

Inventory Replenishment and Logistics Cost Efficiency in Agro-Industrial Company: A Comparative Analysis of POQ and Silver-Meal Algorithm

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Abstract

Herbicides and pesticides are routine, semi-perishable inputs in oil palm plantations, so purchasing policy affects storage cost, working capital, and expiry risk. This study evaluates inventory replenishment and logistics costs at PT XYZ, an Indonesian oil palm company, comparing existing policy with the Periodic Order Quantity (POQ) and Silver-Meal Algorithm (SMA) under time-varying demand. ABC classification identified four category A items, Marshall, Glyphosate 480, Paraquat Primax 280 SL, and Racumin, accounting for 79% of purchase value. Ordering costs (telecommunication, transportation, handling) and holding costs (energy, labor, maintenance, by slot) were estimated from company records; each policy was evaluated on realized 2025 monthly demand. Relative to existing policy, POQ cut total cost 27-56% per item (45,6% overall), SMA 45-64% (57,9%). SMA raised ordering cost 60,4% through more frequent orders but cut holding cost 93,4%; POQ left ordering cost nearly unchanged, cutting holding cost 58,8%. SMA's advantage over POQ ranged 4,8 to 20 percentage points, disappearing for Paraquat Primax 280 SL if cost per order is 35% higher than estimated. Because the evaluation assumes perfect demand knowledge and excludes capital and expiry costs, savings are an upper bound. SMA is recommended, with POQ as a simpler alternative when order frequency is constrained.

JEL classification numbers: M11, D24, Q12, C61.

Keywords: Ordering cost, Holding cost, Time-varying demand, Periodic Order Quantity (POQ), Silver-Meal Algorithm (SMA), Herbicides, Pesticides.

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1. Introduction

Inventory management is central to the operational sustainability of both manufacturing and service organizations. Stock must balance material availability against cost: excess inventory ties up working capital, occupies storage space, and exposes items to damage or expiry, while shortages disrupt operations and reduce performance (Heizer et al., 2020; Chopra and Meindl, 2001). Empirical studies link inventory levels to firm financial performance (Capkun and Weiss, 2009) and show that excessively lean inventories can also be harmful (Eroglu and Hofer, 2011). Controlling inventory is therefore essential to minimizing total inventory cost while preserving operational stability.

In practice, demand is rarely constant. Customer needs, market dynamics, and seasonal or operational cycles cause requirements to vary from period to period, which complicates the choice of order quantity (Martinez-Luna and T, 2026), and the coexistence of regular and urgent demand adds further decision complexity (Ongkunaruk et al., 2026). Without systematic evaluation, firms risk high holding costs and lost opportunities due to stockouts (Dadri and Purnawati, 2023), and must manage the trade-off between inventory costs and service levels (Donselaar et al., 2021). Studies also emphasize that inventory policy should be based on real cost data, including administration, transportation, holding, and the risk of damage, because these components directly determine total inventory cost (Willyanto et al., 2019; Ariana and Candraningrat, 2025).

These issues are especially relevant in the agro-industry. Palm oil is a strategic sector in Indonesia, and its productivity depends on continuous field maintenance across extensive plantation areas (Corley and Tinker, 2016). Crop protection inputs such as herbicides, insecticides, and rodenticides are essential to this maintenance because uncontrolled weeds, insects, and pests cause substantial yield losses (Oerke, 2005; Woittiez et al., 2017). Unlike many industrial materials, these inputs are semi-perishable: they have a finite shelf life, their effectiveness can gradually decline in storage, and they require dedicated warehouse space and handling in accordance with stock control guidelines. Stockouts can delay field operations, whereas overstocking raises holding costs and the risk of quality deterioration and expiry (Zhang et al., 2022). Balancing availability against this risk requires an explicit, quantitative approach (Ali Tamam et al., 2025).

PT XYZ operates a large oil palm plantation and depends heavily on these inputs. Its inventory management, however, remains conventional and lacks a structured quantitative framework, so purchasing tends to involve large lots to avoid shortages. This raises holding costs, increases the risk of damage and expiry, and reduces the efficiency of working capital. An initial ABC analysis of PT XYZ's purchases shows that four items (Marshall, Glyphosate 480; Paraquat Primax 280 SL, and Racumin) account for 79% of the total purchase value. This concentration reflects how the products are used. Two of the items are herbicides for weed control (Glyphosate 480 and Paraquat Primax 280 SL), one is an insecticide (Marshall), and one is a rodenticide (Racumin). These are routine crop-protection inputs applied in

recurring rounds over large planted areas, so they are consumed continuously and in large volumes for 6.500 hectares of oil palm plantation. Warehouse records for 2025 are consistent with this pattern: withdrawals of Marshall, Glyphosate 480, and Paraquat Primax 280 SL occur in nearly every month, while receipts arrive in a small number of lumps, six to seven deliveries per year under the existing policy. The stock carried between deliveries is subject to shelf life limits, which for agrochemicals, are typically around 2 years under recommended storage conditions (FAO, 1996). High value, recurring use, and lumpy purchasing together make these four items the logical priority for tighter control.

Although many lot-sizing approaches exist, comparative evidence on how fixed interval (POQ) and dynamic (Silver-Meal) policies perform for semi perishable crop protection inputs in plantation settings is limited. Applications in other sectors often report ordering and holding costs as a single aggregate value and do not always benchmark the proposed policy against the firm's recorded purchasing history. This study addresses these gaps in four steps. First, ABC classification by purchase cost identifies the items that matter most financially. Second, ordering cost is built from four components (telecommunication, driver, vehicle fuel, and loading and unloading) using the quantity per purchase order, the distance to the supplier, the fuel consumption of the delivery vehicle, and the handling cost per load. Third, holding cost is allocated to each item according to the share of warehouse slots it occupies, using energy, warehouse staff, and maintenance costs. Fourth, the total cost under the existing policy, POQ, and SMA is obtained by simulating the realized monthly demand and, for the existing policy, the number of orders actually placed. Periodically demand is therefore treated as known (time-varying but deterministic), and the study also tests how sensitive the ranking of POQ and SMA is to the assumed cost of an order.

The study contributes in three ways. First, it provides an empirical comparison of the existing policy, POQ, and SMA in an Indonesian plantation setting, benchmarked against the company's actual monthly demand and order history. Second, it offers a transparent, component based procedure for estimating ordering and holding costs that firms without formal inventory systems can replicate. Third, it shows that the advantage of dynamic lot-sizing differs across items and depends on the assumed cost of an order, so that the recommended policy should be checked item by item rather than assumed.

2. Literature Review

ABC classification ranks items by annual usage value (demand multiplied by unit cost) and groups them by cumulative contribution. Category A contains a small number of items that account for a large share of total value and therefore warrant the tightest control (Dadri and Purnawati, 2023; Ray Silaen et al., 2024). Prioritizing in this way lets firms allocate managerial resources to the most critical items (Asthariq et al., 2021). Although value-based ABC is the most common form, multi-criteria extensions and cost oriented evaluations exist (Flores and Whybark, 1986;

Teunter et al., 2010). Integrating ABC with lot-sizing methods such as EOQ, POQ, and SMA has been shown to improve inventory efficiency, particularly for category A items (Ernawati et al., 2021; Ikasari et al., 2019)

The classic EOQ model (Tersine, 1994) remains widely used because it balances ordering and holding costs (Sutejo et al., 2023). It assumes constant, continuous demand, which limits its suitability when demand varies across periods (Afzalabadi et al., 2016; Herlambang and Marikena, 2025), and reviews argue that it does not capture the complexity of modern inventory systems (Jaber and Peltokorpi, 2025). For time-varying demand, the Wagner-Whitin algorithm yields the optimal solution, and multi-period, dynamic approaches better accommodate demand variation than static ones (Bahl et al., 1987; Brahimi et al., 2006; Martinez-Luna and T, 2026). Because exact methods are more difficult to implement in practice, simple heuristics remain attractive (Silver et al., 2016).

