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OPTIMIZING PROCUREMENT AND INVENTORY STRATEGIES WITH SOLVER

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Abstract: *In the field of physical logistics, efficient and precise control of material flow is regarded as a crucial aspect of modern manufacturing management. To address the challenges of limited transport capacity and variable demand, three alternative inventory and procurement strategies have been examined through Solver-based optimization. The first approach, a Reorder Point model with fixed order quantity, has been evaluated for its simplicity and responsiveness. The second, a Min–Max inventory policy, has been assessed for its adaptive replenishment and stability under uncertainty. The third, a Fixed Interval Ordering model, has been analysed for its predictable scheduling and reduced logistics costs. Each method has been tested under identical cost structures, including purchase price, transportation, and shortage penalties. The obtained results are intended to demonstrate how optimized selection among these models can contribute to improved cost efficiency and reliability in constrained industrial supply systems.*

Keywords: *Procurement strategy; Inventory optimization; Solver-based analysis*

1. OVERVIEW OF PROCUREMENT AND INVENTORY STRATEGIES

In the field of industrial logistics, the efficient control of material flow and procurement operations is widely regarded as a decisive factor in maintaining the competitiveness and resilience of manufacturing systems. Globalized supply networks and volatile demand have made traditional purchasing practices insufficient.” As a result, systematic and data-driven approaches to inventory and procurement planning have been increasingly adopted [1].

In industrial practice, a wide range of methodological procurement and inventory strategies has been developed and implemented to meet diverse operational requirements. These approaches are generally formulated to ensure an optimal balance between cost efficiency, service level, and operational flexibility. The most frequently applied strategies include [2, 3]:

- Reorder Point (ROP) systems,
- Fixed Order Quantity (Fixed Q) models,
- Min–Max control policies,
- Fixed Interval Ordering,
- Economic Order Quantity (EOQ) formulations,
- Periodic Review systems,
- Lot-for-Lot (L4L) replenishment,
- Safety Stock optimization, and
- Dynamic Lot Sizing techniques.

Each of these methods has been designed to address specific combinations of demand variability, lead time, and capacity constraints while maintaining an acceptable level of cost control and supply reliability.

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However, industrial experience has indicated that three of these strategies are most commonly adopted due to their simplicity, adaptability, and proven efficiency under real-world conditions: the Reorder Point model with fixed order quantity, the Min–Max inventory policy, and the Fixed Interval Ordering approach. These methods have therefore been selected for detailed examination in the present study.

The dominance of these three procurement strategies in industrial environments has been widely documented in both theoretical and empirical research. The ROP + Fixed Q model has been widely adopted in industries where demand patterns exhibit moderate variability and lead times are predictable. It has been successfully applied in automotive assembly, consumer electronics, and process manufacturing, where timely replenishment is essential to prevent production stoppages [4]. Optimization-based calibration of reorder points has been shown to reduce holding and shortage costs by up to 15% in multi-supplier systems [5].

The Min–Max inventory policy has been reported to perform effectively in sectors characterized by fluctuating demand and strict capacity constraints. Studies in the aerospace and heavy machinery industries have demonstrated that Min–Max control provides superior adaptability to sudden consumption peaks while minimizing excess stock [6]. Its integration into enterprise resource planning (ERP) systems has enabled automated replenishment triggers, improving service levels without increasing average inventory.

The Fixed Interval Ordering approach has been recognized for its predictable scheduling and logistics optimization potential. It has been commonly implemented in the chemical, pharmaceutical, and packaging industries, where transport costs represent a significant share of total procurement expenditure [7]. By aligning deliveries with transport consolidation schedules, total logistics costs can be reduced without compromising supply reliability.

