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DEVELOPMENT OF A SIMULATION MODEL FOR THE SHIPPING PLANNING SYSTEM AND STORAGE CAPACITY FOR BULK MATERIALS

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ABSTRACT

Leveraging maritime transport for bulk material shipments is a common approach in supply chain cost optimization efforts. However, the operational aspects of this shipping method are characterized by limited visibility and high levels of uncertainty. This condition is negatively correlated with the company's ability to meet established service level standards, ultimately leading to a decline in consumer trust. This research develops a simulation model to evaluate three scenarios aimed at improving service level. The three factors evaluated are optimization of port operating hours, implementation of a reorder point system, and increasing ship capacity. By implementing a combination of these strategies, the existing distribution system can be significantly improved. The results of this study indicate that implementing a combination of these scenarios can substantially improve the performance of the existing system. The most influential factor is the implementation of a reorder point (Factor 2), which results in an increase of 13.80%. The factor combination that yields the highest service level is scenario number 10, which achieves a service level of 92.36%.

KEYWORDS *Bulk Material, Simulation, Shipment Planning, Storage Capacity, Uncertainty*

INTRODUCTION

The shipment of bulk materials plays a crucial role in the supply chain of various manufacturing industries. This method is widely used across different sectors, especially in commodity and large-scale manufacturing industries (Salo, 2020). It involves transporting large quantities of material without individual packaging, providing significant cost efficiency compared to shipping goods in unit packaging. Moreover, bulk shipping offers notable cost savings by eliminating

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packaging costs, maximizing load capacity, and enabling faster loading and unloading processes (Troncoso et al., 2020). Industries such as cement, fertilizers, petrochemicals, food processing (especially those using grains), and power plants (using coal) heavily rely on bulk shipping to ensure smooth operations and maintain competitive pricing.

Cost efficiency is the primary reason behind the popularity of bulk shipping. Eliminating packaging costs, maximizing load capacity per shipment, and faster loading and unloading processes significantly reduce the cost per unit of transported material. However, bulk shipping also has its drawbacks. Risks of material contamination, the need for specialized infrastructure (such as silos, conveyors, and dedicated docks), and potential losses due to spillage or damage during transport are some of the challenges that need to be considered. Additionally, careful planning is crucial to ensure that the shipped materials align with production needs, given that bulk shipping typically involves large volumes (Curling, 2016; Siswanto & Wahyuninngsih, 2021).

In the context of supply chain management, there is an important trade-off between material requirements and shipping costs. Companies must balance maintaining adequate material availability to meet production demands with minimizing storage costs (caused by excess inventory) and shipping costs (which can be reduced by bulk shipments). Simulation models can serve as valuable tools for strategic decision-making regarding bulk material shipping planning and storage capacity. By simulating various scenarios, companies can identify the optimal balance between costs and availability, thereby improving operational efficiency and profitability (Engebrethsen & Dauzère-Pérès, 2019; Salo & Vanany, 2021).

Therefore, developing simulation models for bulk material shipping planning and storage capacity becomes highly relevant. These models can help companies optimize shipping strategies, determine appropriate storage capacities, and reduce risks associated with bulk shipments, ultimately contributing to increased efficiency and competitiveness.

The object of this study is a manufacturing company in Indonesia that uses bulk raw materials. The raw materials are shipped by sea to reduce shipping costs. However, this bulk shipping method has its drawbacks, one of which is uncertainty. Many factors contribute to this uncertainty, such as the duration of the ship's journey, which depends on weather and sea conditions (Pradana et al., 2023; Salo, 2021). This uncertainty greatly affects product availability, which, if not properly managed, can result in decreased service levels.

Managing logistics costs and product availability is a primary concern in low-value commodity industries such as wheat. Logistics costs and product availability are heavily influenced by shipping planning and storage capacity. Research on simulation models for wheat shipping has been conducted to improve service levels by considering ship capacity, port operating hours, and reorder points (Isnantoyo, 2016; Mosca et al., 2019).

Simulation is an appropriate method for understanding and modeling manufacturing/operational systems in complex environments (Woo et al., 2018). The complexity of a system arises from interdependence and variability. Interdependence refers to the interconnection between various variables within the system, while variability refers to the diversity of variables within a system (Dong & Transchel, 2020). Simulation has proven beneficial in evaluating different design alternatives, especially when the system under analysis operates under uncertainty or when applying analytical techniques becomes challenging, particularly if the system involves stochastic variables.

