIVE	NO
30	63632,02 51	0	1839623 ,57	1775991 ,545	NO	-	ACTIVE	NO

A 30-day method (s,Q) simulation at a demand increase of 20% showed how the fixed order (Q) system responded to the increase in the daily consumption load. At the beginning of the period, the system started with a stock of 1,401,470 liters, which began to gradually decline due to the fulfillment of higher-than-normal demand, as seen on the 5th and 6th days with the demand exceeding 200,000 liters per day.

The (s,Q) system works by logic: orders of a fixed amount Q are sent whenever the stock touches or is below the reorder point (ROP). In this simulation, the order trigger occurs on day 1, as recorded in the "Order Shipped?" column which is YES, and the system sets the order day

to be entered on day 23. This reflects the use of lead time that resembles real conditions, where the time lag between an order and the arrival of a supply can be variable.

However, due to the long lead time, there was a stockout that started on the 14th day and lasted until the 22nd day, a total of 9 consecutive stockout days. This can be seen from the "Stockout?" column which is valued YES in that period, indicating the system's inability to meet demand due to delays in incoming orders.

Table 5. Simulation of +20% Demand Scenario with Method (s,S)

Day	Demand	Initial stock	Incoming Order	Final stock	Stockout	Day
1	133,733.56	2,500,000.00	-	2,366,266.44	FALSE	TRUE
2	93,550.22	2,366,266.44	-	2,272,716.22	FALSE	FALSE
3	143,287.67	2,272,716.22	-	2,129,428.54	FALSE	FALSE
4	198,681.90	2,129,428.54	-	1,930,746.65	FALSE	FALSE
5	87,482.07	1,930,746.65	-	1,843,264.57	FALSE	FALSE
6	87,483.11	1,843,264.57	-	1,755,781.46	FALSE	FALSE
7	202,237.32	1,755,781.46	-	1,553,544.14	FALSE	FALSE
8	150,865.57	1,553,544.14	-	1,402,678.57	FALSE	FALSE
9	72,590.25	1,402,678.57	-	1,330,088.31	FALSE	FALSE
10	136,634.83	1,330,088.31	-	1,193,453.49	FALSE	FALSE
11	72,973.54	1,193,453.49	-	1,120,479.95	FALSE	FALSE
12	72,827.22	1,120,479.95	-	1,047,652.72	FALSE	FALSE
13	117,612.10	1,047,652.72	-	930,040.63	FALSE	FALSE
14	- 18,778.11	930,040.63	-	948,818.74	FALSE	FALSE
15	- 6,857.98	948,818.74	-	955,676.72	FALSE	FALSE
16	66,716.76	955,676.72	-	888,959.96	FALSE	FALSE
17	38,205.01	888,959.96	-	850,754.95	FALSE	FALSE
18	122,186.51	850,754.95	-	728,568.43	FALSE	FALSE
19	44,837.51	728,568.43	-	683,730.92	FALSE	FALSE
20	12,925.18	683,730.92	-	670,805.74	FALSE	FALSE
21	195,050.65	670,805.74	-	475,755.09	FALSE	FALSE
22	88,012.20	475,755.09	-	387,742.89	FALSE	FALSE
23	106,573.39	387,742.89	-	281,169.50	FALSE	FALSE
24	12,137.66	281,169.50	-	269,031.84	FALSE	FALSE
25	67,849.83	269,031.84	-	201,182.01	FALSE	FALSE
26	109,319.51	534,915.57	333,733.56	425,596.06	FALSE	TRUE
27	29,461.67	425,596.06	-	396,134.39	FALSE	FALSE
28	126,075.30	396,134.39	-	270,059.09	FALSE	FALSE
29	64,289.78	270,059.09	-	205,769.31	FALSE	FALSE
30	83,840.74	205,769.31	-	121,928.56	FALSE	FALSE

A 30-day simulation of the method (s,S) or Min-Max under conditions of increased demand by 20% shows that the inventory control system is able to maintain stock availability quite effectively, despite higher than usual demand pressures.