POQ adapts EOQ to discrete periods by converting the economic quantity into an economic order interval and ordering the aggregated demand of that interval (Tersine, 1994; Herlambang and Marikena, 2025). The Silver-Meal heuristic instead extends the coverage of each order period by period until the average relevant cost per period begins to rise. It therefore adjusts lot sizes to actual demand fluctuations, and its performance is generally close to the optimal Wagner-Whitin solution (Silver et al., 2016; Mikosch et al., 2010). Empirical studies report that Silver-Meal yields lower inventory costs than existing practices or alternative lot-sizing rules (Rini and Ananda, 2021; Hasibuan et al., 2021; Asmal et al., 2023; Sari and Aprilia, 2024). Since POQ fixes the ordering interval and SMA minimizes average cost per period, comparing the two helps determine which approach suits a given demand pattern. These comparisons typically assume that demand over the planning horizon is known. When demand must be forecast on a rolling horizon, the advantage of dynamic rules over simpler ones is less clear (Wemmerlöv and Whybark, 1984; Simpson, 2001), which is why results based on known demand are best read as an upper bound.

The outcome of any lot-sizing comparison depends on the cost parameters. Ordering cost covers the expenses incurred each time an order is placed, such as communication, transport, and handling, while holding cost covers items such as storage space, labor, capital, and obsolescence (Silver et al., 2016; Heizer et al., 2020). Studies stress that these parameters should be estimated from real operational data (Willyanto et al., 2019; Ariana and Candraningrat, 2025). Where firms lack formal costing systems, resource-based allocation, which assigns cost according to the time or space each activity consumes, is a practical approach (Kaplan et al., 2004). This study considers the practical approach which are (1) ordering cost is built from telecommunication, driver, fuel, and loading and unloading costs, computed from the order quantity per purchase order, the distance to the supplier, the fuel consumption of the delivery vehicle, and the handling cost per load, and (2) holding cost from warehouse operating costs (energy, staff, and maintenance) which are allocated to items by the share of warehouse slots they occupy.

Product characteristics also shape inventory decisions. Items whose quality declines over time, called deteriorating items, require ordering policies that account for storage duration (Nahmias, 1982; Goyal and Giri, 2001; Bakker et al., 2012; Janssen et al., 2016). Some products deteriorate only after a delay, a phenomenon known as non-instantaneous deterioration (Khan et al., 2022), and deterioration influences both ordering policy and inventory-related costs (Karimi, 2025). Semi-perishable goods, which are not easily damaged but have a finite shelf life and degrade gradually, fall in this category, as do crop-protection chemicals. Agri-food supply chain research further notes that agricultural systems face seasonality and product quality constraints that make planning models harder to apply (Ahumada and Villalobos, 2009; Shukla and Jharkharia, 2013)

Existing studies mostly examine manufacturing raw materials, construction materials, or food products. Three further gaps stand out. First, lot-sizing applications often present ordering and holding costs as single aggregate values without showing the operational components underlying them, even though studies emphasize that these should be derived from real data (Willyanto et al., 2019; Ariana and Candraningrat, 2025). Second, proposed policies are not always benchmarked against the firm's actual purchasing record, so the reported savings may not reflect what the firm would actually change. Third, method rankings are usually reported without testing how they depend on the assumed cost of an order. This study addresses these gaps by combining ABC prioritization by purchase cost, a component based estimate of ordering cost (telecommunication, driver, fuel, and loading and unloading) and of holding cost (energy, staff, and maintenance allocated by warehouse slots), and a simulation of the existing policy, POQ, and SMA on the same realized monthly demand, followed by a sensitivity check on the cost of an order.

3. Methods

This study adopts a quantitative approach to evaluate inventory control policies by comparing the existing system with the Periodic Order Quantity (POQ) and Silver-Meal Algorithm (SMA) methods. The detail of the step according to the flowchart (Figure 1) are as follows:

Data collection. The data used in this study consists of primary and secondary data obtained from warehouse records. The data include item demand per period, inventory inflows and outflows, unit prices, ordering costs, and holding cost components such as energy, warehouse labor, and maintenance costs. These data serve as the basis for inventory classification and cost analysis.

ABC classification. The first stage involves classifying inventory items using the ABC analysis method. The annual usage value of each item is calculated by multiplying annual demand (R) by unit purchase cost (P). Items are then ranked in descending order and grouped into categories A, B, and C based on cumulative percentage contribution (Ernawati et al., 2021; Ray Silaen et al., 2024). Category A

items, which contribute the most to total inventory cost, are selected for further analysis due to their significant impact.

$$\text{Annual Usage Value} = R \times P \quad (1)$$

$$\text{Percentage} = (\text{Item Value} / \text{Total Value}) \times 100 \% \quad (2)$$

$$\text{Cumulative Percentage} = \sum \text{Percentage} \quad (3)$$

Inventory movement analysis. Inventory movement data are analyzed to determine demand patterns and stock levels for each period. The on hand inventory is calculated using the inventory balance equation, taking into account incoming and outgoing quantities. This analysis provides insight into inventory fluctuations and supports the estimation of average inventory levels.

$$I_t = I_{(t-1)} + In_t - Out_t \quad (4)$$

$$I_{average} = \sum I_t / n \quad (5)$$

where

$I_{(t)}$: inventory at t-period

$I_{average}$: average inventory

$I_{(t-1)}$: inventory at (t-1) period

$\sum I_t$: total inventory at t-period

In_t : incoming quantity

n: sum of period

Out_t : outgoing quantity

Cost determination. Two main cost components are calculated in this study: ordering cost and holding cost. Ordering costs are derived from operational expenses such as communication, transportation (driver and fuel), and handling costs. Meanwhile, holding cost is calculated based on total warehouse operational costs (electricity and warehouse staff salary) allocated proportionally according to storage capacity usage (slot allocation). The average inventory level is used to determine holding cost per unit per period.

Periodic Order Quantity (POQ) method. The POQ method is applied by first determining the Economic Order Interval (EOI), which defines the optimal number of periods between orders. Demand is then aggregated over the determined interval to calculate the order size. Based on this schedule, holding cost and ordering cost are computed, and the total relevant cost (TRC) is obtained (Tersine, 1994).

$$EOI = \sqrt{(2C / (Ph \times R))} \quad (6)$$

where

EOI: economic order interval

Ph: holding cost

C: ordering cost

R: demand

Silver-Meal Algorithm (SMA). The SMA method is implemented by evaluating the average total cost per period. Demand is accumulated incrementally across periods, and the cost per period is calculated. The process continues until the average cost increases, indicating a cut-off point. The optimal order size is determined based on this condition, and the ordering schedule is established accordingly. These are the following equations for the Silver-Meal Algorithm (Tersine, 1994; Mikosch et al., 2010; Ernawati et al., 2021):

$$\frac{TRC(T)}{T} = \frac{Ph \sum_{k=1}^T (k-1)R_k}{T} \quad (7)$$

$$\frac{TRC(T+1)}{T+1} > \frac{TRC(T)}{T} \quad (8)$$

where

TRC(T): total relevant cost over T period

T: time supply of the replenishment in periods

R_k: demand rate in period k

Total cost evaluation. The data used in this study consists of primary and secondary data obtained from warehouse records. The data include item demand per period, inventory inflows and outflows, unit prices, ordering costs, and holding cost components such as energy, warehouse labor, and maintenance costs. These data serve as the basis for inventory classification and cost analysis.