RESEARCH METHOD

System Description

The manufacturing company in this study uses raw materials sent by ship from various countries to Indonesia. The description of the system is obtained from the results of field studies at the Company. A summary of the problem situation in the form of an operational flow can be seen in the following figure.

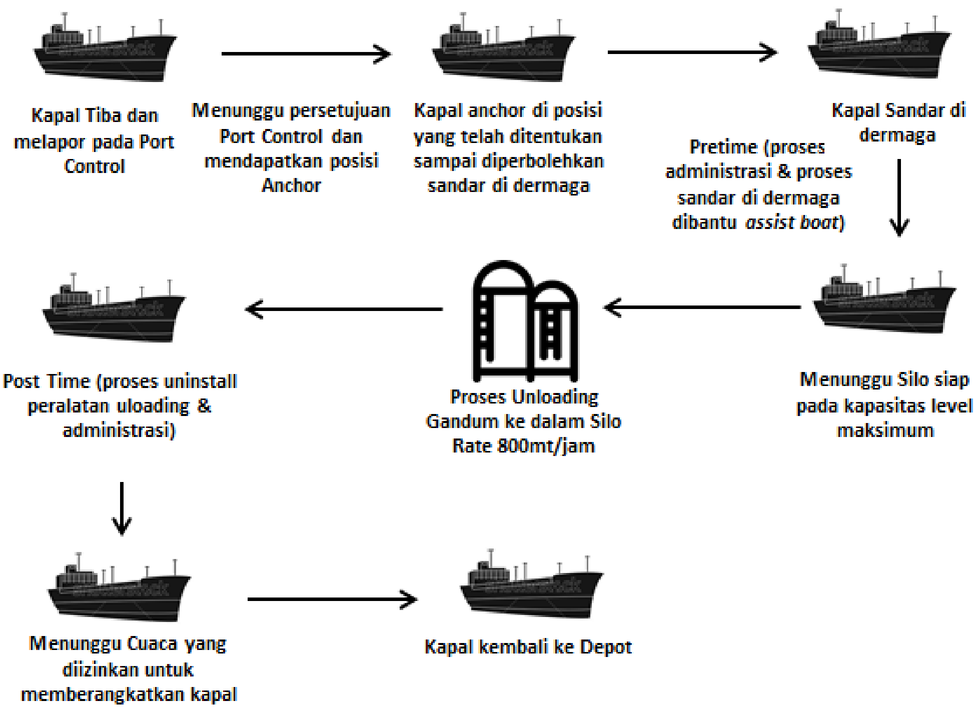

Figure 1. Operational Flow of Existing Conditions

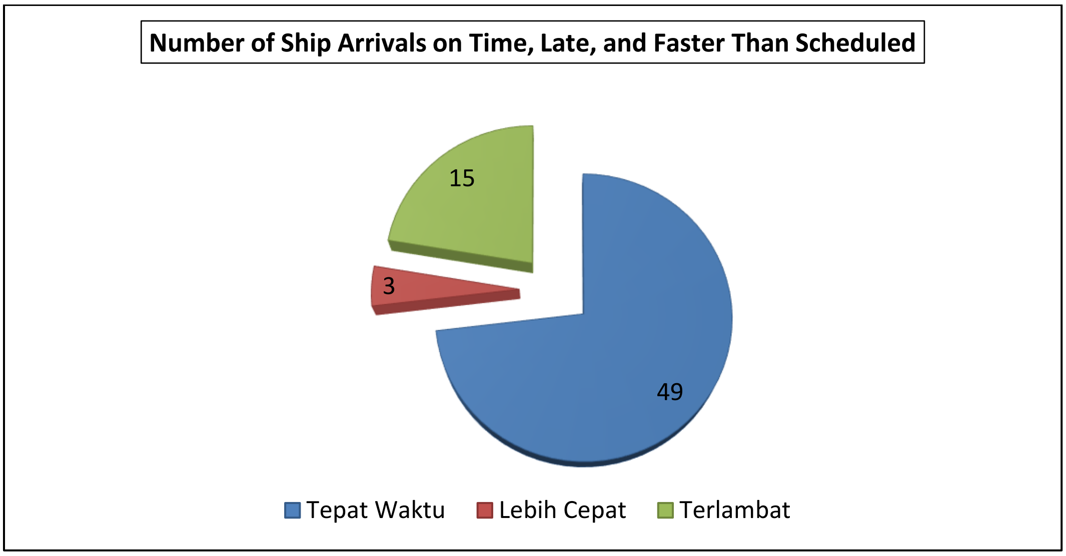

Figure 2. Raw Material Ship Arrival Data

In Figure 2, it can be seen that out of a total of 67 scheduled ships, 15 arrived late, and 3 arrived earlier than expected. Ship delays are influenced by various factors, including bad weather causing departure delays, route changes, or requiring ships to take shelter at ports. Unfavorable sea conditions, such as strong currents, extreme tides, and insufficient water depth, can slow down ship speeds or hinder access to ports. Additionally, poor visibility due to thick fog or heavy rain can reduce visibility and complicate navigation, leading to delays.