At the beginning of the period, the system started with a stock of 1,401,470 liters, which began to gradually decrease as the daily demand was met with relatively high demand—especially on day 5 which recorded a demand of more than 208,000 liters. When the stock

touches the reorder point (ROP), the system automatically triggers a reorder on day 1, as indicated in the "Order Shipped?" column which is YES, and the system schedules incoming orders on day 18. It reflects the application of lead time that resembles real conditions, which takes into account variations in the time of arrival of supplies based on field conditions.

The system managed to maintain stock availability until the 14th day, but started experiencing stockouts for 3 consecutive days (15th to 17th day), marked by a "Stockout?" column with a value of YES. This happens because the stock is completely out of stock ahead of the order coming in. An order of 2,600,000 liters finally came in on the 18th day, replenishing stocks to 2,503,576 liters and restoring fuel availability.

Scenario 3: Low Demand (–15%)

The third scenario in this simulation is designed to represent operational conditions when there is a 15% decrease in demand from the actual average demand. Just like the previous scenarios, the simulated inventory control methods include Min-Max, (s,Q), and (s,S), using pre-calculated EOQ, Safety Stock, and ROP parameters. The difference lies in the adjusted daily demand volume dropping by 15% to test how the system responds to oversupply or potential overstock conditions.

The presentation structure in this section follows the previous pattern, which is to show the first 30 days of simulation footage for each method. However, given that the characteristics of low demand conditions are more relevant to be analyzed as a whole to cost efficiency and overstock risk, the discussion of the results of this scenario will be presented comparatively in the next section, along with the evaluation between methods and scenarios.

Table 6. Demand Scenario Simulation -15% with Min-Max Method

Day	Demand	Initial stock	Incoming Order	Final stock	Stockout
1	54.692,24	1.401.470,44	0	1.346.778,20	0
2	68.824,72	1.346.778,20	0	1.277.953,48	0
3	33.487,08	1.277.953,48	0	1.244.466,40	0
4	61.449,16	1.244.466,40	0	1.183.017,24	0
5	147.366,20	1.183.017,24	0	1.035.651,04	0
6	19.820,87	1.035.651,04	0	1.015.830,17	0
7	113.812,57	1.015.830,17	0	902.017,60	0
8	-	902.017,60	0	902.017,60	0
9	80.695,52	902.017,60	0	821.322,08	0
10	110.401,65	821.322,08	0	710.920,43	0
11	109.563,11	710.920,43	0	601.357,32	0
12	104.040,19	601.357,32	0	497.317,13	0
13	33.835,30	497.317,13	0	463.481,84	0
14	72.451,47	463.481,84	0	391.030,37	0
15	546,83	391.030,37	0	390.483,54	0
16	105.228,54	390.483,54	0	285.254,99	0
17	90.764,55	285.254,99	0	194.490,45	0
18	68.299,72	194.490,45	0	126.190,73	0
19	52.200,45	126.190,73	0	73.990,27	0

Day	Demand	Initial stock	Incoming Order	Final stock	Stockout
20	53.276,47	73.990,27	0	20.713,81	0
21	107.035,45	20.713,81	0	-	1
22	85.830,48	-	0	-	1
23	-	-	0	-	1
24	106.309,11	-	0	-	1
25	96.386,18	-	2600000	2.503.613,82	0
26	-	2.503.613,82	0	2.503.613,82	0
27	45.075,20	2.503.613,82	0	2.458.538,61	0
28	125.272,51	2.458.538,61	0	2.333.266,11	0
29	165.556,97	2.333.266,11	0	2.167.709,14	0
30	45.072,68	2.167.709,14	0	2.122.636,45	0

Simulation of a low demand scenario of –15% conducted using the Min-Max method over a 30-day period shows that this inventory control policy is able to maintain overall stock availability well, but there are still some critical points that require attention. At the beginning of the simulation, the inventory level was in adequate condition with an initial stock of 1,401,470 liters. As the simulation progresses, the stock gradually decreases according to the daily demand pattern. This decrease in stock does not immediately trigger a reorder, because the stock is still above the minimum reorder point/s.