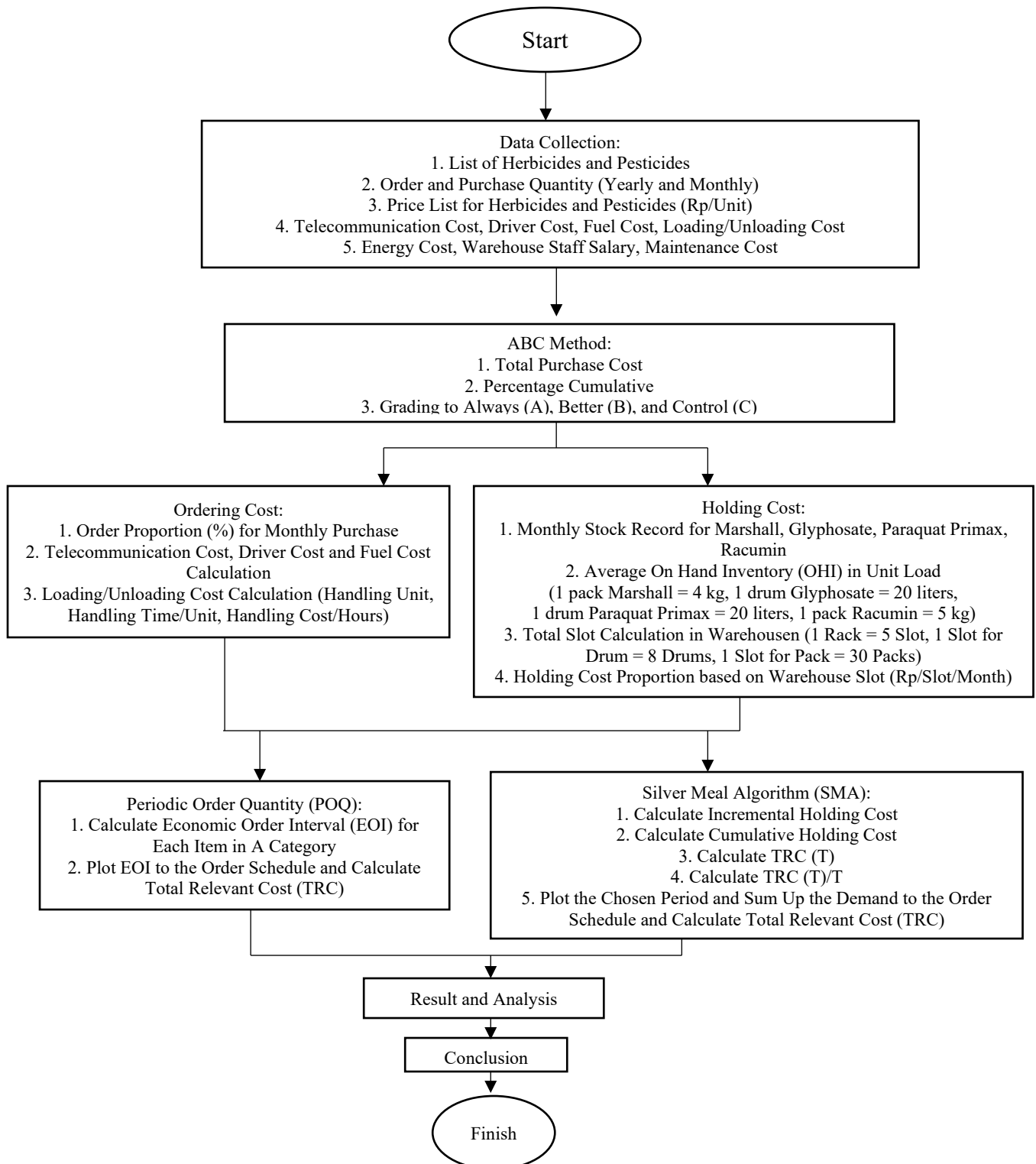


Figure 1: Research methodology

4. Result

Table 1 below presents the results of the ABC analysis of inventory items based on their annual usage value, which is calculated as the product of order quantity and unit cost. This method is employed to classify items into three principal categories (A, B, and C) following the Pareto principle, which posits that a relatively small proportion of items accounts for the majority of the total inventory value. The classification results indicate that four key items: Marshall, Glyphosate 480, Paraquat Primax 280 SL, and Racumin, are categorized as A items, contributing cumulatively to 79% of the total inventory value. This finding implies that these items are of critical importance and therefore require more stringent control and monitoring.

Table 1: ABC analysis

No	Items Description	Order (*unit)	Item Cost (Rp/unit)	Value (Rp)	Percentage	Cum. Percentage	Category
1	Marshall	11.580	28.500	330.030.000	27%	27%	A
2	Glyphosate 480	9.700	31.500	305.550.000	25%	52%	A
3	Paraquat Primax 280 SL	8.200	24.600	201.720.000	17%	69%	A
4	Racumin	1.850	65.700	121.545.000	10%	79%	A
5	Fluroksipir (cenrane)	650	125.000	81.250.000	7%	86%	B
6	Methyl Metsulfuron	880	86.500	76.120.000	6%	92%	B
7	2.4 D, Dimethyl Amine, Abolisi 865 SL	860	40.000	34.400.000	3%	95%	B
8	Triclopyr 480 - Centalon 480EC	350	91.200	31.920.000	3%	97%	C
9	Cypermethrin 250 EC - CYPERIN	137	175.000	23.975.000	2%	99%	C
10	Alkyary Poliglicol Eter	150	25.000	3.750.000	0%	100%	C
11	Spreader	70	43.000	3.010.000	0%	100%	C
12	Sevin	20	33.000	660.000	0%	100%	C

*unit (kg or litres)

Furthermore, category B comprises three items that collectively account for up to 95%, indicating a moderate level of importance within the inventory system. In contrast, category C includes five items that collectively account for only approximately 5% of the total inventory value. These items typically exhibit lower usage frequency or relatively low unit cost, and thus require less intensive control mechanisms. Accordingly, the results of this ABC analysis serve as the basis for establishing inventory management priorities, with primary attention given to category A items.

Table 2: In/Out data record for “A” category items

Items	Unit	Last Stock	Jan		Feb		March		April		May		June	
			in	out	in	out	in	out	in	out	in	out	in	out
Marshall	kg	1.532,32	3.000	916,58	-	973,77	-	662,89	-	566,65	-	702,85	1.500	1.936,39
Glyphosate 480	liters	697,92	2.000	933,64	-	1.143,79	1.200	783,71	-	623,69	1.500	928,42	1.000	943,31
Paraquat Primax 280 SL	liters	8,99	1.500	283	-	358,41	1.200	724,96	-	584,01	1.000	692,55	1.000	618,78
Racumin	kg	12,40	-	-	-	12,40	1.050	152	-	204,50	-	675	-	18,50

Table 2: In/Out data record for “A” category items (con’t)

Items	Last Stock	July		August		Sept		Oct		Nov		Dec	
		in	out	in	out	in	out	in	out	in	out	in	out
Marshall	1.532,32	2.000	946,18	-	1.327,01	-	-	2400	367	480	1.568,80	2.200	925,20
Glyphosate 480	697,92	-	1.041,24	1.000	930,75	1.500	685,78	-	881,75	1.500	557,48	-	888,66
Paraquat Primax 280 SL	8,99	-	705,65	1.000	799,83	1.000	902,91	-	836,32	1.500	598,09	-	366,80
Racumin	12,40	-	-	800	-	-	68,08	-	415,20	-	280,70	-	3,50

Table 2 summarizes the inventory movement (inflow and outflow) of category A items identified through the ABC analysis over the period of January to December 2025. The category A items, Marshall, Glyphosate 480, Paraquat Primax 280 SL, and Racumin, represent the group with the highest contribution to total usage value and therefore require more intensive control. The unit of measurement for each item is adjusted to its product characteristics: Marshall and Racumin are measured in kilograms (kg), while Glyphosate 480 and Paraquat Primax 280 SL are measured in liters. Column “in” denotes the quantity of goods received from suppliers into the warehouse, whereas the column “out” represents the quantity issued to meet operational requirements in the field.

Overall, the data indicate fluctuations in inventory movement for each item throughout the year. Marshall and Glyphosate 480 exhibit relatively high usage frequency with consistent issuance patterns, while Paraquat Primax 280 SL demonstrates a relatively balanced inflow and outflow. Racumin shows a lower

volume of movement; however, it still experiences stock variations during certain periods. Information on initial stock levels and monthly movements provides a critical basis for evaluating inventory control performance and for implementing inventory management methods.