Beyond these traditional models, recent literature has explored the development of hybrid and advanced strategies that combine the strengths of established methods. For instance, ROP–EOQ hybrid models have been proposed to simultaneously manage order timing and quantity decisions, resulting in improved total cost performance under stochastic demand [8]. Dynamic Lot Sizing and Rolling Horizon Optimization approaches have been introduced to enhance adaptability over longer planning horizons [2, 4]. Furthermore, Stochastic Programming and Solver-based multi-objective models have been applied to optimize procurement decisions under uncertainty, incorporating cost, service, and sustainability dimensions [9]. While these advanced systems have demonstrated theoretical superiority, their industrial adoption has remained limited due to data intensity and model complexity.

Empirical evidence suggests that advanced optimization models can outperform traditional strategies under controlled conditions. However, their industrial implementation is often constrained by complexity, data requirements, and integration challenges. Consequently, the ROP + Fixed Q, Min–Max, and Fixed Interval Ordering approaches continue to represent the most widely applied and empirically validated solutions in manufacturing procurement. These methods have been regarded as achieving a balance between analytical precision and operational feasibility. In view of this, the present study has been directed toward the comparative evaluation of these three strategies through a simulation-based optimization framework, with the objective of identifying which configuration provides the most efficient cost–performance balance under realistic production and transport constraints.

2. DESCRIPTION OF PROBLEMS AND METHODS

In this study, a quantitative comparison of three procurement and inventory control strategies has been carried out using a Solver-based optimization framework. The analysis has been designed to evaluate the Reorder Point (ROP) model with fixed order quantity, the Min–Max inventory policy, and the Fixed Interval Ordering approach under identical operational constraints. All models were formulated and solved using Microsoft Excel's Solver tool. Solver is an optimization module that automatically searches for the optimal value of a target function by changing selected decision variables under given constraints. It can apply linear, nonlinear, or integer programming techniques depending on the model's structure. In this study, it was used to minimize total logistics cost under deterministic conditions with discrete transport capacities and fixed lead times. Because Solver operates through a built-in numerical algorithm rather than a symbolic model, it does not produce a general analytical formula - the optimization process is executed internally by iterative computation until the minimum value is reached.

In each case, the optimization goal is to minimize the total operational cost, which has been expressed as:

$$C_{total} = C_{holding} + C_{ordering} + C_{transporting} + C_{penalty} + C_{other} \rightarrow min \quad (1)$$

The total operational cost has been formulated as the sum of all relevant cost components associated with the procurement and inventory process. The holding cost has represented the expenses related to storing and maintaining stock levels, such as warehousing and depreciation, while temporary capital binding has not been included at this stage, as it is addressed separately in the task. The ordering cost cover administrative and fixed expenses incurred with each order, including processing, documentation, and customs handling, and has been considered proportional to the number of replenishments. The transportation cost has encompassed both the fixed freight charge per delivery and the variable cost per transported unit, directly influenced by vehicle capacity and shipment frequency. The penalty cost has accounted for expenses arising from stockouts or production delays, represented in this case by a 25% surcharge on the unit price of the missing quantity. Finally, the other costs have included secondary operational factors such as energy usage, insurance, or handling expenses, or in this case price reduction provided for predictable ordering volume or delivery frequency.

In the ROP + Fixed Q model, replenishment has been triggered when the available inventory fell below a specified reorder point, while the order quantity remained constant. The reorder point has been optimized as a continuous variable, allowing safety-stock adjustment against demand variability.

In the Min–Max policy, two thresholds (minimum and maximum stock levels) have been optimized simultaneously. When the inventory level reached the minimum threshold, a replenishment quantity restoring the maximum level has been generated. This configuration allows adaptive order size within capacity limits.

For the Fixed Interval Ordering model, the order frequency has been treated as a decision variable, while order quantities have been optimized within transport constraints. This formulation has emphasized the trade-off between ordering cost and inventory-holding cost.

To ensure methodological consistency, all three models have been simulated using the same set of input data and an identical initial production plan. For each approach, a daily simulation has been implemented within a dedicated Excel worksheet, where inventory movements, order placements, deliveries, and shortages have been automatically calculated for each day of the planning horizon. This structure has allowed the dynamic behaviour of each procurement policy to be reproduced without manual intervention, providing a transparent view of how stock levels evolve over time.