However, from the 13th to the 24th day, there was a stockout condition which was characterized by the absence of stock left to meet daily demand. This is due to delays in responding to stock declines until they reach the reorder point, while delivery lead times have not been able to compensate for urgent needs. In total, there are 12 consecutive stockout days, which indicates that even though demand is falling, order triggers are too slow in responding to consumption realization. The recovery of new stocks occurred on the 25th day, with incoming orders of 2,600,000 liters, which is the maximum allowable capacity of tanks. After this replenishment, the rest of the simulation runs with stock in safe condition, without any additional stockouts.

Table 7. Simulation of a -15% Demand Scenario with the Method (s,Q)

Day	Demand	Incoming Order	Initial Stock	Ending Stock	Shipped Order	Day of Incoming Order	Stock out
1	54.692,24	-	1.401.470,44	1.346.778,20	YES	29	NO
2	68.824,72	-	1.346.778,20	1.277.953,48	NO	-	NO
3	33.487,08	-	1.277.953,48	1.244.466,40	NO	-	NO
4	61.449,16	-	1.244.466,40	1.183.017,24	NO	-	NO
5	147.366,20	-	1.183.017,24	1.035.651,04	NO	-	NO

Da y	Demand	Incoming Order	Initial Stock	Ending Stock	Shipped Order	Day of Incoming Order	Stock out
6	19.820,87	-	1.035.651, 04	1.015.830, 17	NO	-	NO
7	113.812,5 7	-	1.015.830, 17	902.017,60	NO	-	NO
8	-	-	902.017,60	902.017,60	NO	-	NO
9	80.695,52	-	902.017,60	821.322,08	NO	-	NO
10	110.401,6 5	-	821.322,08	710.920,43	NO	-	NO
11	109.563,1 1	-	710.920,43	601.357,32	NO	-	NO
12	104.040,1 9	-	601.357,32	497.317,13	NO	-	NO
13	33.835,30	-	497.317,13	463.481,84	NO	-	NO
14	72.451,47	-	463.481,84	391.030,37	NO	-	NO
15	546,83	-	391.030,37	390.483,54	NO	-	NO
16	105.228,5 4	-	390.483,54	285.254,99	NO	-	NO
17	90.764,55	-	285.254,99	194.490,45	NO	-	NO
18	68.299,72	-	194.490,45	126.190,73	NO	-	NO
19	52.200,45	-	126.190,73	73.990,27	NO	-	NO
20	53.276,47	-	73.990,27	20.713,81	NO	-	NO
21	107.035,4 5	-	20.713,81	-	NO	-	YES
22	85.830,48	-	-	-	NO	-	YES
23	-	-	-	-	NO	-	NO
24	106.309,1 1	-	-	-	NO	-	YES
25	96.386,18	-	-	-	NO	-	YES
26	-	-	-	-	NO	-	NO
27	45.075,20	-	-	-	NO	-	YES

Da y	Demand	Incoming Order	Initial Stock	Ending Stock	Shipped Order	Day of Incoming Order	Stock out
28	125.272,5 1	-	-	-	NO	-	YES
29	165.556,9 7	2.600.000,0 0	2.600.000, 00	2.434.443, 03	YES	53	NO
30	45.072,68	-	2.434.443, 03	2.389.370, 35	NO	-	NO

Simulation of low demand scenario (–15%) using the method (s,Q) for 30 days showed that the inventory control system was able to manage stock availability in a relatively stable manner, with only two days of stockout, namely on the 22nd and 24th days. This indicates that the method (s,Q) can still work effectively even under conditions of declining demand, provided that the parameters of the order point(s) and the order quantity (Q) are precisely set.

At the beginning of the simulation, the system had an initial stock of 1,401,470 liters, which gradually decreased with the pace of daily demand. The order point(s) in this scenario is used as a reference to trigger a shipment when the stock is close to the minimum level. Orders of 2,600,000 liters (maximum tank capacity limit) only occurred on the 25th day and were received on the 29th day, following the actual lead time.

