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Reassessing EOQ-Based Brown Clay Inventory Control for NPK Fertilizer Production: Model Validation and Scenario Analysis

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ABSTRACT

This study reassesses brown clay inventory control for NPK fertilizer production at PT Pupuk Kujang by replacing a purely formula-driven EOQ application with a retrospective quantitative case-study design that integrates descriptive inventory analytics, arithmetic and semantic data auditing, EOQ identity validation, and scenario-based replenishment analysis. The dataset contains twelve monthly observations for 2023 covering procurement volume, replenishment frequency, and reported cost components. Recalculation from monthly entries yields 13,714.42 tons of annual procurement distributed across 594 reported order events. Monthly procurement is highly variable (coefficient of variation = 0.699), while order frequency is similarly dispersed (coefficient of variation = 0.682). January, February, and November alone account for 49.44% of annual procurement. The audit identifies a critical cost-classification problem: the reported "ordering cost" is almost exactly proportional to purchased tonnage at approximately Rp16,000 per ton, indicating a variable procurement expenditure rather than the fixed per-order setup cost required by the classical EOQ model. The reported EOQ of 3,509.87 tons also implies approximately 3.91 replenishments per year, not seven; seven annual orders would imply 1,959.20 tons per order. Consequently, the previously reported 98.4% cost reduction cannot be interpreted as validated EOQ savings because unlike cost bases were compared. Scenario analysis shows that four to twelve annual replenishments would imply average lot sizes of 3,428.61 to 1,142.87 tons, respectively, but economic ranking requires verified ordering cost, holding cost, lead time, storage capacity, and consumption data. The study contributes a reproducible validation framework for industrial EOQ studies and demonstrates that data semantics must be audited before optimization claims are accepted.

Keywords: *economic order quantity, fertilizer manufacturing, inventory analytics, model validation, raw material control*

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INTRODUCTION

Inventory policy is a core operational decision in process manufacturing because raw-material availability must be maintained without tying up excessive capital, warehouse space, handling effort, or administrative capacity. In fertilizer production, this problem is especially consequential because production continuity depends on coordinated flows of multiple bulk materials. Contemporary inventory research has therefore moved beyond simple stock minimization toward integrated decisions involving order timing, service levels, supply uncertainty, digital visibility, and resilience (Perez et al., 2021; Ralfs & Kiesmüller, 2022; Preil & Krapp, 2022). The practical value of any optimization model, however, depends on whether its input variables correspond to the economic concepts assumed by the model.

The Economic Order Quantity (EOQ) model remains useful as a transparent baseline because it formalizes the trade-off between fixed ordering or setup cost and unit holding cost. Recent applied studies continue to use EOQ for raw-material control, while more advanced research extends inventory decisions to stochastic demand, shipment consolidation, digital-twin environments, and multi-echelon networks (Chinello et al., 2020; Maheshwari & Kamble, 2022; Shofariah & Herdian, 2024). The simplicity of EOQ is both its strength and its principal methodological risk. A numerical result can be obtained easily, but the result is meaningful only when annual requirement, fixed cost per replenishment, annual holding cost per unit, and replenishment assumptions are correctly defined.

This requirement becomes more important in volatile production environments. Digitalization, advanced analytics, and supply-chain integration can improve visibility and resilience, but they do not compensate for incorrectly classified source data (Zouari et al., 2021; Shi et al., 2023; Zhao et al., 2023). Likewise, resilience research shows that firms frequently need to balance efficiency against flexibility, redundancy, and disruption exposure rather than pursue a single minimum-cost point in isolation (Ivanov, 2020; Ivanov & Dolgui, 2021; Kamalahmadi et al., 2022). Inventory optimization should therefore be treated as a model-validation problem as well as a calculation problem.

