

Bottleneck Analysis and Distribution Capacity Optimization in Used Goods Business Using Theory of Constraints: A Case Study of UD. DOA ABADI, Semarang

Fajriansyah Mahdy Tsani ^{1✉}, Dewa Kusuma Wijaya ²

(1,2) Industrial Engineering, Universitas Dian Nuswantoro, Semarang, Indonesia

Abstract: Operational capacity determines the ability of the distribution system to balance the supply in the reverse logistics-based second-hand goods business. This study aims to analyze operational capacity and identify bottlenecks in the UD distribution system. DOA ABADI, a second-hand goods trading business in Semarang City that handles iron, cardboard, paper, and plastic bottles. The study uses a descriptive quantitative approach with a single case study design based on operational data from June 2025–June 2026 and weekly data for 13 weeks of the third quarter of 2025, including fleet ritase, vehicle capacity, loading/unloading time, lead time, demand, and stock. The analysis was carried out through inventory mass balance, fleet and labor utilization, and Theory of Constraints and Supply Chain Operations Reference (SCOR) approaches. The results showed that fleet utilization reached 91.7%, with an average real load of 2.73 tons per ritase from a capacity of 3.0 tons and a lead time of 4.8 hours. This condition is higher than the labor utilization of 81.0%, so the fleet is the main constraint. Demand is not met at an average of 0.25 tons per week, accompanied by an increase in stock from 21.5 tons to 29.4 tons and warehouse utilization from 42.2% to 57.6%. A comparison of three scenarios shows that the addition of weekly ritase without new fleet investment is the most financially feasible and multi-criteria alternative. This study confirms that capacity analysis based on operational data and cost-benefits is effective to identify bottlenecks and determine priorities for increasing distribution in circular economy businesses.

Article history:

Received: 02 September 2026

Revised: 12 October 2026

Accepted: 17 October 2026

Published: 21 October 2026

Keyword:

bottleneck, operational capacity, distribution lead time, reverse logistics, theory of constraints

This is an open-access article under the [CC-BY-SA License](#).



How to cite: Tsani, F. M., & Wijaya, D. K. (2026). Bottleneck Analysis and Distribution Capacity Optimization in Used Goods Business Using Theory of Constraints: A Case Study of UD. DOA ABADI, Semarang. *RESWARA: Journal of Engineering Science Research*, 4(4), 1712–1731. <https://doi.org/10.70716/reswara.v4i4.866>

INTRODUCTION

The business of buying and selling used goods is an important part of the circular economy system because it plays a role in extending the life cycle of materials through collection, sorting, storage, and redistribution activities to processing actors or secondary markets (Biancolin et al., 2023). In contrast to formal manufacturing supply chains, the second-hand supply chain system has uncertain and heterogeneous supply characteristics, so the system's ability to balance operational capacity with supply rates is a key determinant of distribution sustainability (Biancolin et al., 2023; Pushpamali et al., 2021).

Operational capacity in this context includes storage capacity, distribution fleet capacity, and sorting and loading workforce capacity that together form Throughput system. An up-to-date review of identification theories and techniques bottleneck affirms that the overall performance of an operational system is determined by the components with the narrowest capacity and that the establishment of definitions bottleneck is a prerequisite for improving resource allocation and preventing distribution delays (Tang et al., 2024). In the business of trading used goods, identify bottleneck It is important because the limitation of one component of capacity can hinder the smooth

running of the entire distribution system even though the other component still has adequate spare capacity.

UD. DOA ABADI is one of the used goods trading business actors in Semarang City that trades four main commodities, namely iron, cardboard, paper, and plastic bottles, with a warehouse capacity of 51 tons. The company's operational characteristics, namely an average freight picking rate of 1.7 tons per day with a frequency of five days per week and outbound distribution 2 to 3 times per week with a capacity of 2 to 3 tons per shipment, make this company a relevant case study to analyze the adequacy of operational capacity and bottleneck locations in the micro and small-scale second-hand goods business distribution system.

Preliminary operational records indicate that the stock accumulation at UD. DOA ABADI can be traced to distribution capacity using absolute quantities, not merely utilization percentages. Between June 2025 and June 2026, the company received 484.5 tons of material but dispatched only 470.1 tons, so that 14.4 tons accumulated in the warehouse and the final stock rose from 21.5 tons to 29.4 tons. The sorting-loading workforce of three people can process up to 10.5 tons per week, well above the weekly inflow of 8.5 tons, whereas the single distribution vehicle has a rated ceiling of 9.0 tons per week (3 ritases $\times$ 3.0 tons). Moreover, in a 13-week sample in which the vehicle operated at its maximum frequency of three ritases every week, it transported on average only 8.19 tons per week (2.73 tons per ritase), still below the weekly inflow, while customer demand in the same period (109.7 tons) exceeded realized shipments (106.5 tons). These absolute capacity, demand, and stock data indicate that the stock build-up is not caused by weak demand or insufficient labor, and they form the empirical basis for the hypothesis that the distribution fleet is the main constraint, which is tested formally in this study.

To position this study against prior work, the literature on bottleneck management, supply chain performance measurement, and reverse logistics in the informal recycling sector was reviewed using four analytical criteria, namely whether a study (i) measures resource capacity and utilization (Capacity Analysis), (ii) applies the Theory of Constraints (TOC), (iii) uses the Supply Chain Operations Reference (SCOR) model, and (iv) evaluates improvement alternatives through cost-benefit or scenario analysis. The synthesis is presented in Table 1.

Table 1. Synthesis of previous studies and the position of this study

Study	Object / context	CA	TOC	SCOR	CBA	Gap relative to this study
Tang et al. (2024)	Manufacturing systems; review of bottleneck identification techniques	✓	✓	–	–	Manufacturing-oriented; not applied to distribution in informal micro businesses
Stopka et al. (2023)	Logistics enterprise; TOC thinking-process tools	–	✓	–	✓	Qualitative logic trees; resource utilization is not measured
Kusrini & Miranda (2021)	Make-to-order SME; SCOR 12.0 metrics	–	–	✓	–	Measures performance but does not locate the physical constraint
Qurtubi et al. (2022)	Garment SME, Indonesia; SCOR performance measurement	–	–	✓	–	No bottleneck diagnosis and no costed improvement scenarios
Özkanlısoy & Bulutlar (2023)	SCOR v13.0 scale development (survey)	–	–	✓	–	Measurement instrument; no case-level capacity data
Desticioglu et al. (2022)	Reverse logistics network for recycling (e-commerce firm)	✓	–	–	✓	Cost-minimization model for a large firm; capacity is a model input, not a diagnosed bottleneck

Study	Object / context	CA	TOC	SCOR	CBA	Gap relative to this study
Kazancoglu et al. (2021)	Reverse logistics in food supply chains; system dynamics	-	-	-	-	Simulation-based performance evaluation; no bottleneck diagnosis
Pushpamali et al. (2021)	Reverse logistics practices; stakeholder perception	-	-	-	-	Perception-based; no operational data
Kristanto et al. (2022)	Informal waste pickers, Indonesia; field analysis	-	-	-	-	Socio-economic focus; no capacity measurement
Velis et al. (2022)	Informal recycling sector; policy perspective	-	-	-	-	Conceptual and policy-oriented; no operational analysis
This study	Micro-scale second-hand goods business, Semarang	√	√	√	√	Sequential integration of four frameworks using weekly operational data

Note: CA = Capacity Analysis (capacity and utilization measurement); TOC = Theory of Constraints; SCOR = Supply Chain Operations Reference; CBA = cost-benefit or scenario analysis; √ = applied; - = not applied.