This delay in delivery causes stockouts that occur for two days before the order is received. This shows that although the method (s,Q) has been quite efficient in terms of cost and frequency of orders, there is a need for further evaluation of the determination of order points in order to still take into account variations in demand and lead time to avoid supply gaps. After the order came in on the 29th day, the system again had a large amount of inventory of 2,434,443 liters and was able to serve the demand for the rest of the period without experiencing any more vacancies.

Table 8. Demand Scenario Simulation -15% with (s,S) Method

Day	Demand	Incoming Order	Initial Stock	Ending Stock	Shipped Order	Day of Incoming Order	Stockout
1	54.692,24	-	1.401.470,44	1.346.778,20	YES	30	NO
2	68.824,72	-	1.346.778,20	1.277.953,48	NO	-	NO
3	33.487,08	-	1.277.953,48	1.244.466,40	NO	-	NO
4	61.449,16	-	1.244.466,40	1.183.017,24	NO	-	NO
5	147.366,20	-	1.183.017,24	1.035.651,04	NO	-	NO
6	19.820,87	-	1.035.651,04	1.015.830,17	NO	-	NO
7	113.812,57	-	1.015.830,17	902.017,60	NO	-	NO
8	-	-	902.017,60	902.017,60	NO	-	NO
9	80.695,52	-	902.017,60	821.322,08	NO	-	NO
10	110.401,65	-	821.322,08	710.920,43	NO	-	NO
11	109.563,11	-	710.920,43	601.357,32	NO	-	NO
12	104.040,19	-	601.357,32	497.317,13	NO	-	NO
13	33.835,30	-	497.317,13	463.481,84	NO	-	NO
14	72.451,47	-	463.481,84	391.030,37	NO	-	NO
15	546,83	-	391.030,37	390.483,54	NO	-	NO

Day	Demand	Incoming Order	Initial Stock	Ending Stock	Shipped Order	Day of Incoming Order	Stockout
16	105.228,54	-	390.483,54	285.254,99	NO	-	NO
17	90.764,55	-	285.254,99	194.490,45	NO	-	NO
18	68.299,72	-	194.490,45	126.190,73	NO	-	NO
19	52.200,45	-	126.190,73	73.990,27	NO	-	NO
20	53.276,47	-	73.990,27	20.713,81	NO	-	NO
21	107.035,45	-	20.713,81	-	NO	-	YES
22	85.830,48	-	-	-	NO	-	YES
23	-	-	-	-	NO	-	NO
24	106.309,11	-	-	-	NO	-	YES
25	96.386,18	-	-	-	NO	-	YES
26	-	-	-	-	NO	-	NO
27	45.075,20	-	-	-	NO	-	YES
28	125.272,51	-	-	-	NO	-	YES
29	165.556,97	-	-	-	NO	-	YES
30	45.072,68	2.600.000,00	2.600.000,00	2.554.927,32	YES	64	NO

Interpretation of Results

After simulating three inventory control methods, namely Min-Max, (s, Q), and (s, S), in three demand conditions scenarios (normal, high, and low), the next stage is to compare and interpret the results of all the approaches that have been tested. This comparison aims to gain a more comprehensive understanding of the effectiveness and efficiency of each method in maintaining stock availability, avoiding stockouts, and controlling inventory costs, both in stable conditions and when facing fluctuations in demand.

The analysis will focus on a number of key performance indicators, such as the number of days a stockout, the number of orders shipped, the average daily stock, and the total costs incurred, which include the cost of ordering and storage costs. The results of the three methods in various scenarios will be compared for each product, both Gasoline RON 92 and Gasoil 0.05% S, in order to identify the inventory control strategy that best suits the operational dynamics and demand characteristics of each product. The following is a comparison of all scenarios and methods for Gasoline RON 92 products.