The source case concerns brown clay used in NPK fertilizer production at PT Pupuk Kujang. The original manuscript reports 2023 monthly procurement data, 594 order events, annual brown-clay volume of approximately 13.7 thousand tons, and a claimed EOQ of 3,509.87 tons. It further reports a reduction in annual inventory expenditure from Rp230.71 million to Rp3.61 million. Those figures are operationally striking and therefore warrant verification before they are interpreted as evidence of optimization. In particular, the source table labels a large volume-dependent expenditure as "ordering cost", although classical EOQ requires a fixed cost per order. It also reports seven optimal annual orders while the published EOQ quantity and annual volume imply fewer than four.

These inconsistencies identify a broader research gap in applied EOQ studies. Many case-based papers emphasize the difference between a company policy and an EOQ result, but fewer studies explicitly audit whether the accounting labels, aggregation rules, and mathematical identities are internally consistent before calculating savings. This matters because procurement expenditure is generally proportional to purchased volume and, under a constant unit price, does not determine the classical EOQ optimum. Comparing total procurement expenditure plus storage against only EOQ setup and holding cost can therefore generate an artificial savings percentage even when the operational policy has not been validated.

This study addresses that gap by reframing the case as a retrospective quantitative inventory-policy audit. The objectives are to: (1) reconstruct the 2023 brown-clay procurement and replenishment profile from the monthly source data; (2) test arithmetic and semantic consistency of the reported cost variables; (3) validate the reported EOQ result against the identities required by the classical model; and (4) develop order-frequency scenarios that remain interpretable even when verified setup and holding-cost parameters are unavailable. The contribution is methodological as well as managerial. Rather than producing another single-point EOQ estimate, the study proposes a validation sequence that helps industrial researchers determine when EOQ outputs are economically defensible and when additional operational data are required.

METHODS

Research Design and Unit of Analysis

The study employs a retrospective quantitative single-case design focused on brown-clay inventory policy for NPK fertilizer production at PT Pupuk Kujang. The method differs from the original formulation in two ways. First, it does not treat the reported EOQ output as automatically valid; the model is subjected to arithmetic and semantic consistency checks before any optimization claim is accepted. Second, the analysis relies only on traceable quantitative variables presented in the source manuscript. Interview-based claims are not used because the source does not provide an interview protocol, respondent characteristics, coding procedure, or auditable interview data.

The unit of analysis is the monthly brown-clay replenishment record for January to December 2023. The available fields are month, reported replenishment frequency, procurement volume in tons, a value labeled "average", reported "ordering cost", storage cost, and total cost. The study treats procurement volume as observed inbound material flow. Because separate consumption or issue-to-production data are not reported, procurement volume is not assumed to be a perfect measure of stochastic demand; where the EOQ notation uses D, annual procurement volume is treated only as a provisional proxy for annual requirement.

Stage 1: Data Reconstruction and Consistency Audit

All monthly values were transcribed from the source table and recomputed independently. Column totals were compared with the published annual totals, and unit ratios were calculated to determine the economic meaning of each cost category. For every month with positive procurement, the ratio between the reported "ordering cost" and procurement tonnage was calculated. If this ratio is approximately constant per ton, the variable behaves as a purchase or procurement expenditure rather than a fixed setup cost per replenishment.

The audit also tested accounting identities. Monthly total cost was checked against the sum of the two reported components. Annual frequency was compared with average implied lot size, and the published EOQ quantity was checked using $N = D/Q$, where N denotes annual replenishment frequency, D annual requirement, and Q order quantity.

These checks are essential because a model can be algebraically correct while still using economically misclassified inputs.

Stage 2: Descriptive Inventory Analytics

The monthly procurement profile was summarized using mean, sample standard deviation, coefficient of variation, monthly share of annual procurement, and correlation between replenishment frequency and procurement volume. The coefficient of variation was calculated as CV = s/x̄. These statistics were used to assess whether the annual series is reasonably compatible with the constant-demand assumptions of classical EOQ. No inferential significance test was applied because the dataset represents the full twelve-month operational period available in the case rather than a random sample from a larger survey population.