Table 1 reveals three patterns in the prior literature. First, TOC-based studies are concentrated in manufacturing systems and formal logistics enterprises, and they either review bottleneck identification techniques (Tang et al., 2024) or apply TOC thinking-process tools qualitatively (Stopka et al., 2023), without measuring the utilization of each resource from operational data. Second, SCOR-based studies on SMEs (Kusrini & Miranda, 2021; Qurtubi et al., 2022; Özkanlısoy & Bulutlar, 2023) measure supply chain performance but do not identify which physical resource causes weak performance, nor do they cost improvement alternatives. Third, the reverse logistics and informal recycling literature either optimizes the collection networks of large firms (Desticioglu et al., 2022), evaluates performance through simulation or stakeholder perception (Kazancoglu et al., 2021; Pushpamali et al., 2021), or describes the socio-economic conditions of informal actors (Kristanto et al., 2022; Velis et al., 2022). None of the reviewed studies combines more than two of the four frameworks, and none measures weekly fleet and labor capacity in a micro-scale second-hand goods business. This is the gap addressed by the present study.

A study on operational capacity in micro and small enterprises based on Back to Basics is still relatively limited compared to studies in the large manufacturing sector (Biancolin et al., 2023; Kristanto et al., 2022; Velis et al., 2022). This study aims to: (1) analyze the adequacy of fleet capacity and manpower to the load of weekly freight flows in UD. DOA ABADI; (2) identify points bottleneck Limiting main Throughput distribution system using the Theory of Constraints; and (3) evaluate the impact of the limited capacity on distribution performance indicators in the form of warehouse utilization and Inventory turnover during the period of June 2025 to June 2026.

The four analytical approaches are not applied as parallel, stand-alone tools but as a sequential chain in which the output of one method becomes the input of the next, as illustrated in Figure 1. (1) Capacity Analysis serves as the measurement stage: it converts operational data (ritase, real load per ritase, labor productivity, demand, and stock) into the maximum capacity, actual load, utilization, and slack capacity of each resource. (2) The Theory of Constraints serves as the diagnosis stage: the utilization and slack values from the first stage are the input for Identify the constraint, while the Exploit, Subordinate, and Elevate steps translate the identified bottleneck into concrete improvement options. (3) The SCOR model serves as the verification stage: the same operational data are converted into standardized performance attributes (reliability, responsiveness, agility, and asset management) to confirm whether the constraint identified by TOC is reflected in system-level performance, so that the diagnosis does not rest on a single indicator. (4) Cost-benefit analysis and multi-criteria scoring

serve as the selection stage: the Elevate options generated by TOC become alternative scenarios whose investment, operating costs, benefits, and payback are compared, and the selected scenario returns to the Repeat the process step of TOC for re-evaluation after implementation.

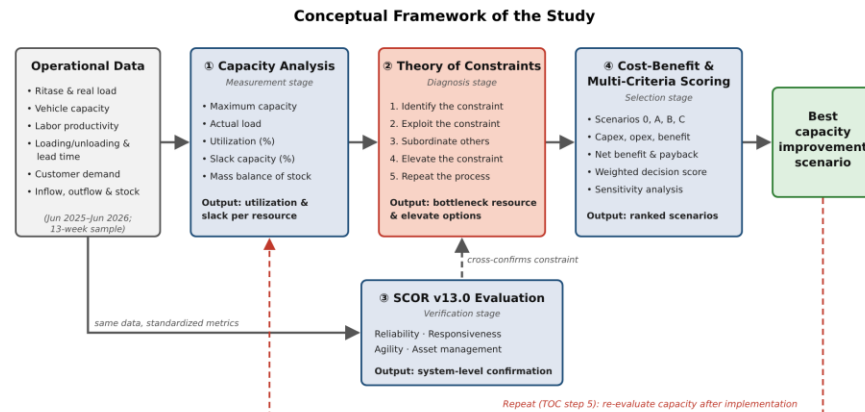


Figure 1. Conceptual framework linking Capacity Analysis, Theory of Constraints, SCOR, and scenario selection

Novelty (novelty) This research lies in three aspects. First, this research integrates four analytical frameworks at once, namely Capacity Analysis, Theory of Constraints, the SCOR model, and the cost-benefit analysis of capacity building scenarios in a single mutually confirmatory evaluation flow, whereas previous studies on small and medium-sized enterprises generally applied only one framework separately, e.g. SCOR on Qurtubi et al. (2022) or TOC on manufacturing studies by Tang et al. (2024), and is rarely applied to micro-scale second-hand businesses operating in the Back to Basics informal. The synthesis in Table 1 substantiates this claim: none of the ten studies reviewed combines more than two of the four frameworks, and none examines a micro-scale second-hand goods business at the level of measured weekly operations. Second, the evaluation of fleet capacity and manpower in this study is supported by detailed weekly operational data, including actual ritase, actual vehicle capacity, time Loading/Unloading, Lead Time distribution, customer demand, and weekly stock that are rarely documented or published for such informal ventures. Thus, the identification of bottleneck Not only descriptive, but also measurable at the daily operational level. Third, this study complements the identification of bottleneck with quantitative cost-benefit analysis of several capacity building scenarios and determination of the best scenario using the Net Benefit and multicriteria decision scores, instead of stopping at purely qualitative recommendations as commonly found in the literature Back to Basics MSMEs in Indonesia.

RESEARCH METHOD

Types and Approaches to Research

This study uses a descriptive quantitative approach with a single case study design (Single case study) in UD. DOA ABADI. This approach was chosen because the research focuses on the measurement and numerical analysis of operational capacity, freight flow loads, and points bottleneck Based on the company's real operational data, it is in line with the approach of a single case study based on operational data which is also applied to the evaluation of the supply chain performance of small and medium enterprises by Kusriani & Miranda (2021).

Location and Research Object

The object of the research is UD. DOA ABADI, a used goods trading business located in Bandarharjo Village, North Semarang District, Semarang City, with a maximum storage capacity of 51 tons. The observation period was carried out for 13 months, namely June 2025 to June 2026, equivalent to 57 weeks of operational activities.

Analysis Methods: Capacity Analysis and Theory of Constraints

This study uses a combination of two analysis methods as the main framework, namely Capacity Analysis and Theory of Constraints (TOC). Both methods were chosen because they directly answer the research objectives in measuring the adequacy of operational capacity and identifying system bottlenecks by utilizing fleet and workforce capacity data that has been available from the company's operational records.

Capacity Analysis

Capacity Analysis is used to measure the adequacy of the capacity of the two main operational resources, namely the distribution fleet and the sorting and loading workforce, against the actual weekly freight flow load. The analysis is carried out in the following steps. (a) Determine the maximum capacity of each resource. Fleet capacity is calculated from the number of fleet units multiplied by the carrying capacity per ritase and the maximum ritase frequency that can be achieved per week, i.e. the maximum capacity, not the average realization. Labor capacity is calculated from the number of workers multiplied by the average productivity in tons per person per day and the number of working days per week. (b) Determine the weekly actual load of each resource based on real operational data, i.e. the average tonnage handled by the fleet and labor per week. For fleets, the actual load is calculated from the real average ritase frequency over the 57 observation weeks multiplied by the average load per ritase. This average frequency value of 2.75 ritases per week differs from the maximum frequency in step a because it includes monthly variations, including months with lower supply volumes that require only 2 ritases per week. (c) Calculate the utilization ratio by the formula:

$$Utilization = (Actual\ Load / Maximum\ Capacity) \times 100\%$$

(d) Calculate slack capacity or reserve capacity with the formula:

$$Slack\ Capacity = 100\% - Utilization$$

Spare capacity is used as an indicator of the operational flexibility of resources against supply fluctuations.

Theory of Constraints (TOC)

After calculating resource utilization and slack capacity, the Theory of Constraints (TOC) approach is applied to identify system bottlenecks. Following Tang et al. (2024), the analysis involves five steps: (a) Identify the constraint by comparing fleet and labor utilization, where the highest utilization and lowest slack capacity indicate the bottleneck limiting system throughput; (b) Exploit the constraint by maximizing bottleneck utilization without additional investment, such as optimizing ritase schedules; (c) Subordinate other resources by aligning non-bottleneck labor capacity with bottleneck

performance to prevent accumulation elsewhere; (d) Elevate the constraint by considering capacity expansion through additional ritase or fleet capacity; and (e) Repeat the process by reassessing constraints after capacity improvements to identify potential bottleneck shifts.