Table 3: Ordering cost calculation for “A” category items

Items	Jan			Feb	Mar			Apr	May			Jun			Jul		
	Order Size	%	OC_n (Rp)		Order Size	%	OC_n (Rp)		Order Size	%	OC_n (Rp)	Order Size	%	OC_n (Rp)	Order Size	%	OC_n (Rp)
Marshall	3.000	46	224.077	-	-			-	-			1.500	43	188.786	2.000	100	418.000
Glyphosate 480	2.000	31	149.385	-	1.200	35	152.957	-	1.500	60	255.300	1.000	29	125.857	-		
Paraquat Primax 280 SL	1.500	23	112.038	-	1.200	35	152.957	-	1.000	40	170.200	1.000	29	125.857	-		
Racumin	-			-	1.050	30	133.837	-	-			-			-		
Total	6.500			-	3.450			-	2.500			3.500			2.000		

Table 3: Ordering cost calculation for “A” category items (con’t)

Items	August			Sept			Oct			Nov			Dec			Ordering Cost (Rp)
	Order Size	%	OC_n (Rp)	Order Size	%	OC_n (Rp)	Order Size	%	OC_n (Rp)	Order Size	%	OC_n (Rp)	Order Size	%	OC_n (Rp)	
Marshall	-	-	-	-	-	-	2.400	100	424.000	480	14	60.717	2.200	100	421.000	289.430
Glyphosate 480	1.000	36	153.571	1.500	60	255.300	-	-	-	1.500	43	189.741	-			183.159
Paraquat Primax 280 SL	1.000	36	153.571	1.000	40	170.200	-	-	-	1.500	43	189.741	-			153.509
Racumin	800	29	122.857	-	-	-	-	-	-	-			-			128.347
Total	2.800			2.500			2.400			3.480			2.200			

Table 3 presents the results of the ordering cost calculation for each category A item, calculated proportionally to the order quantities in each period, derived from purchase order (PO) data. Column “*Order Size*” indicates the quantity ordered in a given period, while the “*%*” column represents the proportional contribution of each item to the total order quantity within that period. Furthermore, column “ OC_n (Rp)” reflects the allocated ordering cost for each item, calculated according to its respective proportion of the total ordering cost in the corresponding period. The “*Ordering Cost*” column represents the precise ordering cost incurred per period, calculated as the average cost over a single time horizon during which the item is received.

The ordering cost is computed as the aggregation of several operational cost components, including telecommunication expenses, driver wages, fuel costs, and loading and unloading costs. Telecommunication costs are derived from the per-minute telephone charges incurred by procurement staff when communicating with vendors prior to the issuance of a Purchase Order (PO). The rate used for this calculation is Rp 1.100 per minute, based on an average call duration of 5 minutes. Driver costs are calculated by dividing the employee's monthly salary of Rp 3.000.000 by the 25 working days in a month. Delivery vehicle fuel costs are calculated based on a total round trip distance of 210 km; given a fuel efficiency of 8 km per liter of diesel, the resulting fuel cost is Rp 262.500 per delivery. Loading and unloading costs are calculated based on the time required to handle goods in 500 kg or 500 litres increments, with an average duration of 30 minutes per unit. For example, if the total order volume in January is 6.500 units, the time required would be 6,5 hours. This duration is then multiplied by the handling rate of Rp 15.000 per hour, derived by dividing the monthly salary of Rp 3.000.000 by the total working hours (calculated based on 25 working days at 8 hours per day).

Table 4: Holding cost factors

Component of Holding Cost	Yearly	Monthly
Energy Cost	Rp 4.704.480	Rp 392.040
Warehouse Staff Salary	Rp 35.940.000	Rp 2.995.000
Maintenance Cost	Rp 15.000.000	Rp 1.250.000
Total	Rp 55.644.480	Rp 4.637.040

The total holding cost is derived by aggregating electricity expenses, warehouse personnel salaries, and maintenance costs, as presented in Table 4. These components result in a total annual holding cost of Rp 55.644.480, equivalent to Rp 4.637.040 per month. Subsequently, the holding cost is allocated to each item based on its proportion of storage capacity utilization, measured by the number of slots it occupies relative to the total available warehouse slots. This approach implies that items occupying larger storage space incur a correspondingly higher share of holding costs.

Table 5: Allocated slot in warehouse for “A” category items

No	Items	Unit	Σ Slot
1	Marshall	pack	15
2	Glyphosate 480	drum	5
3	Paraquat Primax 280 SL	drum	6
4	Racumin	pack	3
1 rack = 5 slot; 1 slot = 8 drums; 1 slot = 30 packs			

Based on Table 5, the slot allocation for category A items exhibits considerable variation. Marshall occupies the largest allocation with 15 slots (measured in packs), followed by Paraquat Primax 280 SL with 6 slots and Glyphosate 480 with 5 slots (both measured in drums). In comparison, Racumin has the smallest allocation with 3 slots. The warehouse has a maximum capacity of 100 slots. Given that one rack has 5 slots and each slot holds 8 drums or 30 packs, the storage space utilization for each item can be determined. This proportional allocation serves as the basis for a more accurate distribution of total holding costs among items, thereby supporting a comprehensive estimate of inventory costs.

Table 6: Inventory movement for Marshall and Glyphosate 480

No	Period	Marshall			Glyphosate 480		
		In (kg)	Out (kg)	On Hand Inventory	In (ltr)	Out (ltr)	On Hand Inventory
1	Dec-24	0	0	1.532	0	0	698
2	Jan-25	3.000	917	3.616	2.000	934	1.764
3	Feb-25	0	974	2.642	0	1.144	620
4	Mar-25	0	663	1.979	1.200	784	1.037
5	Apr-25	0	567	1.412	0	624	413
6	May-25	0	703	710	1.500	928	985
7	Jun-25	1.500	1.936	273	1.000	943	1.041
8	Jul-25	2.000	946	1.327	0	1.041	0
9	Aug-25	0	1.327	0	1.000	931	69
10	Sept-25	0	0	0	1.500	686	884
11	Oct-25	2.400	367	2.033	0	882	2
12	Nov-25	480	1.569	944	1.500	557	944
13	Dec-25	2.200	925	2.219	0	889	56

Table 7 presents an illustrative calculation of holding costs based on the monthly inventory movements in Table 6, accounting for the remaining stock carried over to subsequent periods. This ending inventory constitutes a critical component in determining the average inventory level over the planning horizon. The average inventory is then used to estimate the monthly holding cost proportion, expressed in Rp/pack/month, which subsequently serves as the basis for calculating the total annual holding cost in accordance with each item's order schedule.

Table 7: Holding cost summary

Marshall (1 pack = 4 kg)
Average On Hand Inventory (kg) = 1.699
Average On Hand Inventory (pack) = 425
Holding cost proportion (slot) = Rp 695.556/slot/month
Holding cost proportion (pack) = Rp 1.638/pack/month
Glyphosate 480 (1 drum = 20 litres)
Average On Hand Inventory (lt) = 651
Average On Hand Inventory (pack) = 33
Holding cost proportion (slot) = Rp 231.852/slot/month
Holding cost proportion (drum) = Rp 7.120/drum/month

The results indicate that the average inventory of Marshall over 13 periods is 1.699 kg, equivalent to 425 packs. Based on the proportional allocation of holding costs, the resulting holding cost is Rp 1.638 per pack per month. This value reflects the magnitude of costs incurred from storing the product in the warehouse, influenced by both the average inventory level and the storage duration. Therefore, this approach enables more accurate and dynamic estimates of holding costs and is a key component of total inventory cost analysis, particularly in supporting the application of the Periodic Order Quantity (POQ) and the Silver-Meal Algorithm (SMA).

Table 8 below presents the order schedule generated using the POQ method, which emphasizes determining the Economic Order Interval (EOI) as the primary basis for decision making. The obtained EOI value of 2 indicates that orders are placed by aggregating demand over the subsequent two periods and executing them at the beginning of the cycle. Consequently, the order size in a given period represents the cumulative demand across several forthcoming periods, brought forward as part of anticipatory planning. For instance, an order size of 472 units in the first period reflects the aggregation of demand from upcoming periods, scheduled earlier to ensure supply continuity. This approach aims to balance ordering frequency with the associated costs, thereby enhancing efficiency within the inventory system.

Table 8: Order schedule for Marshall by Periodic Order Quantity (POQ)

Period	1	2	3	4	5	6	7	8	9	10	11	12
Demand	229	243	166	142	176	484	237	332	0	92	392	231
Order Size	472	0	308	0	660	0	569	0	92	0	623	0
Inventory	243	0	142	0	484	0	332	0	92	0	231	0
Holding Cost	397.960	0	232.553	0	792.645	0	543.715	0	150.668	0	378.308	0
Ordering Cost	289.430	0	289.430	0	289.430	0	289.430	0	289.430	0	289.430	0
TRC	687.390	0	521.983	0	1.082.075	0	833.145	0	440.098	0	667.738	0
Total TRC	Rp 4.232.428											

Furthermore, the cost components presented in this table consist of holding cost and ordering cost, both of which are calculated in accordance with the characteristics of the POQ method. Holding cost is determined based on the average inventory remaining before being utilized to satisfy demand in subsequent periods, and is therefore highly influenced by the magnitude of the order size as well as the ordering interval. In contrast, ordering cost is calculated based on the frequency of orders; it is treated as a fixed cost per order and is independent of the quantity ordered, depending instead on the timing of order placement. Accordingly, the total relevant cost (TRC) represents the aggregation of these two cost components, which in this case amounts to Rp 4.232.428. This value reflects the effectiveness of the POQ method in optimizing ordering policies by comprehensively considering the trade-off between holding and ordering costs.