Table 9. Comparison table

Prod uct	Scenar io	Method	Sent order	Days of Stockou t	Cost of saving	Cost of order	Total cost (IDR)	Stockout percentag e
Gasoline RON 92	Normal	Min-Max	34	8	IDR 31.124.590.838,49	IDR 183.292.636.878,54	IDR 214.417.227.717,03	0,94%
		(s,Q)	28	23	IDR 6.854.007.426,59	IDR 150.946.877.429,39	IDR 157.800.884.855,97	2,70%
		(s,S)	34	22	IDR 6.157.925.035,10	IDR 183.292.636.878,54	IDR 189.450.561.913,64	2,59%
	High Demand (+20%)	Min-Max	34	33	IDR 7.591.227.198,03	IDR 183.292.636.878,54	IDR 190.883.864.076,57	3,88%
		(s,Q)	31	107	IDR 5.446.628.420,78	IDR 167.119.757.153,96	IDR 172.566.385.574,74	12,57%
		(s,S)	37	70	IDR 5.306.241.968,34	IDR 199.465.516.603,12	IDR 204.771.758.571,45	8,23%

Prod uct	Scenar io	Method	Sent order	Days of Stockou t	Cost of saving	Cost of order	Total cost (IDR)	Stockout percentag e
Gaso il 0,05 % S	Low Deman d (- 15%)	Min- Max	34	37	IDR 7.098.766.289,90	IDR 183.292.636.878,54	IDR 190.391.403.168,44	4,35%
		(s,Q)	25	6	IDR 8.373.761.596,70	IDR 134.773.997.704,81	IDR 143.147.759.301,51	0,71%
		(s,S)	36	13	IDR 6.950.791.142,75	IDR 194.074.556.694,93	IDR 201.025.347.837,67	1,53%
	Norma l	Min- Max	34	115	IDR 5.399.809.783,46	IDR 183.292.636.878,54	IDR 188.692.446.662,00	13,51%
		(s,Q)	33	171	IDR 3.974.196.511,04	IDR 177.901.676.970,35	IDR 181.875.873.481,39	20,09%
		(s,S)	32	216	IDR 3.395.500.776,41	IDR 172.510.717.062,16	IDR 175.906.217.838,57	25,38%
	High Deman d (+20%)	Min- Max	34	163	IDR 4.586.874.081,83	IDR 183.292.636.878,54	IDR 187.879.510.960,37	19,15%
		(s,Q)	33	300	IDR 3.010.929.740,34	IDR 177.901.676.970,35	IDR 180.912.606.710,69	35,25%
		(s,S)	34	211	IDR 4.069.492.295,99	IDR 183.292.636.878,54	IDR 187.362.129.174,53	24,79%
	Low Deman d (- 15%)	Min- Max	34	82	IDR 6.085.239.739,23	IDR 183.292.636.878,54	IDR 189.377.876.617,77	9,64%
		(s,Q)	31	141	IDR 4.436.181.958,96	IDR 167.119.757.153,96	IDR 171.555.939.112,92	16,57%
		(s,S)	34	48	IDR 5.801.762.203,39	IDR 183.292.636.878,54	IDR 189.094.399.081,93	5,64%

The results of the comparative simulation showed significant performance differences between the inventory control methods (Min-Max, (s,Q), and (s,S)) in the face of three demand conditions: normal, increasing by 20%, and decreasing by 15%. This simulation was conducted for two main products, namely Gasoline RON 92 and Gasoil 0.05% S, and ran for 851 days for each combination of methods and demand scenarios. The long duration of the simulation aims to ensure that order patterns, response to demand, and the effects of lead time and demand variations can be analyzed comprehensively and reflect more realistic operational conditions.

In normal demand scenarios, the Min-Max method performs best in terms of maintaining stock availability, with the lowest stockout percentage (0.94% for Gasoline RON 92 and 7.02% for 0.05% S Gasoil). However, such performance has to be paid for with very high storage costs, resulting in the largest total cost among other methods. In contrast, the (s,S) method offers the lowest total cost, but sacrifices service levels with a very high number of stockout days (22 days for Gasoline RON 92 and 326 days for 0.05% S Gasoil). Method (s,Q) indicates a middle position—moderate operating costs and a tolerable stockout—making it the most balanced method for normal conditions.

In high demand scenarios (+20%), all methods experience increased pressure on stocks. For Gasoline RON 92, the Min-Max and (s,Q) methods were able to maintain a fairly good level of service, while (s,S) showed efficient performance in terms of cost but with a higher number of stockout days (70 days). At 0.05% S Gasoil, the (s,Q) method still provides the best performance in cost efficiency, despite recording 300 days of stockout. In contrast, (s,S) experienced a significant spike in the number of stockout days up to 324 days, indicating a high risk to product availability under extreme demand conditions.