Three complementary analyses are conducted: (1) Mass Balance Inventory to assess stock accumulation caused by capacity gaps; (2) warehouse utilization trends and inventory turnover to evaluate the effects of capacity constraints on distribution performance; and (3) a SCOR-based assessment of reliability, responsiveness, agility, and asset management to cross-validate the Capacity Analysis and TOC findings. The assessment follows the SCOR v13.0 scale (Özkanlısoy and Bulutlar, 2023), supported by previous applications in small and medium-sized enterprises (Kusrini & Miranda, 2021; Qurtubi et al., 2022).

The study assumes an initial stock of 15 tons and an outbound goods distribution proportional to incoming goods: iron 35%, cardboard 28%, paper 22%, and plastic bottles 15%. These assumptions are explicitly stated to allow recalibration when more detailed operational data become available.

Additional Operational Data Coverage

To improve the accuracy of Capacity Analysis and TOC, six categories of operational data were collected through transaction records and direct observation (time-motion study) over a representative 13-week period in the third quarter of 2025 (July–September). The data comprise: (1) weekly actual fleet ritase; (2) average actual vehicle load per ritase compared with the rated capacity of 3.0 tons; (3) loading and unloading time per ritase; (4) distribution lead time from shipment readiness to unloading completion at the buyer's location; (5) weekly demand from secondary buyers; and (6) weekly stock levels to capture fluctuations not reflected in monthly data. The period covers four operational weeks each in July and August and five in September, representing weekly workload variations during the observation period.

Cost Analysis and Comparison of Capacity Building Scenarios

As part of the TOC Elevate the Constraint stage, a cost-benefit analysis compares three fleet capacity expansion scenarios identified in Table 9: (A) increasing weekly ritase without new fleet investment; (B) adding one similar fleet unit; and (C) replacing the existing fleet with a larger-capacity vehicle. Each scenario is compared with the existing condition (Scenario 0) using five components: (1) initial investment (capex); (2) additional annual operating costs (opex); (3) additional fleet capacity; (4) estimated annual benefits based on the value of additional capacity effectively absorbed, limited by projected actual supply growth needs over the next three years rather than full theoretical capacity; and (5) payback period.

The preferred scenario is selected using two complementary methods: first-year net benefit, calculated as first-year benefits minus total first-year costs, and a multicriteria decision matrix weighted by initial investment, payback period, capacity suitability (right-sizing), operational flexibility, and implementation risk. All cost and margin figures are illustrative estimates based on market price ranges for light commercial vehicles and MSME fleet operating costs in Semarang. They are stated transparently for recalibration when actual company cost data become available.

RESULTS AND DISCUSSION

Operational Capacity Parameters

Table 2 summarizes the parameters of UD's operational capacity. DOA ABADI is the basis for the bottleneck analysis. The total supply of materials reaches about 8.5 tons per week, while the outgoing distribution capacity depends on the fleet and available manpower.

Table 2. Parameters of UD's operational capacity. ABADI PRAYER

Parameters	Value	Remarks
Warehouse capacity	51 tons	Maximum storage limit
The rate of incoming goods	1.7 tons/day	Daily routine intake
Pick-up day	5 days/week	Incoming goods 8.5 tons/week
Outbound shipping size	2–3 tons	Per shipment
Frequency of delivery	2–3 times/week	Distribution to buyers
Commodities	4 types	Iron, cardboard, paper, plastic bottles
Observation period	June 2025–June 2026	13 months / 57 weeks

Ritase Data, Actual Vehicle Capacity, and Loading-Unloading Time

Table 3 presents the actual ritase data of the fleet and actual vehicle capacity (average real load per ritase) during the 13 weeks of the sample in the third quarter of 2025. It should be noted that the average frequency of ritase of 2.75 times/week reported in Table 8 is the average OVER ALL 57 WEEKS of the observation period (including months with lower supply volumes that only require 2 ritases/week). The 13-week sample in Table 3 is taken from the third quarter of 2025, which is the quarter with relatively high distribution volumes (close to or above the annual average), so that the fleet consistently operates at a frequency of 3 ritases/week (maximum frequency) throughout this sample is not an inconsistency, but rather a reflection that the variation of 2–3 ritases occurs between months, not in the same quarter of high activity. In another dimension, although the rated capacity of the fleet is 3.0 tonnes per ritase, the real cargo transported is generally below that value because light commodities such as cardboard and plastic bottles fill the tub volume before reaching the maximum weight limit, so the load efficiency (real load ratio to rated capacity) ranges from 83% to 94%.

Table 3. Actual ritase and weekly actual vehicle capacity (sample Jul–Sep 2025)

Sunday	Actual Ritase	Average Load/Ritase (Tons)	Total Transported (Tons)
Jul-2025 M1	3	2,50	7,5
Jul-2025 M2	3	2,53	7,6
Jul-2025 M3	3	2,63	7,9
Jul-2025 M4	3	2,63	7,9
Aug-2025 M1	3	2,77	8,3
Aug-2025 M2	3	2,80	8,4
Aug-2025 M3	3	2,80	8,4
Aug-2025 M4	3	2,83	8,5
Sep-2025 M1	3	2,77	8,3
Sep-2025 M2	3	2,80	8,4
Sep-2025 M3	3	2,80	8,4
Sep-2025 M4	3	2,80	8,4
Sep-2025 M5	3	2,83	8,5
Average	3,0	2,73	8,19

In addition to the load aspect, the processing time in each shipment also determines the effective throughput of the fleet. Table 4 summarizes the results of the observation of loading time in the warehouse, travel time, unloading time at the buyer's location, and total distribution lead time per shipment, which is input for the Exploit the Constraint stage in the TOC analysis.

Table 4. Loading, unloading, and lead time distribution per ritase

Stages	Average Time	Remarks
Ritase scheduling waiting time	0.5–1.0 hours	Waiting for the load to be sorted and the fleet available
Loading time in the warehouse	58 minutes/ritase	Performed by 3 manual sort-load workers
Travel time to buyer location	1.5–3.0 hours	Depending on distance and traffic/inundation conditions
Unloading time at the buyer's location	38 minutes/ritase	Weighing and verification process by the buyer
Total distribution lead time per ritase	average 4.8 hours (range 3.5–7.0 hours)	From ready-to-ship goods to finished unloading at the buyer

The average loading and unloading time of approximately 96 minutes per ritase (58 minutes of loading + 38 minutes of unloading) indicates that almost 1.6 hours of each ritase are allocated to non-travel activities. Together with scheduling lead times, this component contributes to a total distribution lead time of an average of 4.8 hours per ritase, so that the fleet is only able to complete a maximum of three full ritases in one effective working day.

Weekly Customer Demand and Stock Data

Table 5 compares the weekly customer demand from secondary buyers to the realization of outbound goods, incoming goods, and stock dynamics in the 13 weeks of the sample. This data confirms that the root of the problem lies not in weak market demand of customer demand consistently exceeding the realization of outbound goods every week but in the limited distribution capacity to meet this demand, in line with the findings of Capacity Analysis.