Table 9 below presents the computational results of the Silver-Meal Algorithm (SMA) for determining an optimal ordering policy that minimizes the average cost per period. This method operates by progressively expanding demand coverage across periods until the point is reached where the average total cost, expressed as total relevant cost (TRC) per period, begins to increase. In the table, the incremental holding cost and cumulative holding cost columns represent the accumulation of holding costs resulting from the inclusion of additional demand periods. Meanwhile, the TRC(T) and TRC(T)/T columns serve as the primary decision criteria for identifying the optimal boundary. Rows labeled as cut-off indicate that extending coverage to the next period increases the average cost, thereby defining the limit of demand aggregation. For example, when a cut-off occurs at period 3, the demand in that period is not combined with the previous periods but instead initiates a new calculation cycle.

Table 9: Silver-Meal Algorithm (SMA) calculation for Marshall

Period	T	RT Demand	Ph (T-1)RT Incremental Holding Cost			Cum Holding Cost	(C+Col 5) TRC(T)	(Col 6) TRC(T)/T	Remarks
			Ph	T-1	Ph (T-1)R _T				
1	1	229	Rp1.638	0	0	0	Rp289.430	Rp289.430	← 1
2	2	243	Rp1.638	1	397.960	397.960	Rp687.390	Rp343.695	
2	1	243	Rp1.638	0	0	0	Rp289.430	Rp289.430	2 + 3
3	2	166	Rp1.638	1	271.857	271.857	Rp561.287	Rp280.644	← cut off
4	3	142	Rp1.638	2	465.105	736.963	Rp1.026.393	Rp342.131	
4	1	142	Rp1.638	0	0	0	Rp289.430	Rp289.430	4 + 5
5	2	176	Rp1.638	1	288.234	288.234	Rp577.664	Rp288.832	← cut off
6	3	484	Rp1.638	2	1.585.289	1.873.523	Rp2.162.953	Rp720.984	
6	1	484	Rp1.638	0	0	0	Rp289.430	Rp289.430	← 6
7	2	237	Rp1.638	1	388.134	388.134	Rp677.564	Rp338.782	
7	1	237	Rp1.638	0	0	0	Rp289.430	Rp289.430	← 7
8	2	332	Rp1.638	1	543.715	543.715	Rp833.145	Rp416.572	
8	1	332	Rp1.638	0	0	0	Rp289.430	Rp289.430	8 + 9
9	2	0	Rp1.638	1	0	0	Rp289.430	Rp144.715	← cut off
10	3	92	Rp1.638	2	301.336	301.336	Rp590.766	Rp196.922	
10	1	92	Rp1.638	0	0	0	Rp289.430	Rp289.430	← 10
11	2	392	Rp1.638	1	641.977	641.977	Rp931.407	Rp465.703	
11	1	392	Rp1.638	0	0	0	Rp289.430	Rp289.430	← 11
12	2	231	Rp1.638	1	378.308	378.308	Rp667.738	Rp333.869	← 12

Based on these results, the ordering policy consists of nine order placements within a year, with order quantities summarized in Table 10 below as follows: 229 packs (period 1), 409 packs (period 2), 318 packs (period 4), 484 packs (period 6), 237 packs (period 7), 332 packs (period 8), 92 packs (period 10), 392 packs (period 11), and 231 packs (period 12). This pattern indicates that the SMA method yields a more flexible ordering frequency than the POQ approach, with order sizes dynamically adjusted to demand fluctuations. As a result, the average inventory level can be reduced, lowering holding costs, although ordering frequency tends to be higher.

Table 10: Order schedule for Marshall by Silver Meal Algorithm (SMA)

Period	1	2	3	4	5	6	7	8	9	10	11	12
Demand	229	243	166	142	176	484	237	332	0	92	392	231
Order Size	229	409	0	318	0	484	237	332	0	92	392	231
Inventory	0	166	0	176	0	0	0	0	0	0	0	0
Holding Cost	0	271.857	0	288.234	0	0	0	0	0	0	0	0
Ordering Cost	289.430	289.430	0	289.430	0	289.430	289.430	289.430	0	289.430	289.430	289.430
TRC	289.430	561.287	0	577.664	0	289.430	289.430	289.430	0	289.430	289.430	289.430
Total TRC	Rp 3.164.962											

Table 11: Inventory replenishment and logistics cost summary

Herbicides and Pesticides	Ordering Cost (Yearly)			Holding Cost (Yearly)		
	Existing	POQ	SMA	Existing	POQ	SMA
Marshall	Rp1.736.580	Rp1.736.580	Rp2.604.870	Rp7.033.901	Rp2.495.848	Rp560.092
Glyphosate 480	Rp1.282.111	Rp1.098.952	Rp2.197.905	Rp2.833.610	Rp1.922.298	Rp0
Paraquat Primax 280 SL	Rp1.074.565	Rp921.056	Rp1.535.093	Rp3.359.853	Rp1.035.770	Rp209.482
Racumin	Rp256.694	Rp513.388	Rp641.735	Rp1.250.381	Rp514.655	Rp185.700

Table 11: Inventory replenishment and logistics cost summary (con't)

Herbicides and Pesticides	Order Frequency (/Year)			Total Inventory Cost (Yearly)			Inventory Cost Efficiency (%)	
	Existing	POQ	SMA	Existing	POQ	SMA	POQ	SMA
Marshall	6	6	9	Rp8.770.481	Rp4.232.428	Rp3.164.962	51,74%	63,91%
Glyphosate 480	7	6	12	Rp4.115.721	Rp3.021.251	Rp2.197.905	26,59%	46,60%
Paraquat Primax 280 SL	7	6	10	Rp4.434.418	Rp1.956.826	Rp1.744.574	55,87%	60,66%
Racumin	2	4	5	Rp1.507.075	Rp1.028.043	Rp827.435	31,79%	45,10%

After determining the ordering periods and quantities based on the order size plot for Marshall, as illustrated in Tables 9 and Table 10 using both the POQ and SMA methods, the same calculations were performed for the other three items: Glyphosate 480, Paraquat Primax 280, and Racumin. Table 11 summarizes the calculations for inventory replenishment and logistics costs, serving as an evaluation of the operational performance used to determine inventory policy. Inventory replenishment is based on the annual ordering frequency, while logistics

costs are based on inventory cost efficiency and account for both ordering and holding costs. Total inventory cost is another term for total relevant cost (TRC) since it associates holding cost and ordering cost. The company's historical demand and ordering patterns were evaluated by comparing the total inventory costs associated with the POQ and SMA methods.

5. Discussion

5.1 Ordering cost and order frequency

Figure 2 compares the annual ordering cost across the three policies. SMA produces the highest ordering cost for all four items. For Marshall, it rises from Rp1.736.580 (existing and POQ) to Rp2.604.870 (+50%). For Glyphosate 480, it rises from Rp1.282.111 to Rp2.197.905 (+71,4%); for Paraquat Primax 280 SL, from Rp1.074.565 to Rp1.535.093 (+42,9%); and for Racumin, from Rp256.694 to Rp641.735 (+150%). POQ leaves Marshall unchanged, lowers ordering cost by 14,3% for Glyphosate 480 and Paraquat Primax 280 SL, and doubles it for Racumin (Rp256.694 to Rp513.388), because POQ prescribes four orders per year against two in current practice. In aggregate, ordering cost under SMA is Rp6.979.603, 60,4% above the existing Rp4.349.950, while POQ (Rp4.269.976) is 1,8% below it.