Visual analysis was retained and strengthened because the source manuscript already contained inventory and cost graphics. The original visual concepts were remade using the source monthly values to preserve the information while improving readability and ensuring consistency with the revised analysis.

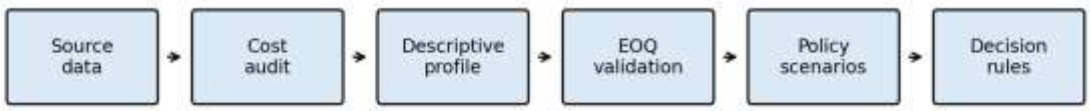

Figure 1. Revised Analytical Workflow for the Retrospective Inventory-Policy Audit

Stage 3: EOQ Model Validation

The classical EOQ identity is $Q = \sqrt{(2DS/H)}$, where D is annual requirement, S is the fixed cost incurred each time an order is placed, and H is the annual holding cost per unit. The associated annual replenishment frequency is $N = D/Q$. The analysis does not recompute a new monetary EOQ optimum because the source data do not provide independently verifiable S and H parameters in these required units. Instead, the published EOQ quantity of 3,509.87 tons is treated as a benchmark claim and tested against the source annual volume and reported annual order frequency.

Total relevant inventory cost under the classical model comprises annual setup cost, $(D/Q)S$, and annual holding cost, $(Q/2)H$, subject to model assumptions. Unit purchasing cost is normally omitted from the optimization term when unit price is constant because the annual purchase expenditure $D \times c$ is identical across feasible lot-size policies. This distinction is central to the revised analysis because the source manuscript appears to compare a procurement-linked expenditure in the baseline with a setup-plus-holding expression in the EOQ case.

Stage 4: Scenario-Based Replenishment Analysis

Because verified setup cost, unit holding cost, storage capacity, service-level target, and lead-time distribution are unavailable, the study avoids presenting a false precision cost optimum. Instead, five transparent replenishment-frequency scenarios are evaluated: 4, 6, 7, 8, and 12 orders per year. For each scenario, implied average lot size is calculated as $Q = D/N$ and the reduction in order events relative to the reported 594 annual events is computed. The scenarios are not ranked as economically optimal; they are operational reference points that must be stress-tested against warehouse capacity, supplier constraints, material handling limits, production consumption, and lead-time risk before implementation.

This staged method reflects recent inventory and supply-chain research emphasizing that optimization models should be embedded within uncertainty, information quality, and resilience considerations rather than interpreted as stand-alone arithmetic outputs (Perez et al., 2021; Ivanov, 2022; Zhao et al., 2023).

RESULTS AND DISCUSSION

Reconstructed 2023 Procurement and Replenishment Profile

Recomputation of the twelve monthly entries yields 13,714.42 tons of brown-clay procurement and 594 reported order events. The recomputed tonnage differs by 0.06 ton from the annual total printed in the source table (13,714.36 tons), a negligible operational difference but an important traceability signal. Mean monthly procurement is 1,142.87 tons with a sample standard deviation of 798.99 tons, producing a coefficient of variation of 0.699. Replenishment frequency averages 49.5 order events per month with a coefficient of variation of 0.682. These dispersion levels indicate that the year is not characterized by a smooth, stationary monthly procurement pattern.

January, February, and November together account for 49.44% of annual procurement. October records no procurement, whereas November records the highest replenishment frequency despite lower tonnage than January and February. The correlation between monthly replenishment frequency and procurement volume is only 0.381. This weak-to-moderate association suggests that order-event counts are not simply proportional to monthly volume and reinforces the need to distinguish order frequency, shipment size, and material requirement as separate operational variables.