Table 5. Customer demand, freight flow, and weekly stock (sample Jul–Sep 2025)

Sunday	Customer Demand (Tons)	Incoming Goods (Tons)	Outgoing Goods (Tons)	Initial Stock (Tons)	Final Stock (Tons)
Jul-2025 M1	7,7	8,5	7,5	21,5	22,5
Jul-2025 M2	7,8	8,5	7,6	22,5	23,4
Jul-2025 M3	8,1	8,5	7,9	23,4	24,0
Jul-2025 M4	8,2	8,5	7,9	24,0	24,6
Aug-2025 M1	8,5	8,5	8,3	24,6	24,8
Aug-2025 M2	8,6	8,5	8,4	24,8	24,9
Aug-2025 M3	8,6	8,5	8,4	24,9	25,0
Aug-2025 M4	8,7	8,5	8,5	25,0	25,0
Sep-2025 M1	8,6	8,5	8,3	25,0	25,2
Sep-2025 M2	8,7	8,5	8,4	25,2	25,3
Sep-2025 M3	8,7	8,5	8,4	25,3	25,4
Sep-2025 M4	8,7	8,5	8,4	25,4	25,5
Sep-2025 M5	8,8	8,5	8,5	25,5	25,5
Total 13 weeks	109,7	110,5	106,5	—	—

During the 13 weeks of the sample, total customer demand reached 109.7 tons, while the realization of outbound goods was only 106.5 tons, a difference of 3.2 tons, or an average of 0.25 tons of unmet demand per week. This value is consistent with the distribution capacity deficit of 0.25 tons per week identified in the 57-week aggregate analysis (Subchapter 3.4), thus strengthening the conclusion that fleet capacity limitations, not market demand, are the main constraints of the distribution system.

Capacity Gap: Inflow vs Outbound Distribution Capacity

In aggregate, the total incoming goods during the observation period reached 484.5 tons, while the total outbound goods only reached 470.1 tons, leaving a difference of 14.4 tons accumulated as additional stock. On a weekly scale, the average incoming goods were recorded at 8.5 tons per week, while the outgoing distribution capacity was only around 8.25 tons per week, resulting in a capacity deficit of 0.25 tons per week. Although the difference is small in absolute terms, the long-term accumulation shows a structural imbalance between the pace of supply and distribution capacity (Ivanov, 2021).

Based on commodities, iron accounted for 169.6 tons of total incoming goods and 164.5 tons of outbound goods with the highest accumulated final stock of 10.3 tons compared to other commodities. Cardboard, paper, and plastic bottles left final stocks of 8.2 tons, 6.5 tons, and 4.4 tons, respectively. The dominance of iron (35% of total tonnage) puts the greatest capacity pressure on warehouses due to its high physical density, so accelerating the distribution of iron commodities is a strategic priority in managing storage capacity (Kazancoglu et al., 2021).

Table 6. Total final flows and stocks per commodity (Tons, Jun 2025–Jun 2026)

Commodities	Incoming Goods (Tons)	Outgoing Goods (Tons)	Stock End Jun-26 (Tons)
Iron	169,6	164,5	10,3
Cardboard	135,7	131,6	8,2
Paper	106,6	103,4	6,5
Plastic bottles	72,7	70,5	4,4
Total	484,5	470,1	29,4

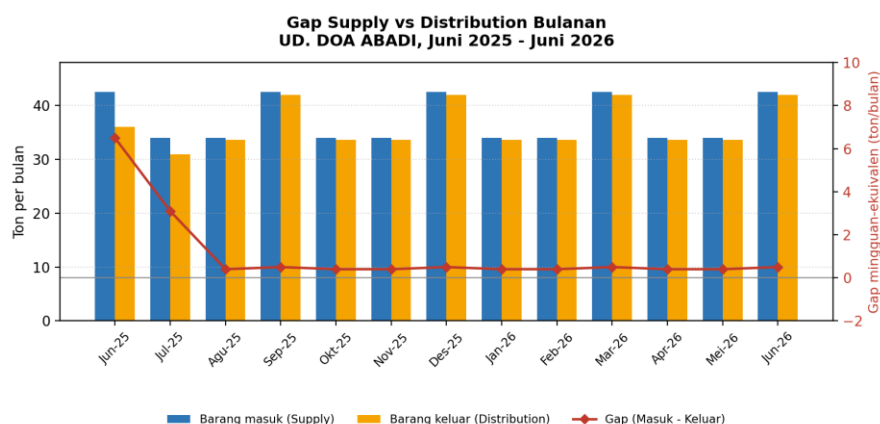


Figure 2. Monthly supply gap vs distribution chart, June 2025–June 2026

The graph in Figure 2 shows that the largest gap occurred in the first month of observation (June 2025), then narrowed and was relatively stable in the range of 0.4–0.6 tonnes per month from August 2025 until the end of the period. This pattern is consistent with near-equilibrium supply chain conditions: distribution capacity almost always follows the pace of supply, but it is the small gaps that repeat each month that accumulate into long-term stock increases as shown in Figure 3.

The Impact of Limited Capacity on Warehouse Utilization and Inventory Turnover

The limited outbound distribution capacity is directly reflected in the dynamics of warehouse utilization. Monthly final stock has consistently increased from 21.5 tons (June 2025) to 29.4 tons (June 2026), with warehouse utilization rates increasing from 42.2% to 57.6%, an increase of 15.4 percentage points in 13 months, or an average of 1.0 percentage points per month. A simple linear extrapolation shows that if operational patterns do not change, warehouse capacity has the potential to reach a maximum point in about the next 42 months. Boysen et al. (2021) emphasized that the continuous increase in storage utilization is an early indicator of logistics bottlenecks, especially in systems with limited outbound transportation capacity.

In line with this, monthly inventory turnover decreased from 1.97 times in June 2025 to a range of 1.2–1.4 times in the second half of the observation period, with an annual average of 1.41 times per month. This decrease indicates that materials are staying longer in warehouses before being successfully distributed, indicating longer retained working capital in the form of inventories (Breivik et al., 2021). This pattern is consistent with findings in the context of developing countries, where the limited operational capacity of reverse logistics is often reflected in a slowdown in inventory circulation before having a real impact on the overall decline in distribution volume (Mukherjee et al., 2024).

Table 7. Selected monthly summary of goods flows and distribution performance indicators

Month	Incoming (Tons)	Out (Tons)	Final Stock (Tons)	Utilization	Turnover
Jun-2025	42,5	36,0	21,5	42,2%	1.97×
Sep-2025	42,5	42,0	25,5	50,0%	1.66×
Un-2025	42,5	42,0	26,8	52,5%	1.58×
Mar-2026	42,5	42,0	28,1	55,1%	1.51×
Jun-2026	42,5	42,0	29,4	57,6%	1.44×
Total/Average	484,5	470,1	29,4	52,1%	1.41×

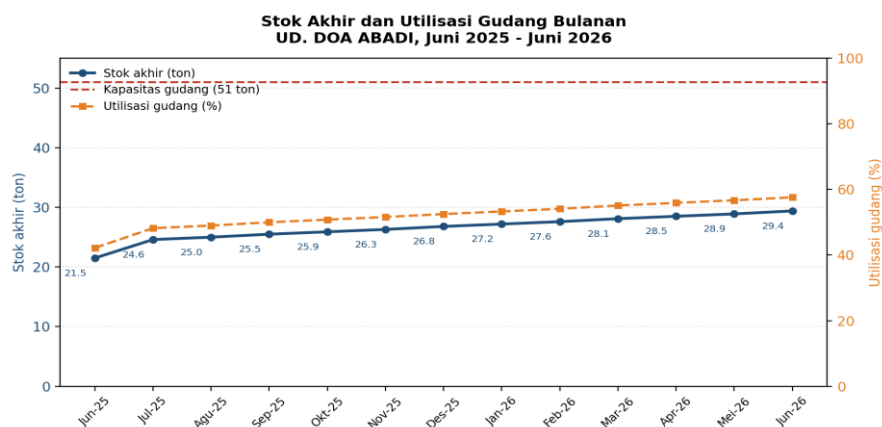


Figure 3. Graph of final stock and monthly warehouse utilization, June 2025–June 2026

Figure 3 visually confirms that the final stock line moved consistently and monotonous upward throughout the 13 months of observation, with no decrease in any month, while the warehouse utilization line (right axis) moved parallel following the same pattern. Although the final stock was still well below the maximum capacity line of 51 tonnes, the linear uptrend showing no signs of slowing down became a visual indicator that this accumulation was structural, not short-term random fluctuations.