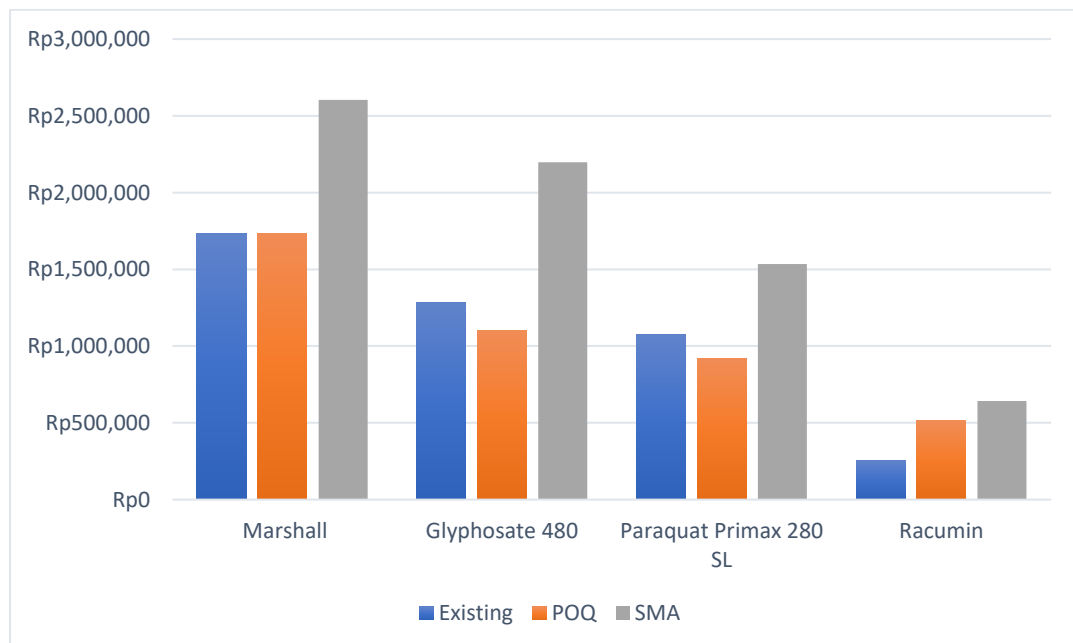


Figure 2: Annual ordering cost by policy

Figure 3 shows the source of this increase. SMA requires more orders per year for every item: 9 for Marshall (versus 6 under both existing and POQ), 12 for Glyphosate 480 (versus 7 and 6), 10 for Paraquat Primax 280 SL (versus 7 and 6), and 5 for Racumin (versus 2 and 4). Since the model applies a constant average cost per order to each item, the percentage increase in ordering cost equals the percentage increase in frequency. Hence, Figures 2 and 3 have the same shape and differ only in scale (rupiah versus number of orders).

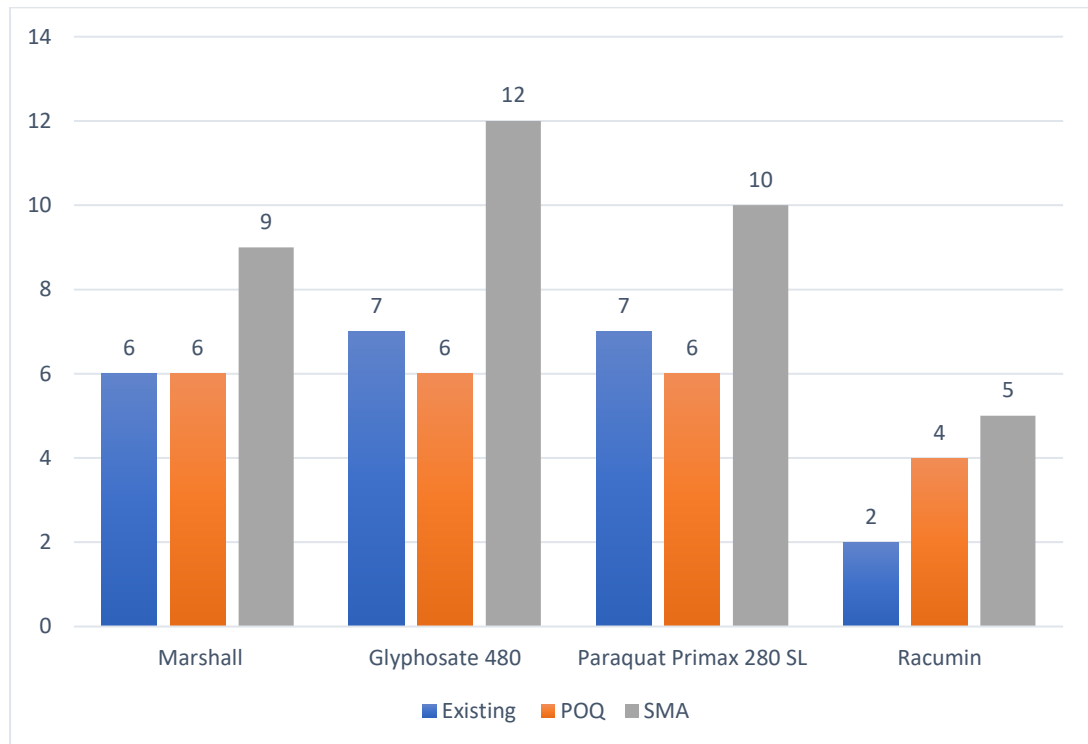


Figure 3: Annual order frequency by policy

The result follows from the algorithm's logic. SMA extends a lot to cover further periods only while the average relevant cost per period keeps falling, and it closes the lot as soon as that average rises. Because demand for these inputs fluctuates between months, the algorithm favors smaller, more frequent lots.

5.2 Holding cost

Figure 4 below shows the study's most important result. Under the existing policy, holding cost exceeds ordering cost for every item: 4,1 times for Marshall (Rp7.033.901); 3,1 times for Paraquat Primax 280 SL (Rp3.359.853); 2,2 times for Glyphosate 480 (Rp2.833.610); and 4,9 times for Racumin (Rp1.250.381). This imbalance indicates persistent excess stock, consistent with the large lot purchasing behavior.

The Rp0 holding cost for Glyphosate 480 under SMA, which is why no SMA bar appears for this item in Figure 4, arises because the algorithm orders every month, so each order equals that month's demand, and no stock is carried past a period end. This is a consequence of the calculation convention (holding costs are charged to the end of period inventory) and should not be read as an indication of no storage need. SMA outperforms POQ in holding costs for every item, consistent with the principle of dynamic lot-sizing which quantities follow actual periodically demand, whereas POQ imposes a fixed interval regardless of the demand shape. However, both POQ and SMA reduce the holding cost but in different magnitude (see Table 12).

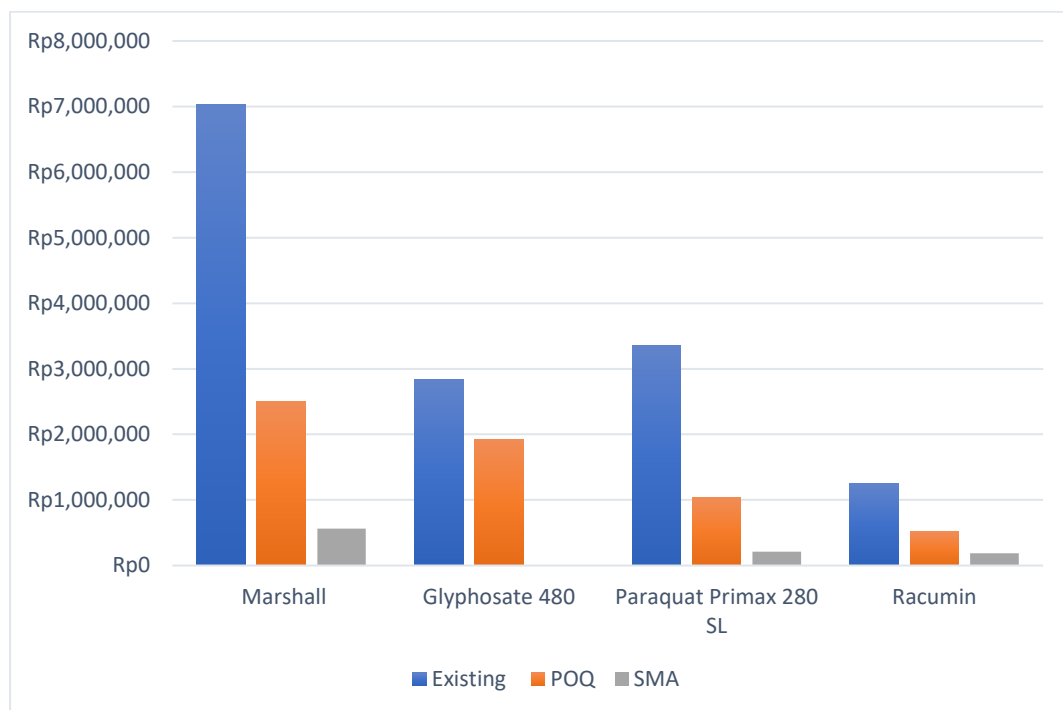


Figure 4: Annual holding cost by policy

Table 12: Holding cost reduction relative to the existing policy

Item	POQ reduction	SMA reduction
Marshall	64,5%	92,0%
Glyphosate 480	32,2%	100%
Paraquat Primax 280 SL	69,2%	93,8%
Racumin	58,8%	85,1%
All four items	58,8%	93,4%

5.3 Total inventory cost and the ordering holding cost trade-off

Figure 5 below shows that the extra ordering cost under SMA is far smaller than its holding cost savings, so SMA gives the lowest total cost for every item. The figure shows the pattern, and Table 13 gives the exact values of the POQ reduction and SMA reduction percentage of each items partially and all four items in a whole.