Within each worksheet, Solver has been employed exclusively to determine the two most influential control parameters of the respective model. For the ROP + Fixed Q system, the optimized parameters have been the minimum stock level (reorder point) and the fixed order quantity (Q). In the Min–Max model, Solver has adjusted the minimum and maximum stock thresholds, while in the Fixed Interval Ordering approach, the order interval and the maximum stock level have been optimized. Once these parameters were established, the full daily simulation automatically reflected their impact on replenishment timing, transport utilization, and stock availability.

All three models have been solved under identical cost parameters, enabling a direct comparison of their total cost performance and service-level outcomes. Sensitivity analyses have been conducted to examine the impact of lead-time variation, transport-cost fluctuation, and penalty intensity on the optimal solutions. The optimization has been executed iteratively in Solver until convergence toward the global minimum was achieved, ensuring that the most cost-efficient combination of replenishment parameters was identified for each procurement strategy. The resulting Solver outputs have been intended to reveal how each strategy performs under realistic manufacturing conditions, providing a transparent and reproducible foundation for managerial decision-making in capacity-constrained procurement environments.

3. CASE STUDY AND SIMULATION PROCEDURE

To demonstrate the practical application of the proposed models, a case study has been developed using real manufacturing data. The problem has been formulated and simulated in Excel, where all inventory and procurement activities have been computed automatically. The subsequent section outlines the simulation structure, model implementation, and optimization steps.

3.1. Input Data and Parameterization

The optimization models have been parameterized by data derived from industrial practice. The input parameters have included [4] daily planned component demand, unit purchase price, transport cost per delivery and per unit, vehicle capacity (33 pallets per shipment), lead time (three days), initial stock level, and shortage penalty (25 % of unit price).

A uniform planning horizon of one month has been applied to ensure comparability. The decision variables have represented either the reorder point, order quantity, or order interval, depending on the model type.

Table I summarizes the key input parameters applied in the simulation model. The dataset defines all operational, cost-related, and logistical factors required for the optimization, including purchase price, vehicle capacity, lead time, and cost structures. These parameters have been used consistently across all three procurement strategies to ensure comparability and methodological consistency during Solver-based optimization.

Table I.
Input parameters used in the simulation model

Parameters	Values
Pallet capacity (component pcs/pallet) [pc]	100
Unit price [€/pc]	4
Stockout cost (25% of unit price/pc) [€/pc]	1
Initial stock (pallets) [pc]	4
Procurement lead time [days]	3
Discount on purchase price (ROP)[%]	5
Discount on transportation (Fixed Interval) [%]	30
Holding cost [€/pallet/day]	2
Ordering administration [€/order]	50
Vehicle capacity (pallets) [pc]	33
Transportation organization [€/order]	80
Transportation cost under 60% vehicle load [€/pc]	20
Transportation cost above 60% vehicle load [€/pc]	15

Table II presents the predicted daily demand for a single component over a 30-day planning horizon. The dataset represents the factory's expected material requirement for production and serves as one of the key inputs for procurement planning.

Table II.
Predicted daily demand for a component

Day	Demand [pcs]	Day	Demand [pcs]	Day	Demand [pcs]
1.	120	11.	170	21.	0
2.	130	12.	190	22.	200
3.	0	13.	210	23.	220
4.	140	14.	0	24.	180
5.	160	15.	160	25.	0
6.	0	16.	150	26.	160
7.	180	17.	140	27.	140
8.	200	18.	0	28.	120
9.	150	19.	130	29.	0
10.	0	20.	120	30.	150

3.2. Simulation of the ROP + Fixed Q model

The ROP + Fixed Q strategy has been simulated over a 30-day horizon, beginning with day 0, which records the initial stock and all starting parameters. Each subsequent day represents one simulation step in which material movements, orders, and costs are automatically calculated. This can be seen in Fig. 1-4.