Capacity Analysis: Fleet Capacity vs Workforce

Following the Capacity Analysis step in Subchapter 2.3.1, fleet and workforce capacity are calculated separately and compared to the actual weekly freight flow load. Two ritase frequency values are used for different purposes and do not replace each other: (i) the MAXIMUM frequency of 3 ritase/week is used to calculate the maximum capacity (ceiling) of the fleet, i.e. $1 \text{ unit} \times 3.0 \text{ tons/ritase} \times 3 \text{ ritase/week} = 9.0 \text{ tons/week}$; and (ii) the REAL AVERAGE frequency of 2.75 ritase/week (57 weeks average, including low volume months with 2 ritases/week and high volume months with 3 ritases/week as in the sample Table 3) is used to calculate the actual load, which is $2.75 \text{ ritase/week} \times 3.0 \text{ tons/ritase} = 8.25 \text{ tons/week}$. Thus, utilization = $(\text{Actual Load} / \text{Maximum Capacity}) \times 100\% = (8.25 / 9.0) \times 100\% = 91.7\%$ and slack capacity = $100\% - 91.7\% \approx 8.3\%$. This condition indicates that the fleet is operating very close to the maximum capacity limit (near full capacity condition).

On the other hand, a sort-loading workforce of 3 people with a productivity of 0.7 tons/person/day and 5 working days per week produces a maximum capacity of 10.5 tons per week ($3 \times 0.7 \times 5$), against an actual load of 8.5 tons per week, so that utilization = $(8.5 / 10.5) \times 100\% = 81.0\%$ and slack capacity $\approx 19.0\%$. This value shows that the workforce still has a much more adequate spare capacity than the fleet.

Table 8. Fleet and manpower capacity analysis (per week)

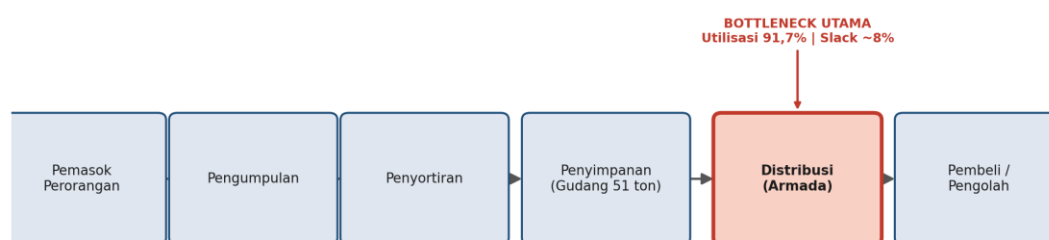
Components	Parameters	Value
Navy	Number of fleets (units)	1
Navy	Capacity per ritase (tons)	3,0
Navy	Maximum ritrate frequency/week (ceiling)	3
Navy	Real average ritrate frequency/week (57 mg)	2.75 (range 2–3)
Navy	Maximum capacity (tons/mg) = $1 \times 3.0 \times 3$	9,0
Navy	Actual load (tons/mg) = 2.75×3.0	8,25
Navy	Utilization = Actual Load / Maximum Capacity	91,7%
Workforce	Number of sort-load workers	3
Workforce	Productivity (tons/org/day)	0,7
Workforce	Maximum capacity (tons/mg)	10,5
Workforce	Actual load (tons/mg)	8,5
Workforce	Utilization	81,0%

To ensure that the identification of the fleet as the main constraint does not rest solely on a comparison of utilization percentages, the result was cross-checked against three sets of absolute capacity data. First, in terms of throughput ceiling, the workforce can handle up to 10.5 tons per week, 2.0 tons above the weekly inflow of 8.5 tons, whereas the fleet, even when operating at its maximum frequency of three ritases every week in the 13-week sample (Table 3), transported on average only 8.19 tons per week because the real load per ritase was 2.73 tons rather than the rated 3.0 tons. The

fleet is therefore the only resource whose effective capacity is below the inflow rate. Second, on the market side, customer demand during the sample (109.7 tons) exceeded realized shipments (106.5 tons) (Table 5), so the stock build-up cannot be attributed to a lack of buyers. Third, the inventory mass balance is consistent: the cumulative difference between inflow and outflow over the 57 weeks ($484.5 - 470.1 = 14.4$ tons) equals the increase in stock from the assumed initial 15 tons to 29.4 tons at the end of the period (Table 6). Taken together, these absolute capacity, demand, and stock data corroborate the utilization-based finding that the distribution fleet is the binding constraint of the system.

Identifying Bottlenecks with the Theory of Constraints

Diagram Alir Proses Rantai Pasok UD. DOA ABADI dan Posisi Bottleneck



Aliran material reverse logistics (pascakonsumsi -> pasar sekunder)

Figure 4. UD supply chain process flow diagram. DOA ABADI and bottleneck position

Figure 4 maps the six main nodes of the UD supply chain process. DOA ABADI individual suppliers, collection, sorting, storage, distribution, to buyers/processors and marking the Distribution node (Fleet) as the main bottleneck position, consistent with the results of the Capacity Analysis in Subchapter 3.6 which shows a fleet utilization of 91.7% with slack capacity of only about 8%. This bottleneck position is just before the final node (buyer/processor), so its limitations directly inhibit the material exit rate from all previous nodes, including storage nodes that experience stock accumulation as shown in Figure 3.

The results of the Capacity Analysis in Subchapter 3.6 are then processed through the five stages of TOC described in Subchapter 2.3.2, as follows:

Table 9. Application of the Theory of Constraints stages to the UD DOA ABADI

Stages of TOC	Application to UD. DOA ABADI
1. Identify the constraint	The comparison of fleet utilization (91.7%) to labor (81.0%) sets the distribution fleet as the main constraint because it has the lowest slack capacity ($\approx 8\%$).
2. Exploit the constraint	Maximize each existing fleet ritase, for example ensuring the load is close to a capacity of 3.0 tons per ritase and avoiding ritase with an unloaded line.
3. Subordinate other resources	Labor capacity (slack $\approx 19\%$) is aligned with the rhythm of the fleet—sorting and loading priorities are directed to iron commodities to be in sync with fleet departure schedules.
4. Elevate the constraint	Fleet capacity increase options: weekly ritase additions, fleet units, or the use of vehicles with larger carrying capacity.
5. Repeat the process	Once fleet capacity is increased, utilization evaluations need to be repeated to check if bottlenecks are shifting to manpower or warehouse capacity.

Based on the Theory of Constraints approach (Tang et al., 2024), the overall performance of the operational system is determined by the components with the narrowest capacity. The comparison of 91.7% utilization in the fleet to 81.0% in the workforce shows that the distribution fleet is the main bottleneck that limits the throughput of the system. The low slack capacity of the fleet ($\approx 8\%$) makes the system vulnerable to even minor operational disruptions, so capacity-building interventions both through the addition of ritase and the use of larger capacity vehicles are expected to have the greatest impact in eliminating the identified distribution deficit of 0.25 tons per week. Since the workforce still has a larger slack capacity, the increase in fleet capacity needs to be balanced with adjustments to labor scheduling so that constraints do not suddenly move to sorting-loading nodes.

SCOR Model-Based Capacity Evaluation

In summary, the performance of the distribution is mapped using the state-of-the-art SCOR framework version 13.0 (Özkanlısoy & Bulutlar, 2023) on four attributes: reliability, responsiveness, agility, and asset management. In order to ensure that the assessment is not purely qualitative, each metric is calculated using an explicit formula sourced from actual operational data in Tables 2–8, as summarized in Table 10.