Table 13: Total annual inventory cost by policy

Item	Existing	POQ (reduction)	SMA (reduction)
Marshall	Rp8.770.481	Rp4.232.428 (51,7%)	Rp3.164.962 (63,9%)
Glyphosate 480	Rp4.115.721	Rp3.021.251 (26,6%)	Rp2.197.905 (46,6%)
Paraquat Primax 280 SL	Rp4.434.418	Rp1.956.826 (55,9%)	Rp1.744.574 (60,7%)
Racumin	Rp1.507.075	Rp1.028.043 (31,8%)	Rp827.435 (45,1%)
Total	Rp18.827.695	Rp10.238.548 (45,6%)	Rp7.934.876 (57,9%)

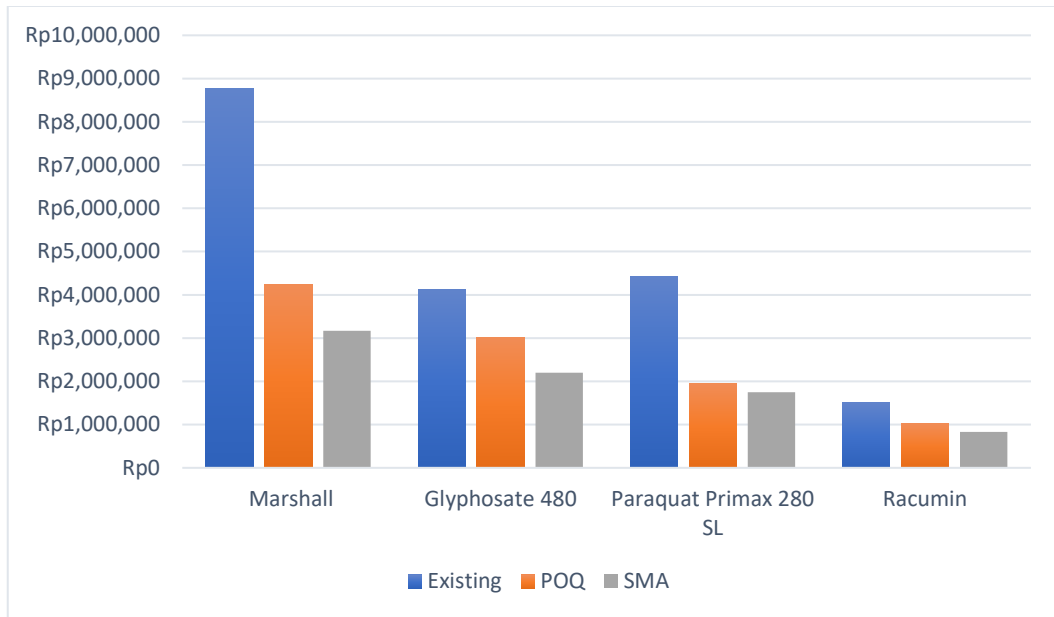


Figure 5: Total annual inventory cost by policy

Table 14 below breaks down the trade-off between SMA and POQ. Moving from POQ to SMA adds Rp2.709.627 per year in ordering costs across the four items and removes Rp5.013.297 per year in holding costs, a net saving of Rp2.303.670 per year. The ratio is therefore $5.013.297 / 2.709.627 = 1,85:1$; each additional Rp1 spent on ordering under SMA removes Rp1,85 in holding costs. The ratio is above 1 for each item, which is why SMA has the lower total cost.

Table 14: Trade-off of moving from POQ to SMA

Item	Extra Ordering Cost	Holding Cost Saved	Net Saving	Ratio	Break-Even Rise in Cost per Order
Marshall	Rp868.290	Rp1.935.756	Rp1.067.466	2,23	+123%
Glyphosate 480	Rp1.098.953	Rp1.922.298	Rp823.345	1,75	+75%
Paraquat Primax 280 SL	Rp614.037	Rp826.288	Rp212.251	1,35	+35%
Racumin	Rp128.347	Rp328.955	Rp200.608	2,56	+156%
Total	Rp2.709.627	Rp5.013.297	Rp2.303.670	1,85	+85%

Compared with the existing policy, SMA adds Rp2.629.653 per year in ordering costs and removes Rp13.522.471 per year in holding costs, yielding a ratio of 5,14 and a net saving of Rp10.892.818 per year, equal to the reduction in total cost from Rp18.827.695 to Rp7.934.877 (Table 13). POQ, by contrast, obtains its savings almost entirely from holding cost, with essentially no change in ordering cost (-1,8%). In short, POQ lowers holding cost while leaving ordering cost nearly unchanged, whereas SMA achieves a much larger reduction in holding cost by deliberately buying it with a substantial increase in ordering cost (+60,4%).

5.4 Order frequency and cost efficiency

Figures 3 and 4 together should not be read as implying that higher-order frequency automatically yields larger holding savings. Racumin has the largest relative increase in frequency (from 2 to 5 orders per year, +150%) but the smallest percentage reduction in holding cost under SMA (85,1%). In contrast, Glyphosate 480 (from 7 to 12 orders per year, +71,4%) reaches the largest (100%). Percentages and rupiah amounts also tell different stories: Racumin's holding cost falls by Rp1.064.681 per year, against Rp6.473.809 per year for Marshall, because Racumin starts from a much smaller base. What matters is how well the timing of orders matches the demand pattern, not the number of orders alone. Higher frequency is the mechanism through which SMA reduces stock, but its effectiveness varies by item.

Figure 6 summarizes cost efficiency, defined as the percentage reduction in total cost relative to the existing policy which is calculated by $[(\text{total cost existing} - \text{total cost of the method}) / \text{total cost existing}]$. SMA achieves 64% for Marshall, 61% for Paraquat Primax 280 SL, 47% for Glyphosate 480, and 45% for Racumin, a simple average of 54,25%. POQ achieves 52%, 56%, 27%, and 32%, a simple average of 41,75%. Weighting by cost, so that items with larger cost count more, yields 57,9% for SMA $[1 - (7.934.877 / 18.827.695)]$ and 45,6% for POQ $[1 - (10.238.547 / 18.827.695)]$. The two averages differ because Marshall, the item with the highest cost, also has one of the highest efficiency gains. SMA exceeds POQ across all four items, by 4,8 to 20 percentage points.