Ship arrival delays impact product availability as production processes are disrupted due to insufficient raw materials. The company's inability to meet customer demand results in a decline in service levels (Riskadayanti & Hisjam, 2019). Ships arriving earlier than scheduled can lead to unloading queues since the vessels may arrive while the silo is still full. This situation delays the unloading process, which ideally should begin immediately upon the ship's arrival at the port. Consequently, the ship's utility rate decreases. If the unloading exceeds the allotted time limit, it results in penalty costs (demurrage), ultimately increasing the overall shipping costs (Oumer et al., 2016).

Table 1. Company Service Level Data

Month	***Total Demand***	***Fullfill Demand***	***Service Level***
1	76,845	75,500	98.25%
2	91,929	91,929	100.00%
3	75,502	75,502	100.00%
4	71,855	71,855	100.00%
5	77,196	62,500	80.96%

6	77,144	65,200	84.52%
7	91,592	55,000	60.05%
8	82,300	35,750	43.44%
9	80,374	55,290	68.79%
10	67,761	64,500	95.19%
11	61,166	39,779	65.03%
12	82,521	32,500	39.38%
Average			77.97%

Table 1 shows the service level data for one year. In months five to nine the service level drops and starts to rise again in the tenth month, then drops again in months 11 to 12. The service level target set by the company is 90%. The decrease in service level is caused by raw material stocks that cannot meet production needs due to ship delays in these months.
The service level calculation uses the following formula (Law et al., 2000):

$$Service\ level = 1 - \left(\frac{number\ of\ cycles\ with\ stockout}{total\ number\ of\ order\ cycles}\right) \qquad (1)$$

Simulation Model

The method used is simulation, which can evaluate the trade-off between transportation costs and service level. The first stage involves designing a conceptual model visualized through an activity cycle diagram and logic flow for each scenario. Following this, a discrete simulation model is developed using ARENA software, incorporating parameters, ship and silo capacities, and details of the material distribution process by sea. The simulation model is built using ARENA software.

Validation and Verification

The purpose of model verification is to ensure that the simulation model accurately represents the logical flow and operational mechanisms of the modeled system. This process is carried out in two stages. The first stage involves debugging, which is the process of eliminating errors (bugs) that may occur when running the simulation model. The second stage focuses on validating the internal logic of the model, ensuring that the simulation flow aligns with the logic formulated during the design phase.

Model validation is conducted by comparing the simulation output with real system data using statistical methods. The comparison focuses on key metrics such as cycle time, service level, and costs associated with the material distribution system. A hypothesis test using the *t-test* is applied to determine if there are statistically significant differences between the simulation results and actual data. If the test indicates no significant difference, the simulation model is considered valid and reliable.

Replication

Given the stochastic nature of input parameters in the simulation method, determining an adequate number of replications is essential to achieve the desired result accuracy. This process begins with conducting an initial set of replications, followed by calculating the confidence interval for the population mean (*half-width*). The number of replications obtained from this process is then used to analyze the output produced by the existing simulation model and different scenarios.

The values of half-width and *n* are obtained using the following formula:

$$hw = e = \frac{t_{n-1,1-\frac{\alpha}{2}} \times \sqrt{\frac{std^2}{n}}}{|\bar{x}|}$$

Where:
t = The value of t is obtained from the student's t distribution table
α = error rate
n = number of replications
std = standard deviation of the population
$|\bar{x}|$ = average value

$$n' = \left| \frac{z_{(\frac{\alpha}{2})} \times std}{\left(\frac{\gamma}{1+\gamma}\right) \bar{x}} \right|^2$$

Scenarios and Experiments

This study uses a full factorial design to create various scenarios by combining service levels, silo capacity, number of ships, and operating hours. Each scenario is then tested on a simulation model to observe the resulting response variables.

ANOVA Test

The data generated from the simulation was then analyzed using the ANOVA test to identify factors or combinations of factors that had a significant impact on the measurement variables. The results of this ANOVA test are then used to analyze the significance of each factor.