Table 10. Basis and formula for calculating SCOR Level-1 UD metrics. UD.DOA ABADI

SCOR Attributes	Metrics	Formula/Basis of Calculation	Data Source
Reliability	Fulfillment ratio (proxy Perfect Order Fulfillment)	Total Goods Outbound $\div$ Total Goods Coming In $\times$ 100% = $470.1 \div 484.5 \times 100\% = 97.0\%$	Table 7 (57 weeks aggregate)
Responsiveness	Proxy Order Fulfillment Cycle Time	The average distribution lead time per ritase (4.8 hours) was assessed against the actual delivery frequency (2–3 ritase/mg) relative to the maximum achievable frequency (3 ritase/mg)	Table 4 and Table 8
Agility	Proxy Upside Supply Chain Flexibility (Slack Capacity)	$100\% - \text{Fleet Utilization} = 100\% - (\text{Actual Load} \div \text{Maximum Capacity} \times 100\%) = 100\% - 91.7\% = 8.3\%$	Table 8
Asset management	Inventory Turnover & Days of Supply	Turnover = Goods Out $\div$ Average Inventory (average $1.41\times/\text{month}$); Days of Supply = Number of days in the month $\div$ Monthly Turnover $\approx 30 \div 1.41 \approx 21.3$ days	Table 7

The formula in Table 10 shows that reliability and agility are calculated directly from the aggregate data (Table 7 and Table 8) using a precise ratio, while responsiveness is assessed by proxy due to UD. DOA ABADI does not have a formal ordering system as in the proxy manufacturing supply chain used is a combination of direct observation lead time (Table 4) and actual delivery frequency ratio to maximum. This proxy approach is consistent with SCOR adaptation in small-medium enterprises with limited formal data, as applied by Kusriani & Miranda (2021) and Qurtubi et al. (2022). The results of the calculation are then mapped into a scorecard in Table 11.

Table 11. SCOR Level-1 UD scorecard. DOA ABADI

SCOR Attributes	Metrics	Value	Rating
Reliability	Fulfillment rate (outbound/inbound)	97,0%	Well, not 100%
Responsiveness	Frequency of delivery	2–3 ritasses/mg	Limited fleet
Agility	Fleet capacity slack	≈8%	Low, vulnerable
Asset management	Turnover; utilization; inventory days	1.41×; 52,1%; ~21 hr	Turnover slows down

The reliability attributes were in a relatively good condition (97.0%), but the responsiveness and agility attributes showed weaknesses consistent with the fleet bottleneck findings, while asset management confirmed the trend of weakening asset utilization efficiency due to limited distribution capacity (Özkanlısoy & Bulutlar, 2023).

External Factors on Operational Capacity

In addition to internal factors, the operational capacity of UD. DOA ABADI is also influenced by the spatial context of the business location in the coastal area of Bandarharjo, North Semarang District, which is adjacent to the Tanjung Emas Port area. This area has a high and recurrent rate of land subsidence and the incidence of flash floods (Hamdani et al., 2021). Identification based on Sentinel-1 satellite imagery shows that the area of flash inundation in North Semarang District reached around 44.5% of the area of the sub-district in December 2020 and still covers around 38.7% in June 2023, making it one of the coastal sub-districts with the highest level of flash exposure in Semarang City (Zulfikar & Indra, 2024). Urban freight systems are particularly sensitive to these kinds of local accessibility disruptions (Silva et al., 2023), so that the risk of flash flooding has the potential to increase fleet capacity limitations which have been identified as a major bottleneck, especially during the rainy season. Field findings on coastal MSMEs in Jakarta and Semarang show that micro-small business actors in flood-prone areas generally have limited adaptive capacity to contribute to collective mitigation (Neise et al., 2021), while aspects of economic sensitivity in the form of loss of income and daily operational disruption due to floods tend to be more dominant vulnerability factors than physical exposure alone (Isa & Mardalis, 2022). This condition reinforces the urgency of proactively managing distribution capacity bottlenecks, given the limitations of UD's adaptive capacity. UD. DOA ABADI for similar external disturbances.

Cost Calculation and Capacity Increase Scenario Comparison

As a quantitative follow-up to the Elevate the Constraint stage (Table 9), this section calculates the costs and benefits of three scenarios of increasing fleet capacity compared to existing conditions. It should be emphasized from the outset the differences in the nature of the data used: Tables 2–11 in Subchapters 3.1–3.9 are all sourced from the company's actual operational data (transaction records, direct observations, and time-motion study documentation), while all cost, price, and margin figures in the following tables 12–15 are illustrative estimates based on the market price range of light commercial vehicles and operational costs of the MSME fleet in Semarang in 2026 – not actual financial or audited UD data. DOA ABADI. This estimate is used solely to demonstrate a cost-benefit analysis framework and still needs to be recalibrated using the company's real cost data before being used as a basis for investment decisions.

Basic Validation of Cost Estimation

In order to ensure that the estimate is not arbitrary, each cost component is cross-validated against the reasonable market reference range for light commercial enterprises in Semarang City in 2026, as summarized in Table 12.

Table 12. Validation of the cost and margin estimated reference range

Components	Assumed Value	Market Reference Range	Validation Basis
Driver salary/month	IDR 3,000,000	IDR 2,800,000–IDR 3,500,000	Salary range for non-formal commercial / logistics drivers in Semarang City
Fuel/month	IDR 1,500,000	IDR 1,300,000–IDR 1,800,000	Estimated mileage from travel time per ritase (Table 4, 1.5–3.0 hours) × fuel consumption of light commercial vehicles ($\pm 1:8-10$ km/litre) × ± 12 ritase/month
Maintenance & levy/month	IDR 1,000,000	IDR 800,000–IDR 1,300,000	$\pm 10-15\%$ of fuel costs and salaries, following the maintenance cost pattern of middle-aged commercial commercial vehicles
Vehicle shrinkage/month	IDR 1,500,000	IDR 1,125,000–IDR 1,560,000	The straight-line method is based on an estimated vehicle price of IDR 108-150 million with an economic life of 8 years
Capex Scenario B (additional fleet)	IDR 120,000,000	IDR 95,000,000–IDR 140,000,000	Market price range of used light commercial pick-up cars roadworthy in Central Java, 2026
Capex Scenario C (net trade-in)	IDR 95,000,000	IDR 80,000,000–IDR 115,000,000	The price of a commercial vehicle with a capacity of 5 tons minus the estimated exchange-plus value of the existing fleet (IDR 30–45 million)
Distribution margin	Rp200.000/ton	IDR 150,000–IDR 250,000/ton	Estimated gross margin blended for four commodities (iron, cardboard, paper, plastic) from the difference between the selling price to the collector/recycling industry and the purchase price from individual suppliers

The values used in Table 13–15 are taken from the midpoint or representative values in each reference range of Table 12, rather than extreme values, in order to make estimates conservative-realistic. The reference range in Table 12 is also the basis for the sensitivity analysis, which tests how robust the best scenario selection conclusions are against variations in margin values and supply growth assumptions. Table 13 first details the structure of fleet operational costs at baseline conditions (estimates) as a reference for comparison.

Table 13. Fleet operating cost structure under existing conditions — illustrative estimate (Scenario 0)

Cost Component (Estimated)	Value per Month	Value per Year
Driver salary	IDR 3,000,000	IDR 36,000,000
Fuel (BBM)	IDR 1,500,000	IDR 18,000,000
Maintenance & levy	IDR 1,000,000	IDR 12,000,000
Vehicle shrinkage	IDR 1,500,000	IDR 18,000,000
Total fleet operating costs	IDR 7,000,000	IDR84,000,000

Based on the baseline, three elevate scenarios were formulated: Scenario A increases the average ritase from 2.75 to 3.5 ritase/week through schedule optimization and additional ritase on weekends without adding fleet units; Scenario B adds one unit of the same fleet (capacity of 3.0 tons/ritase); and Scenario C replaces the fleet with a rated capacity of 5.0 tons (average real load of 4.55 tons at the same load efficiency, $\approx 91\%$) through a trade-in scheme. The estimated annual benefit is calculated from the value of additional capacity that can realistically be absorbed according to the projected supply growth of 15% in the next 3 years (equivalent to ± 1.3 tons/week or 67.6 tons/year), assuming a distribution margin of Rp200,000 per ton. Because the additional capacity in all three scenarios exceeds the growth needs, the effectively realized annual benefits in all three scenarios that exceed the real need do not provide any additional financial benefits over the 3-year horizon.