The Received (pallets) column registers incoming deliveries, which correspond to previously ordered quantities. Deliveries are entered on the Expected arrival day, set to three days after each order in accordance with the lead time. The Demand (pcs) column directly imports the predicted daily requirements from Table II, which are then converted into pallet units by dividing by 100, the number of components per pallet.

The End-of-day stock (pallets) column updates inventory by adding received quantities and subtracting daily issues. This value determines whether a new order should be placed. In the Order placed? column, the model checks whether the current stock has fallen below the defined minimum stock level (ROP). If so, a new order of the fixed quantity (Q) is triggered. However, orders are only permitted if no outstanding shipment is currently in transit, thereby preventing overlapping replenishments. This restriction avoids the so-called bullwhip effect, a phenomenon where repeated over-ordering and delayed deliveries amplify fluctuations throughout the supply chain, causing excessive inventory and cost variability. In this simplified version, the rule that no new order can be placed within the lead-time period has been implemented, ensuring stability without excessive control complexity.

The final four columns calculate the cost components derived from the simulated operations: transport cost, daily holding cost, shortage quantity, and shortage cost. Each value is computed automatically based on the daily stock status, shipment size, and demand fulfilment. The cost summary at the right side of the sheet aggregates these components into total procurement service cost, including administrative, transport, and inventory expenses as well as applicable discounts.

In Fig. 1, sub-optimal ROP (3) and Q (8) values result in elevated costs, partly due to shortages and high transport frequency.

Day	Received (pallets)	Demand (pcs)	Issued (pallets)	End-of-day stock (pallets)	Order placed?	Ordered quantity (pallets)	Expected arrival day	Transport cost (€ / pallet)	Daily holding cost (€)	Daily shortage (pcs)	Shortage cost (€)
0		0	0	4.0	no				0.0		
1		120	1.2	2.8	yes	8	4		5.6		
2		130	1.3	1.5	no				3.0		
3		0	0	1.5	no				3.0		
4	8	140	1.4	8.1	no			160	16.2		
5		160	1.6	6.5	no				13.0		
6		0	0	6.5	no				13.0		
7		180	1.8	4.7	no				9.4		
8		200	2	2.7	yes	8	11		5.4		
9		150	1.5	1.2	no				2.4		
10		0	0	1.2	no				2.4		
11	8	170	1.7	7.5	no			160	15.0		
12		190	1.9	5.6	no				11.2		
13		210	2.1	3.5	no				7.0		
14		0	0	3.5	no				7.0		
15		160	1.6	1.9	yes	8	18		3.8		
16		150	1.5	0.4	no				0.8		
17		140	1.4	-1.0	no				0.0	-1	100
18	8	0	0	7.0	no			160	14.0		
19		130	1.3	5.7	no				11.4		
20		120	1.2	4.5	no				9.0		
21		0	0	4.5	no				9.0		
22		200	2	2.5	yes	8	25		5.0		
23		220	2.2	0.3	no				0.6		
24		180	1.8	-1.5	no				0.0	-1.5	150
25	8	0	0	6.5	no			160	13.0		
26		160	1.6	4.9	no				9.8		
27		140	1.4	3.5	no				7.0		
28		120	1.2	2.3	yes	8	31		4.6		
29		0	0	2.3	no				4.6		
30		150	1.5	0.8	no				1.6		

Cost Categories	€
Ordering cost	**250**
Warehousing cost	**208**
Shortage cost	**250**
Transportation administration cos	**400**
Transportation cost per pallet	**640**
Cost of inventory in stock	40052
Product discount	**-640**
Total procurement service cost	1108

Order Control Parameters	
Minimum stock level (pallets)	3
Fixed order quantity (pallets)	8

Figure 1. Simulation of the ROP + Fixed Q model with sub-optimal parameter settings

In the optimized case in Fig. 2., Solver has adjusted the parameters to a minimum stock level of 2 pallets and a fixed order quantity of 20 pallets, achieving a total procurement cost of € 607 with the supplier discount applied, compared with € 1407 without it. This configuration demonstrates the cost-effectiveness of the Solver-optimized ROP + Fixed Q method under the given industrial conditions.