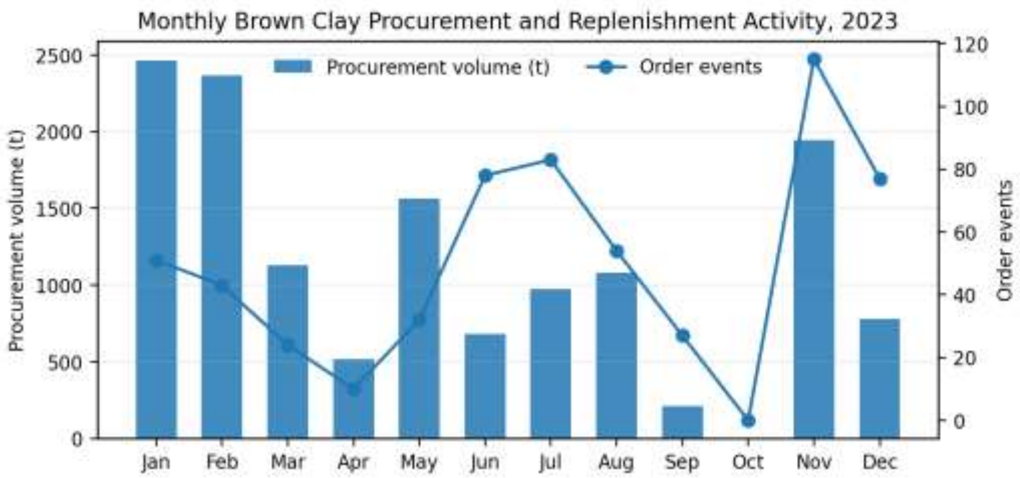

Figure 2. Monthly Brown Clay Procurement and Replenishment Activity in 2023

Month	Order events	Procurement (t)	Monthly share (%)	Avg. t/order
Jan	51	2,466.94	17.99	48.37
Feb	43	2,365.68	17.25	55.02
Mar	24	1,127.54	8.22	46.98
Apr	10	517.18	3.77	51.72
May	32	1,564.86	11.41	48.90
Jun	78	679.26	4.95	8.71
Jul	83	976.26	7.12	11.76
Aug	54	1,081.54	7.89	20.03
Sep	27	209.82	1.53	7.77
Oct	0	0.00	0.00	0.00
Nov	115	1,947.58	14.20	16.94
Dec	77	777.76	5.67	10.10
Total / overall	594	13,714.42	100.00	23.09

Source: Authors' recalculation from the monthly data reported in the source manuscript.

Table 1. Reconstructed Monthly Brown Clay Procurement Profile

Cost-Semantics Audit: Procurement Expenditure Is Not EOQ Ordering Cost

The most consequential finding emerges from the semantic audit of the cost data. For every positive-procurement month, the amount labeled "ordering cost" is approximately equal to procurement tonnage multiplied by Rp16,000 per ton. The mean implied rate is approximately Rp16,000 per ton, with only trivial deviations attributable to apparent transcription or rounding errors. This behavior is inconsistent with the EOQ parameter S, which must represent a fixed cost incurred per replenishment event, such as purchase-order processing, transport setup, receiving administration, inspection setup, or other order-triggered cost.

The reported storage cost shows the opposite pattern. It is Rp960,000 in almost every month and Rp720,000 in October, including months with radically different procurement volumes. Without a documented basis for allocating this cost to average on-hand inventory, it cannot be converted reliably into H, the annual holding cost per ton. Therefore, neither of the two reported cost series can be used directly as the pair of EOQ parameters S and H without additional cost-accounting evidence.

This distinction is not a minor accounting preference. In classical EOQ, annual procurement expenditure D×c is independent of lot size when unit price c is constant. It may be included in a full budget, but it cancels when comparing alternative Q values. If a procurement-linked expenditure is included in the current-policy denominator but omitted from the EOQ-policy numerator, the calculated savings rate will be mechanically inflated. Modern inventory research similarly distinguishes between procurement, ordering, holding, shortage, and service-related cost components because each responds differently to policy decisions (Perez et al., 2021; Ralfs & Kiesmüller, 2022; San-José et al., 2022).