Table 14. Comparison of costs and benefits of distribution capacity building scenarios – illustrative

Criteria	Scenario 0 (Existing)	Scenario A (Add Rate)	Scenario B (Add 1 Fleet Unit)	Scenario C (Vehicle Capacity Upgrade)
Initial investment (capex, estimate)	IDR0	IDR0	IDR120,000,000	IDR 95,000,000 (net trade-in)
Maximum fleet capacity (tons/mg, actual/projection)	9,0	10,5	18,0	13,65
Additional operating costs/year (estimated)	—	IDR 7,800,000	IDR84,000,000	IDR14,400,000
Estimated annual benefits (margin assumptions)	IDR0	IDR 13,520,000	IDR 13,520,000	IDR 13,520,000
Annual net cash flow (benefits – additional opex)	IDR0	+IDR 5.720.000	–IDR70,480,000	–IDR 880,000
First-year net benefit (net cash flow – capex)	IDR0	+IDR 5.720.000	–Rp190.480.000	–Rp95.880.000
Payback period (= Capex ÷ Annual Net Cash Flow)	Not valid (without capex)	Not applicable (without capex, immediate benefits are earned from the first year)	Unmet (∞) – negative annual net cash flow	Unmet (∞) – negative annual net cash flow

The payback period is calculated using the standard formula $\text{Capex} \div \text{Annual Net Cash Flow}$, and is only meaningful if the annual net cash flow is positive. Scenario A does not require an initial investment (capex Rp0) so the term payback period by definition does not apply to it, there is no capital that needs to be "returned"; the net benefit of IDR 5,720,000 is realized immediately from the first year. Scenarios B and C, on the other hand, have negative annual net cash flows (–Rp70,480,000 and –Rp880,000, respectively), which mathematically means that the payback period will never be achieved (towards infinity) as long as the structure of costs and benefits does not change not just "qualitatively", but an investment that is formally unable to return its own capital from the difference in benefits and additional operational costs generated.

Table 14 shows that only Scenario A generated positive net benefits in the first year, as it did not require an initial investment and the additional operating costs were much lower than the benefits obtained. Scenario B had the largest capacity (18.0 tons/week) but was scaled far beyond the supply

growth needs of the next 3 years, so the large additional operating costs (Rp84,000,000/year) were not proportional to the benefits that could be realized, resulting in the largest negative annual net cash flow among the three scenarios. Scenario C is in the middle position, with significant capex but much lower additional opex than Scenario B; although the annual net cash flow is close to break-even (−Rp880,000), the figure remains negative so that the payback period remains unachieved within the 3-year horizon. For the record, the maximum capacity of the existing fleet (9.0 tons/mg) is the actual figure from Table 8, while the resulting capacity of the three scenarios (10.5; 18.0; and 13.65 tons/mg) is a projection based on the technical specifications of the vehicle, not the results of real operational measurements as the scenario has not yet been implemented.

To verify these conclusions more comprehensively, a multi-criteria assessment was conducted with weighting on five aspects: initial investment (30%), payback period (25%), capacity suitability to needs/right-sizing (20%), operational flexibility (15%), and implementation risk (10%). Each criterion was scored 1–5, with 5 indicating the best performance.

Table 15. Multi-criteria decision score matrix for best-case selection

Criteria (Weight)	Scenario A	Scenario B	Scenario C
Initial investment (30%)	5	1	2
Payback period (25%)	5	1	1
Capacity suitability/right-sizing (20%)	5	2	3
Operational flexibility (15%)	4	5	4
Implementation risk (10%)	4	3	3
Weighted score (scale 1–5)	4,75	2,00	2,35

Scenario A obtained the highest weighted score (4.75 on a scale of 5), far above Scenario C (2.35) and Scenario B (2.00), consistent with the results of the net benefit analysis in Table 14. Thus, Scenario A increasing weekly rates through schedule optimization without adding fleet units is determined as the best scenario to be implemented in the short to medium term. This scenario is in line with the TOC principle which emphasizes that constraints are exploited to the maximum (exploit) before additional investments (elevate) are made (Tang et al., 2024); investments in Scenario B or C are only relevant to be considered if future supply growth significantly exceeds the capacity resulting from the optimization of Scenario A.

Sensitivity Analysis

Since all cost and benefit figures in Subchapter 3.10 are illustrative estimates (Table 12), the conclusion of selecting the best scenario needs to be tested for robustness against variations in assumptions. The sensitivity analysis is carried out by examining the two most influential and least uncertain parameters, namely distribution margin (range of Rp150,000–Rp250,000/ton according to Table 12) and supply growth assumptions for the next 3 years (range 10–20%, with 15% as baseline), while the additional opex component of each scenario is held at the baseline value of Table 14. Table 16 presents the sensitivity of the first-year net benefit of Scenario A to the combination of the two parameters.

Table 16. Sensitivity of the first-year net benefit of Scenario A to margin and supply growth (*baseline value, as per Table 14)

Distribution Margin\Supply Growth	10%	15% (baseline)	20%
IDR150,000/ton	-IDR 1,040,000	+IDR2.340.000	+IDR 3.900.000
IDR 200,000/ton (baseline)	+IDR 1.214.000	+Rp5.720.000*	+IDR 7.800.000
IDR 250,000/ton	+IDR 3.468.000	+IDR 9.100.000	+IDR 11.700.000

Table 16 shows that Scenario A remained positive in eight of the nine combinations of assumptions tested, and only turned negative in the most conservative combination (the lowest margin of Rp150,000/ton along with the lowest supply growth of 10%), even with relatively small losses (-Rp1,040,000/year). This condition suggests that the conclusion to choose Scenario A is robust against the uncertainty of cost and margin estimates, as this scenario does not require an initial investment and therefore the financial risk is inherently low.

The same sensitivity was also tested for Scenarios B and C to check whether there was a combination of assumptions that made them feasible. Table 17 summarizes the breakeven point of the minimum supply growth approach required for the annual net benefit of both scenarios to be positive, at each margin level.

Table 17. Breakeven of supply growth required for Scenarios B and C to achieve positive net benefits

Distribution Margin	Break-even Supply Growth – Scenario B	Break-even Supply Growth – Scenario C	Remarks
IDR150,000/ton	> 100% (out of the reasonable range)	≈21%	C is close to feasible only on high margins and high growth
IDR 200,000/ton (baseline)	> 90% (out of reasonable range)	≈16%	C breaks evenly above the baseline assumption (15%)
IDR 250,000/ton	> 70% (out of reasonable range)	≈13%	C is already feasible at growth slightly below baseline

The results in Table 17 show two important findings. First, Scenario B remains unfeasible for the entire combination of margin and realistic supply growth – supply growth above 70–100% per 3 years (well beyond the historical trend of UD. DOA ABADI) in order for its large additional operating costs (Rp84,000,000/year) to be covered, so the conclusion that Scenario B is not feasible is robust and insensitive to assumption uncertainty. Second, Scenario C is much more sensitive: at the baseline margin (Rp200,000/ton), Scenario C breaks even at a supply growth of around 16% just slightly above the baseline assumption of 15% used in Table 14. In other words, Scenario C is in a marginal (borderline) position and has the potential to be a viable option if the realization of supply growth or UD distribution margins is realized. UD. DOA ABADI in the future is slightly higher than the conservative assumptions used. These findings reinforce the recommendations in Subchapter 3.10: Scenario A remains the best option for now because the risk is the lowest and the outcome is the most robust, but Scenario C is worth monitoring as a follow-up elevate option if the real supply growth trend in the next observation period is confirmed to be close to or exceeding 16% in 3 years.