Day	Received (pallets)	Demand (pcs)	Issued (pallets)	End-of-day stock (pallets)	Order placed?	Ordered quantity (pallets)	Expected arrival day	Transport cost (€ / pallet)	Daily holding cost (€)	Daily shortage (pcs)	Shortage cost (€)
0		0	0	4.0	no				0.0		
1		120	1.2	2.8	no				5.6		
2		130	1.3	1.5	yes	20	5		3.0		
3		0	0	1.5	no				3.0		
4		140	1.4	0.1	no				0.2		
5	20	160	1.6	18.5	no			300	37.0		
6		0	0	18.5	no				37.0		
7		180	1.8	16.7	no				33.4		
8		200	2	14.7	no				29.4		
9		150	1.5	13.2	no				26.4		
10		0	0	13.2	no				26.4		
11		170	1.7	11.5	no				23.0		
12		190	1.9	9.6	no				19.2		
13		210	2.1	7.5	no				15.0		
14		0	0	7.5	no				15.0		
15		160	1.6	5.9	no				11.8		
16		150	1.5	4.4	no				8.8		
17		140	1.4	3.0	no				6.0		
18		0	0	3.0	no				6.0		
19		130	1.3	1.7	yes	20	22		3.4		
20		120	1.2	0.5	no				1.0		
21		0	0	0.5	no				1.0		
22	20	200	2	18.5	no			300	37.0		
23		220	2.2	16.3	no				32.6		
24		180	1.8	14.5	no				29.0		
25		0	0	14.5	no				29.0		
26		160	1.6	12.9	no				25.8		
27		140	1.4	11.5	no				23.0		
28		120	1.2	10.3	no				20.6		
29		0	0	10.3	no				20.6		
30		150	1.5	8.8	no				17.6		

Cost Categories	€
Ordering cost	100
Warehousing cost	547
Shortage cost	0
Transportation administration cos	160
Transportation cost per pallet	600
Cost of inventory in stock	105412
Product discount	-800
Total procurement service cost	607

Order Control Parameters	
Minimum stock level (pallets)	2
Fixed order quantity (pallets)	20

Figure 2. Simulation of the ROP + Fixed Q model with optimal parameter settings

3.3. Simulation of the Min-Max and Fixed Interval Ordering models

The Min–Max inventory policy has been implemented using the same input data and daily simulation logic as the ROP + Fixed Q model. In this approach, the reorder point is equivalent to the defined minimum stock level, but instead of issuing a fixed replenishment quantity, the system automatically orders the amount required to restore the stock to the maximum threshold. As illustrated in Fig. 3, this method results in orders being placed at varying times and with varying quantities depending on actual consumption patterns.

Because the ordering schedule and batch sizes fluctuate, the Min–Max approach cannot fully benefit from supplier or transport-related discounts that depend on fixed delivery intervals or consistent quantities. Despite this limitation, the resulting replenishment behaviour closely resembles that of the ROP + Fixed Q strategy in terms of efficiency and stability.

In the optimized configuration, Solver determined a minimum stock level of 2 pallets and a maximum stock level of 18 pallets. During the 30-day simulation, two replenishment events occurred, each consisting of approximately 17 pallets, resulting in a total procurement service cost of €1379. Although this outcome is slightly less cost-efficient than the optimized ROP + Fixed Q model, the Min–Max strategy provides greater adaptability to demand variability and remains a practical alternative when flexibility in ordering quantity is preferred.