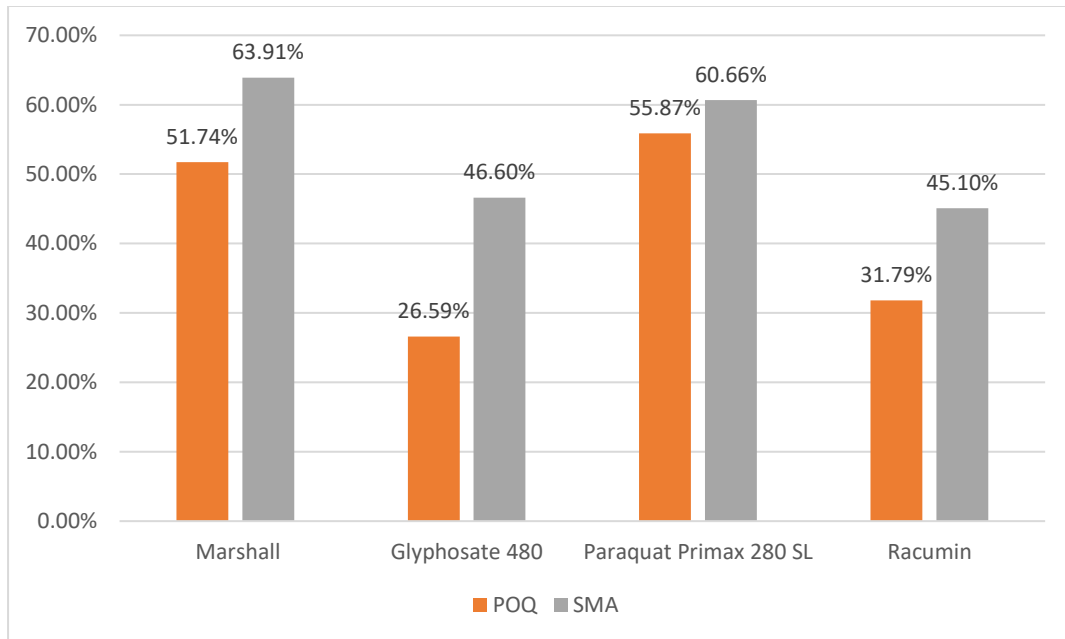


Figure 6: Inventory cost efficiency relative to the existing policy

5.5 Interpretation and boundaries of the findings

First, the comparison is not fully like-for-like. POQ and SMA are deterministic lot-sizing methods that require demand to be known for each period, which in practice would be supplied by a demand forecast. POQ and SMA are evaluated on the realized 2025 demand schedule, so the demand input matches the eventual outcome exactly, with no forecast error. This is an ex-post, or perfect foresight, evaluation which tests how well each method performs once the year's demand is already known, not how either method would perform using a forecast made in advance. In contrast, the existing cost is derived from the average on hand inventory recorded in the warehouse. In practice, both methods would rely on forecasts and would need safety stock, which would reduce the savings, most notably for SMA, whose small lots leave little buffer against demand surprises. The results are therefore best read as an upper bound on attainable savings.

Second, the ranking of SMA and POQ is sensitive to the assumed cost of an order, and this sensitivity differs by item. The estimated cost of one order is Rp289.430 for Marshall, Rp183.159 for Glyphosate 480, Rp153.509 for Paraquat Primax 280 SL, and Rp128.347 for Racumin (Table 3). Suppose the true cost of one order is higher than estimated by the same percentage under both methods, while the holding cost stays unchanged. SMA then loses its advantage over POQ once that increase reaches the break-even value for +85% in aggregate (Table 14), but only +35% for Paraquat Primax 280 SL, +75% for Glyphosate 480, +123% for Marshall, and +156% for Racumin. The aggregate result is therefore reasonably robust, but the result for Paraquat Primax 280 SL is not, because an underestimate of about 35% in its

ordering cost (for example, in fuel, material handling, or communication) would make POQ the cheaper choice for that item. The result is also sensitive to the holding cost side. Holding cost in this study is allocated by warehouse slot occupancy, and its underlying components, energy, staff salary, and maintenance, are largely fixed costs that do not vary automatically with the quantity of inventory held. Consequently, the holding-cost reduction reported in Table 11 represents an accounting reallocation rather than an automatic cash saving. It becomes an actual cash saving only under two conditions: the freed warehouse slots are reused for other purposes under the allocation or it can be called by shared storage policy, or the underlying staffing, energy, and maintenance costs are deliberately reduced in response to the lower space requirement. In addition, the ordering cost in this study is per order on average. In contrast, Table 3 shows that it varies with order volume and the number of items shared on a delivery. Separately, more frequent orders per item could therefore raise deliveries by more than the model implies, which argues for considering joint replenishment.

Third, the absolute savings are modest. SMA saves Rp10.892.818 per year across the four items. Their combined annual purchase value is Rp958.845.000 (Table 1), so the total inventory cost falls from 1,96% of purchase value under the existing policy (Rp18.827.695) to 0,83% under SMA (Rp7.934.877), a saving equal to 1,14% of purchase value. The economic significance lies less in the size of the savings and more in its structure, because SMA shifts cost from carrying inventory, which ties up working capital and creates exposure to expiry for semi-perishable inputs, toward transaction cost, which is easier to observe and control. Neither the cost of capital nor expiry losses is included in the holding cost, so both would strengthen the case for SMA if they were included.

5.6 Summary of findings

Taken together, Figures 2 through 6 show a consistent pattern across all four items. SMA increases ordering cost and order frequency relative to both the existing policy and POQ (Figures 2 and 3), yet this increase is more than offset by a substantially larger reduction in holding cost (Figure 4). Consequently, SMA achieves the lowest total inventory cost (Figure 5) and the highest cost efficiency (Figure 6) for every item, followed by POQ, with both methods outperforming the existing policy. These findings corroborate earlier studies reporting that the Silver-Meal Algorithm reduces inventory cost relative to existing practice (Rini and Ananda, 2021; Hasibuan et al., 2021; Asmal et al., 2023; Sari and Aprilia, 2024), and extend that evidence to semi-perishable crop-protection inputs in a plantation setting.

6. Conclusion

This study evaluated inventory replenishment and logistics cost efficiency for the four category A crop-protection items at PT XYZ, Marshall, Glyphosate 480, Paraquat Primax 280 SL, and Racumin, together accounting for 79% of purchase value, by comparing the existing policy with POQ and the Silver-Meal Algorithm (SMA). Three findings stand out. *First*, the existing policy carries substantial excess stock. Holding costs exceed ordering costs for every item, and Marshall's holding cost is about four times its ordering cost. *Second*, both methods reduce total inventory cost, by 27-56% per item under POQ and 45-64% per item under SMA. Across the four items combined, total cost falls from Rp18,83 million to Rp10,24 million under POQ (-45,6%), and to Rp7,93 million under SMA (-57,9%). *Third*, SMA's larger saving comes from a deliberate trade-off. SMA raises ordering cost by about 60% through more frequent, smaller orders, and in exchange cuts holding cost by about 93%. POQ instead leaves ordering cost almost unchanged (-1,8%) and cuts holding cost by about 59%. The resulting advantage of SMA over POQ varies from 4,8 to 20,0 percentage points across items, which suggests that the size of SMA's benefit depends on each item's demand pattern.

Managerial implications. SMA is recommended as the replenishment policy for these items, because it adapts order size to periodically demand and keeps stock close to requirements, which also limits exposure to expiry for semi-perishable products. Where ordering frequency is constrained by supplier or transport arrangements, POQ is a simpler alternative that still delivers sizable savings. Firms with similar cost structures can also adopt the ABC first procedure to concentrate effort on the few items that drive most of the value.

Limitations. First, the analysis uses realized 2025 demand for a single year, so it evaluates the policies ex post with perfect demand information, whereas in practice SMA would depend on demand forecasts and safety stock. Second, ordering cost is treated as a per order average even though it varies with order volume, and holding cost is allocated by warehouse slot and excludes the cost of capital and losses from deterioration or expiry. Third, lead times, supplier minimum order quantities, and service level constraints were not modelled. Fourth, the absolute savings are modest at the scale of four items, and the warehouse-related savings materialize only if released slots are reused or costs are actually reduced.

Future research. Future work could add forecast uncertainty and safety stock, explicitly model shelf life and capital cost, consider joint replenishment across items to consolidate deliveries, and extend the analysis to category B and C items and to multiple plantation sites. A comparison with the Wagner-Whitin algorithm would also be informative. Wagner-Whitin guarantees the cost minimizing solution for deterministic time-varying demand, so it would not perform worse than SMA. However, prior studies suggest its advantage over Silver-Meal is often marginal, while it requires substantially more computation as the number of periods grows. Whether that marginal gain is worth the added computational effort for a firm the size of PT XYZ remains an open question for future work.

Data availability statement

The data supporting this study's findings are fully available from the corresponding author upon reasonable request.

Declaration

Generative AI in scientific writing. During the preparation of this work, the authors used Grammarly, Claude, and ChatGPT to check the quality of our language and improve its clarity and readability. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

Conflict of interest. On behalf of all authors, the corresponding author declares that there are no conflicts of interest.

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