RESULT AND DISCUSSION

Analysis of Current Conditions

Currently, the company's distribution system uses 10 vessels with varying loading capacities to distribute materials from three supplier ports to one destination port, using a dedicated system. Each ship carries only one type of material: six ships carrying grain 1 from Supplier Port 1, two ships carrying material 2 from Supplier Port 2, and two ships carrying material 3 from Supplier Port 3. Ships depart as soon as they are available at the depot because the company uses a time charter scheme for boat rentals, which necessitates maximizing the ship's utilities to avoid losses. Based on data for one year, the *service level* achieved with this system is 77.97%.

Experiment

The experiment was carried out on the simulation model by varying three main factors, namely:

1. Port Operating Hours: extend the operating hours of supplier ports from 07.00-17.00 to 24 hours to reduce ship waiting time.
2. Reorder Point: changed the ship's departure policy from "depart when ready" to "depart when material stock reaches the reorder *point limit*".
3. Ship Capacity: increase the loading capacity of the ship to increase the amount of wheat flour distributed, with the aim of increasing *the service level*.

The ROP calculation uses the formula [5]:

$$ROP = LT \times D + (Z \times \sqrt{LT \times \sigma_{D^2} + D^2 \times \sigma_{LT^2}})$$

Where:
LT = *Lead time*
D = *Average Demand*
Z = *Safety Factor*
σ_{D^2}= Standar Deviasi *Demand*
σ_{LT^2}= Standar Deviasi *Lead Time*

Full factorial *design* is used to design the following combinations of factors. There are three factors used, each of which has two levels. The first level is the existing condition, the second and third levels are the improvement scenario.

1. Factor 1: Port Operating Hours

Level 1: current conditions, the port operates from 7 am to 7 pm.
Lever 2: the port working hours scenario is extended to 24 hours.

2. Factor 2: Reorder Point

Level 1: current conditions, the ship will depart whenever the ship is available at the depot.
Level 2: Scenarios with ROP applications (ships only depart when material stocks have reached ROP limits).

3. Factor 3: Ship Capacity

Level 1: 146,000 mt
Level 2: 162,000 mt
Level 3: 195,000 mt

The experiment used three factors, with the first and second factors each having two levels, and the third factor having three levels. This full factorial design results in 12 different scenario combinations. Replication was carried out 15 times, resulting in a total of 180 experiments in the simulation.

Simulation Results

Table 2. *Service Level* of the Three Factors

Factor	***Service level***		**Changing**
	Factor	**Existing**	
1	81.18%	77.97%	3.21%
2	91.77%	77.97%	13.80%
3 (level 2)	84.52%	77.97%	6.55%
3 (level 3)	88.02%	77.97%	10.05%

The data analysis from table 2 shows that each factor applied in the experiment contributes to the increase *in service level*. The most influential factor is the implementation of the reorder point (Factor 2), which resulted in an increase of 13.80%. The increase in ship capacity (Factor 3, level 3) made the second largest contribution, which was 10.05%, followed by Factor 3 (level 2) of 6.55%. The extension of port operating hours (Factor 1) provided an increase of 3.21%.

After analyzing the effects of individual factors, simulations were conducted to evaluate 12 scenarios, the result of the combination of the three factors. The service *level results* for each combination are presented in the following table:

Table 3 Results of the Combination of the Three Factors

Skenario	Faktor 1 (*Operating Hour Port*)	Faktor 2 (*Reorder Point*)	Faktor 3 (Kapasitas Kapal)	*Service level*
1	1	1	1	81.13%
2	1	1	2	84.52%
3	1	1	3	88.02%
4	**1**	**2**	**1**	**91.77%**
5	1	2	2	88.58%
6	1	2	3	86.90%
7	2	1	1	81.18%
8	2	1	2	85.55%
9	2	1	3	77.50%
10	**2**	**2**	**1**	**92.36%**
11	2	2	2	88.68%
12	2	2	3	86.00%

Data analysis from table 3 shows that the combination of factors that produce the highest *service level* is scenario number 10, which is 92.36%. This scenario involves extending port operating hours to 24 hours, implementing Reorder Points (ROP), and using ships with a capacity of 146,000 MT. The increase in *service level* achieved with this combination is 13.95% compared to the current condition.

Before this scenario is applied to increase the service level in the Company, the ANOVA Test is first carried out. The one-way ANOVA aims to compare the averages of two or more groups to determine if there is a statistically significant difference between the groups.