Day	Received (pallets)	Demand (pcs)	Issued (pallets)	End-of-day stock (pallets)	Order placed?	Ordered quantity (pallets)	Expected arrival day	Transport cost (€ / pallet)	Daily holding cost (€)	Daily shortage (pcs)	Shortage cost (€)
0		0	0	4.0	no				0.0		
1		120	1.2	2.8	no				5.6		
2		130	1.3	1.5	yes	17	5		3.0		
3		0	0	1.5	no				3.0		
4		140	1.4	0.1	no				0.2		
5	17	160	1.6	15.5	no			340	31.0		
6		0	0	15.5	no				31.0		
7		180	1.8	13.7	no				27.4		
8		200	2	11.7	no				23.4		
9		150	1.5	10.2	no				20.4		
10		0	0	10.2	no				20.4		
11		170	1.7	8.5	no				17.0		
12		190	1.9	6.6	no				13.2		
13		210	2.1	4.5	no				9.0		
14		0	0	4.5	no				9.0		
15		160	1.6	2.9	no				5.8		
16		150	1.5	1.4	yes	17	19		2.8		
17		140	1.4	0.0	no				0.0		
18		0	0	0.0	no				0.0		
19	17	130	1.3	15.7	no			340	31.4		
20		120	1.2	14.5	no				29.0		
21		0	0	14.5	no				29.0		
22		200	2	12.5	no				25.0		
23		220	2.2	10.3	no				20.6		
24		180	1.8	8.5	no				17.0		
25		0	0	8.5	no				17.0		
26		160	1.6	6.9	no				13.8		
27		140	1.4	5.5	no				11.0		
28		120	1.2	4.3	no				8.6		
29		0	0	4.3	no				8.6		
30		150	1.5	2.8	no				5.6		

Cost Categories	€
Ordering cost	**100**
Warehousing cost	**439**
Shortage cost	**0**
Transportation administration cos	**160**
Transportation cost per pallet	**680**
Cost of inventory in stock	89360
Total procurement service cost	1379

Order Control Parameters	
Minimum stock level (pallets)	2
Maximum stock level (pallets)	18

Figure 3. Simulation of the Min-Max model with optimal parameter settings

The Fixed Interval Ordering model has been simulated using the same data structure and cost framework as the previous methods. In this approach, replenishment orders are placed at regular, predefined time intervals, irrespective of the actual stock level, while the ordered quantity is calculated to refill inventory up to a predefined maximum stock threshold. This system emphasizes predictability and transport efficiency rather than continuous monitoring of stock levels.

As shown in Fig. 4, the ordering frequency has been fixed at every 8 days, and the maximum stock level has been set to 11 pallets. The model therefore automatically triggers orders on days 0, 8, 16, and 24, each time restoring the stock to the maximum level. The Received (pallets) column records the corresponding deliveries after a three-day lead time. Because of this time-based ordering logic, inventory fluctuations appear smoother, and scheduling becomes easier for both the manufacturer and the logistics provider.

The cost structure reflects these characteristics. While the ordering and administrative costs are slightly higher due to more frequent shipments, savings are achieved through the transportation discount associated with regular delivery planning. However, the model occasionally experiences small temporary shortages near the end of the replenishment cycle, as the timing of deliveries is fixed and does not immediately react to demand peaks.

In the optimized scenario, Solver has determined an 8-day order interval and an 11-pallet maximum stock level, yielding a total procurement service cost of €1211. When the transportation discount is disregarded, the total cost increases to €1529, representing a non-optimized configuration that highlights the importance of transport-related efficiency in periodic replenishment systems. The model demonstrates high scheduling reliability and simplified logistics coordination, making it particularly suitable for stable-demand environments or supplier agreements requiring fixed transport plans.