CONCLUSION

Analysis of operational capacity in UD. DOA ABADI shows that the distribution system is not fully able to keep up with the pace of supply, with a distribution capacity deficit of 0.25 tons per week which accumulates into an increase in warehouse utilization, a slowdown in inventory turnover, and a gradual accumulation of stock. The comparison of fleet utilization (91.7%) and labor (81.0%) identifies distribution fleets as the main bottleneck that limits system throughput, with very low slack capacity ($\approx 8\%$) making it vulnerable to operational disruptions. External factors in the form of flash flood vulnerability in the coastal area of North Semarang have the potential to increase the limitation of distribution capacity. Cost calculations and comparisons of three capacity increase scenarios (increased ritase, additional fleet units, and vehicle capacity upgrade) showed that the scenario of increasing weekly ritase without new fleet investment was the most feasible option, with a positive first-year net benefit (+Rp5,720,000), no need for a payback period because it did not require an initial investment (capex Rp0), and the highest multi-criteria decision score (4.75 on a scale of 5), while the addition of fleet units and vehicle capacity upgrades resulted in capacity far exceeding real needs relative to the projected supply growth in the next 3 years so that the payback period was not achieved (negative annual net cash flow). The sensitivity analysis confirmed that the selection of Scenario A was robust against the uncertainty of cost and margin assumptions, remaining positive in eight of the nine scenario combinations tested, while Scenario B remained unfeasible on all reasonable combinations and Scenario C was in a marginal position that was worth monitoring in the future. This study shows that capacity analysis that compares utilization between operational resources, combined with Theory of Constraints, SCOR model, and cost-benefit analysis scenarios, is effectively used to identify bottlenecks as well as formulate and prioritize the most efficient distribution capacity building interventions in micro-scale circular economy-based informal businesses. Further research is recommended to validate cost and margin assumptions with actual company financial data and add flash flood risk mitigation scenarios in long-term distribution capacity planning.

REFERENCES

- Biancolin, M., Capoani, L., & Rotaris, L. (2023). Reverse logistics and circular economy: A literature review. *European Transport/Trasporti Europei*, 94, 1-19. <https://dx.doi.org/10.48295/ET.2023.94.7>
- Boysen, N., Fedtke, S., & Schwerdfeger, S. (2021). Last-mile delivery concepts: A survey from an operational research perspective. *OR Spectrum*, 43(1), 1-58. <https://doi.org/10.1007/s00291-020-00607-8>
- Breivik, J., Larsen, N. M., Thyholdt, S. B., & Myrland, Ø. (2021). Measuring inventory turnover efficiency using stochastic frontier analysis: Building materials and hardware retail chains in Norway. *International Journal of Systems Science: Operations & Logistics*, 10(1). <https://doi.org/10.1080/23302674.2021.1964635>
- Desticioglu, B., Calipinar, H., Ozyuruk, B., & Koc, E. (2022). Model for reverse logistic problem of recycling under stochastic demand. *Sustainability*, 14(8), 4640. <https://doi.org/10.3390/su14084640>
- Hamdani, R. S., Hadi, S. P., & Rudiarto, I. (2021). Progress or Regress? A Systematic Review on Two Decades of Monitoring and Addressing Land Subsidence Hazards in Semarang City. *Sustainability (Switzerland)*, 13, 1-26.
- Isa, M., & Mardalis, A. (2022). Flood vulnerability and economic valuation of small and medium-sized

- enterprise owners to enhance sustainability. *Jambá: Journal of Disaster Risk Studies*, 14(1), a1306. <https://doi.org/10.4102/jamba.v14i1.1306>
- Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: A conceptual and formal generalisation of four major adaptation strategies. *International Journal of Production Research*, 59(12), 3535–3552. <https://doi.org/10.1080/00207543.2021.1890852>
- Kazancoglu, Y., Ekinici, E., Mangla, S. K., Sezer, M. D., & Kayikci, Y. (2021). Performance evaluation of reverse logistics in food supply chains in a circular economy using system dynamics. *Business Strategy and the Environment*, 30(1), 71–91. <https://doi.org/10.1002/bse.2610>
- Kristanto, G. A., Kemala, D., & Nandhita, P. A. C. (2022). Challenges confronting waste pickers in Indonesia: An on-field analysis. *Waste Management & Research*, 40(9), 1381–1389. <https://doi.org/10.1177/0734242X211029181>
- Kusrini, E., & Miranda, S. (2021). Determining performance metrics of supply chain management in make-to-order small-medium enterprise using Supply Chain Operation Reference Model (SCOR Version 12.0). *Mathematical Modelling of Engineering Problems*, 8(5), 750–756. <https://doi.org/10.18280/mmep.080509>
- Mukherjee, S., Nagariya, R., Mathiyazhagan, K., Baral, M. M., Pavithra, M. R., & Appolloni, A. (2024). Artificial intelligence-based reverse logistics for improving circular economy performance: A developing country perspective. *The International Journal of Logistics Management*, 35(6), 1779–1806. <https://doi.org/10.1108/IJLM-03-2023-0102>
- Neise, T., Sambodo, M. T., & Revilla Diez, J. (2021). Are micro-, small- and medium-sized enterprises willing to contribute to collective flood risk reduction? Scenario-based field experiments from Jakarta and Semarang, Indonesia. *Organization & Environment*, 34(2), 219–242. <https://doi.org/10.1177/1086026619875435>
- Özkanlısoy, Ö., & Bulutlar, F. (2023). Measuring supply chain performance as SCOR v13.0-based in disruptive technology era: Scale development and validation. *Logistics*, 7(3), 65. <https://doi.org/10.3390/logistics7030065>
- Pushpamali, N. N. C., Agdas, D., Rose, T. M., & Yigitcanlar, T. (2021). Stakeholder perception of reverse logistics practices on supply chain performance. *Business Strategy and the Environment*, 30(1), 60–70. <https://doi.org/10.1002/bse.2609>
- Qurtubi, Q., Yanti, R., & Maghfiroh, M. F. N. (2022). Supply chain performance measurement on small medium enterprise garment industry: Application of supply chain operation reference. *Jurnal Sistem dan Manajemen Industri*, 6(1), 14–22. <https://doi.org/10.30656/jsmi.v6i1.4536>
- Silva, V., Amaral, A., & Fontes, T. (2023). Sustainable urban last-mile logistics: A systematic literature review. *Sustainability*, 15(3), 2285. <https://doi.org/10.3390/su15032285>
- Stopka, O., Zitrický, V., Lupták, V., & Stopková, M. (2023). Application of specific tools of the Theory of Constraints—a case study. *Cognitive Sustainability*, 2(1). <https://doi.org/10.55343/CogSust.48>
- Tang, J., Dai, Z., Jiang, W., Wu, X., Zhuravkov, M. A., Xue, Z., & Wang, J. (2024). A comprehensive review of theories, methods, and techniques for bottleneck identification and management in manufacturing systems. *Applied Sciences*, 14(17), 7712. <https://doi.org/10.3390/app14177712>
- Velis, C. A., Hardesty, B. D., Cottom, J. W., & Wilcox, C. (2022). Enabling the informal recycling sector to prevent plastic pollution and deliver an inclusive circular economy. *Environmental Science & Policy*, 138, 20–25. <https://doi.org/10.1016/j.envsci.2022.09.008>
- Zulfikar, A. I., & Indra, T. (2024). Identifikasi banjir rob di kota semarang, Provinsi Jawa Tengah berbasis citra satelit sentinel-1 menggunakan metode change detection. *Prosiding FTSP Series*, 639–644.