Table 4. ANOVA Test Results

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2583.640	11	234.876	4.205	0.000
Within Groups	7372.693	132	55.854		
Total	9956.333	143			

Table 4 shows that the p-value is less than 0.05, so the null hypothesis is rejected. This indicates that there is a significant difference *in service levels* in at least one group. Therefore, the Post Hoc test is necessary to identify which groups differ significantly.

CONCLUSION

This study produced a model design by identifying three effective scenarios in increasing service levels: extension of port operating hours, implementation of reorder points, and increasing ship capacity. The results of this study show that the implementation of a combination of these scenarios can substantially improve the performance of existing systems. The most influential factor is the implementation of *the reorder point* (Factor 2), which resulted in an increase of 13.80%. The combination of factors that produced *the highest service level* was scenario number 10, which was 92.36%.

Simulation provides advantages by accelerating analysis, integrating various aspects, anticipating risks, adjusting scale, conducting iterative testing, and providing control, simulation becomes a powerful tool. The development of simulation models for bulk material delivery and storage allows companies to significantly reduce transportation costs while improving service levels to customers.

REFERENCES

Curling, T. A. (2016). *USMC inventory control using optimization modeling and discrete event simulation*. Monterey, California: Naval Postgraduate School.

Dong, C., & Transchel, S. (2020). A dual sourcing inventory model for modal split transport: Structural properties and optimal solution. *European Journal of Operational Research*, *283*(3), 883–900.

Engebrethsen, E., & Dauzère-Pérès, S. (2019). Transportation mode selection in inventory models: A literature review. *European Journal of Operational Research*, *279*(1), 1–25.

Isnantoyo, F. A. (2016). *Model Transportasi Laut Untuk Mendukung Manajemen Rantai Pasok: Studi Kasus Komoditas Ayam Beku Dari Surabaya Ke Indonesia Timur*. Institut Teknologi Sepuluh Nopember.

Law, A. M., Kelton, W. D., & Kelton, W. D. (2000). *Simulation modeling and analysis* (Vol. 3). Mcgraw-hill New York.

Mosca, A., Vidyarthi, N., & Satir, A. (2019). Integrated transportation–inventory models: A review. *Operations Research Perspectives*, *6*, 100101.

Oumer, A., Atnaw, S. M., Cheng, J. K., & Singh, L. (2016). Improving energy efficiency for the vehicle assembly industry: a discrete event simulation approach. *IOP Conference Series: Materials Science and Engineering*, *160*(1), 12069.

Pradana, A., Marikena, N., & Hilmy, M. F. (2023). Penerapan Metode Transportasi Dalam Optimasi Biaya Pengiriman Komponen Mesin Kelapa Sawit Pada CV. Adi Jaya Teknik. *Prosiding CORISINDO 2023*.

Riskadayanti, O., & Hisjam, M. (2019). Discrete-event simulation of a production process for increasing the efficiency of a newspaper production. *IOP*

Conference Series: Materials Science and Engineering, *495*(1), 12026.

Salo, L. A. (2020). *Model Simulasi Perencanaan Pengiriman Dan Kapasitas Penyimpanan Untuk Bahan Baku Gandum*. Institut Teknologi Sepuluh Nopember.

Salo, L. A. (2021). Model Simulasi Perencanaan Pengiriman Bahan Baku Tepung Terigu Untuk Meningkatkan Service Level. *Prosiding Seminar Nasional Tahunan Teknik Mesin UKI Toraja 2021*.

Salo, L. A., & Vanany, I. (2021). A simulation model of shipment planning and storage capacity for wheat material. *IOP Conference Series: Materials Science and Engineering*, *1034*(1), 12119.

Siswanto, N., & Wahyuninngsih, A. T. (2021). Discrete event simulation approach for container terminal loading and unloading productivity evaluation. *11th Annual International Conference on Industrial Engineering and Operations Management, IEOM 2021*, 1181.

Troncoso, A., Sanchez, A., & Gonzalez, J. (2020). Discrete Events Simulation Method for Analyze Cycle Time: A Case Study in the Plastics Industry Sector. *IOP Conference Series: Materials Science and Engineering*, *844*(1), 12063.

Woo, S.-H., Kim, S.-N., Kwak, D.-W., Pettit, S., & Beresford, A. (2018). Multimodal route choice in maritime transportation: the case of Korean auto-parts exporters. *Maritime Policy & Management*, *45*(1), 19–33.