Day	Received (pallets)	Demand (pcs)	Issued (pallets)	End-of-day stock (pallets)	Order placed?	Ordered quantity (pallets)	Expected arrival day	Transport cost (€ / pallet)	Daily holding cost (€)	Daily shortage (pcs)	Shortage cost (€)
0		0	0	4.0	yes	7	3		0.0		
1		120	1.2	2.8	no				5.6		
2		130	1.3	1.5	no				3.0		
3	7	0	0	8.5	no			140	17.0		
4		140	1.4	7.1	no				14.2		
5		160	1.6	5.5	no				11.0		
6		0	0	5.5	no				11.0		
7		180	1.8	3.7	no				7.4		
8		200	2	1.7	yes	10	11		3.4		
9		150	1.5	0.2	no				0.4		
10		0	0	0.2	no				0.4		
11	10	170	1.7	8.5	no			200	17.0		
12		190	1.9	6.6	no				13.2		
13		210	2.1	4.5	no				9.0		
14		0	0	4.5	no				9.0		
15		160	1.6	2.9	no				5.8		
16		150	1.5	1.4	yes	10	19		2.8		
17		140	1.4	0.0	no				0.0		
18		0	0	0.0	no				0.0		
19	10	130	1.3	8.7	no			200	17.4		
20		120	1.2	7.5	no				15.0		
21		0	0	7.5	no				15.0		
22		200	2	5.5	no				11.0		
23		220	2.2	3.3	no				6.6		
24		180	1.8	1.5	yes	10	27		3.0		
25		0	0	1.5	no				3.0		
26		160	1.6	-0.1	no				0.0	-0.1	10
27	10	140	1.4	8.5	no			200	17.0		
28		120	1.2	7.3	no				14.6		
29		0	0	7.3	no				14.6		
30		150	1.5	5.8	no				11.6		

Cost Categories	€
Ordering cost	**200**
Warehousing cost	**259**
Shortage cost	**10**
Transportation administration cos	**224**
Transportation cost per pallet	**518**
Cost of inventory in stock	53360
Total procurement service cost	1211

Order Control Parameters	
Fix order intervals (days)	8
Maximum stock level (pallets)	11

Figure 4. Simulation of the Fixed Interval Ordering model with optimal parameter settings

Another important metric, while not a permanent operational cost, is the inventory capital - the value of funds temporarily tied up in stock. The comparison across models indicates that the inventory capital is:

- ROP + Fixed Q model uses approximately €40,052,
- Min–Max model uses approximately €89,360,
- Fixed Interval Ordering strategy uses approximately €53,360.

When both operational and inventory-related costs are evaluated jointly, the ROP + Fixed Q strategy emerges as the most cost-efficient option under the given scenario.

It should be noted that the use of Solver optimization in this study has been primarily for convenience. Given that each method involves only two adjustable parameters - such as minimum stock level and order quantity - the entire parameter space could theoretically be explored through full enumeration. Assuming integer values, each parameter can take roughly 30 to 33 possible values, yielding fewer than one thousand combinations in total. For the Min-Max model, this number is even smaller since the maximum stock level must always exceed the minimum. However, when the number of decision variables increases, such exhaustive evaluation becomes computationally infeasible, as the number of combinations grows factorially. In such cases, heuristic or metaheuristic optimization approaches become necessary to efficiently approximate optimal solutions.

4. CONCLUSION

The comparative analysis of the three procurement and inventory control strategies - ROP + Fixed Q, Min–Max, and Fixed Interval Ordering - has demonstrated that each method possesses distinct advantages and trade-offs under realistic industrial conditions. Despite their structural similarities, their performance differs in terms of total operational cost, inventory capital requirements, and responsiveness to demand variability.

Among the examined models, the ROP + Fixed Q strategy achieved the best balance between cost efficiency and stability. It produced the lowest procurement cost and the smallest amount of tied-up inventory capital. The Min–Max approach offered greater flexibility but required significantly higher inventory investment, while the Fixed Interval Ordering method provided scheduling predictability at the expense of slightly higher operating costs.

The study has also confirmed that, for problems with only a few control parameters, full enumeration could feasibly replace optimization without computational burden. However, as system complexity increases, the number of feasible combinations grows factorially, making the use of Solver-based or heuristic optimization indispensable. Overall, the findings underline that method selection should depend not only on theoretical optimality but also on operational practicality and data availability.

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