Meanwhile, in the low demand scenario (−15%), the Min-Max method excels in terms of service by not experiencing stockouts at all, but storage costs become very high due to the

high average daily stock. On the other hand, the method (s,Q) is the most cost-efficient option, with a very low stockout rate (only 6 days for Gasoil 0.05% S and 0.71% for Gasoline RON 92). The (s,S) method still shows low operating costs, but has a higher number of stockout days than (s,Q), which is 48 days for both products.

Overall, the results of the simulation over 851 days prove that there is no single method that is absolutely superior. Choosing the most appropriate method depends largely on the organization's priorities: whether it prioritizes product availability and customer satisfaction or logistics cost efficiency. For situations that demand high availability, Min-Max is an ideal choice despite its high cost. However, if cost efficiency is the main goal, especially in conditions of declining demand, then the (s,Q) method is more recommended. The method (s,S) is only suitable for use if the company is able to manage stockout risk with a backup strategy or distribution flexibility, considering that its performance is highly dependent on accurate reorder point and lead time parameters.

Managerial Implications

The results of the simulation that have been carried out provide various important implications for PT XYZ's management, especially in designing a fuel inventory control strategy that is adaptive to demand dynamics. One of the key findings is that there is no one method of inventory control that is completely superior in all scenarios. Therefore, logistics managers need to consider the trade-off between the cost of inventory and the service level in every operational decision.

The Min-Max method has proven to be the most stable in maintaining stock availability, with very low stockout rates even in high demand conditions. This suggests that this approach is suitable for use in environments that require consistent product availability and minimal risk of shortages, although storage costs tend to be higher. These findings are in line with the views of Chopra and Meindl (2019), who emphasize the importance of balancing inventory costs with customer service levels in supply chain strategies.

Meanwhile, the (s,Q) and (s,S) methods show efficiency in terms of cost, but with the consequence of increased stockout risk, especially in an increasing demand scenario. The high number of stockout days can interfere with the reliability of distribution services, which according to Zinn and Liu (2001) can negatively impact customer satisfaction and loyalty in the long run. Therefore, the use of efficiency-based methods such as (s,Q) or (s,S) should be done with dynamic parameter adjustments, especially in periods of fluctuation or when supply uncertainty occurs.

Furthermore, Rosič et al. (2020) assert that the performance of inventory systems is highly dependent on the match between demand methods and scenarios. Adjustments to stock control strategies based on historical, seasonal, and short-term demand patterns will be a determining factor for logistics effectiveness in the energy sector. In this context, the use of historical data for data-driven simulation and planning is also highly recommended. Waller and Fawcett (2013) stated that the integration of predictive analytics and modern logistics information systems can improve the accuracy of managerial decisions and operational resilience in the fuel supply chain. Overall, fuel inventory management at PT XYZ should be geared towards a responsive and data-driven approach, considering the balance between cost efficiency and service reliability. Simulations such as those conducted in this study can be a

strong basis in strategic decision-making to ensure smooth distribution, avoid potential losses due to stock shortages, and optimize the use of the company's logistics resources.

CONCLUSION

The simulation analysis of PT XYZ's 851-day fuel supply chain for *Gasoline RON 92* and *Gasoil 0.05% S* reveals that the current system struggles to address demand uncertainty and supply chain dynamics, particularly due to untimely ship arrivals, supply-consumption mismatches, and *demurrage* costs from cargo buildup during ullage shortages. The (s,Q) method emerged as the most optimal inventory policy, balancing cost efficiency and stock availability across normal and low-demand scenarios, while the Min-Max method, despite higher costs, proved reliable for critical high-demand contexts by ensuring service levels. Future research should prioritize integrating real-time data and advanced forecasting models (e.g., machine learning) to enhance demand prediction accuracy, alongside automated inventory tracking systems to reduce *demurrage* risks and improve operational agility in volatile markets.

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