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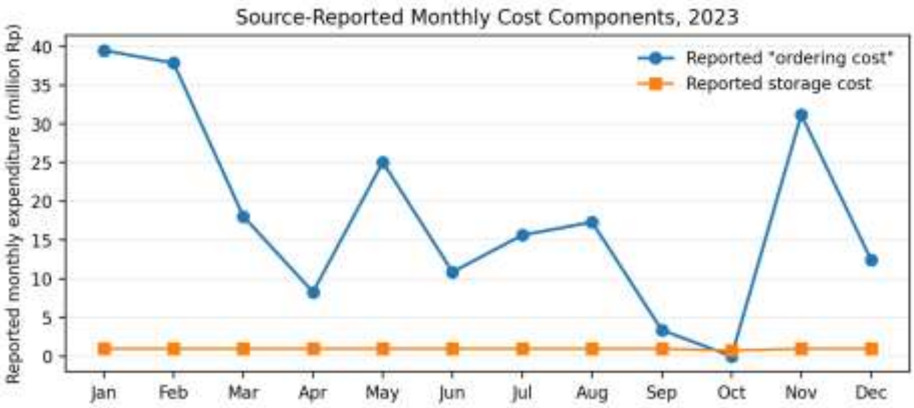

Figure 3. Source-Reported Monthly Cost Components

Audit item	Source claim /value	Independent check	Interpretation
Annual procurement	13,714.36 t	Monthly sum = 13,714.42 t	0.06 t transcription/aggregation difference
Annual "ordering cost"	Rp219,429,760	Monthly sum = Rp219,429,580	Rp180 arithmetic difference
Cost meaning	Reported as ordering cost	≈ Rp16,000 × monthly tonnage	Behaves as variable procurement expenditure, not fixed cost per order
Reported EOQ	Q = 3,509.87 t	13,714.42 / 3,509.87 = 3.91 orders/year	Inconsistent with seven annual orders
Seven-order policy	7 orders/year	13,714.42 / 7 = 1,959.20 t/order	Not equivalent to reported Q = 3,509.87 t
Reported cost reduction	Rp230.71m to Rp3.61m	Nominal reduction = 98.44%	Not validated because baseline and EOQ cost bases are not comparable
ROP = 206.46 t	Reported in source	Lead time and actual daily consumption not reported	Cannot be independently reproduced

Table 2. Internal Consistency and Model-Input Audit

Reassessment of the Reported EOQ and Cost-Saving Claim

Using the recomputed annual procurement proxy D = 13,714.42 tons, the published EOQ quantity of 3,509.87 tons implies 3.91 replenishments per year. Because operational replenishments are discrete, this corresponds approximately to four annual orders, not seven. Conversely, a seven-order policy implies an average lot size of 1,959.20 tons. The difference is too large to be explained by rounding. It indicates that at least one of the reported

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EOQ quantity, annual volume, or order-frequency outputs was calculated under a different parameter set or transferred incorrectly into the manuscript.

The cost-saving claim requires even greater caution. The source baseline of Rp230,709,760 combines Rp219,429,760 labeled "ordering cost" with Rp11,280,000 storage cost. The EOQ total of Rp3,608,471 is then compared directly with this baseline. If the Rp219.43 million component is effectively a procurement-volume expenditure, it should remain approximately constant across lot-size policies when the same annual volume is purchased at a constant unit price. Removing that term from only the EOQ side creates an apparent 98.44% reduction that does not represent like-for-like inventory cost savings.

For an internationally publishable inventory study, the defensible procedure is therefore to reconstruct S and H from transaction-level or cost-center data. S should include only costs that change with each replenishment event. H should be expressed per ton per year and include relevant warehousing, insurance, handling, capital, obsolescence, shrinkage, and other carrying components as applicable. Only after those parameters are verified can Q*, N*, and annual relevant inventory cost be compared consistently. This approach aligns with recent work that treats inventory optimization as a parameter-sensitive decision system rather than a mechanical formula exercise (Chinello et al., 2020; Preil & Krapp, 2022; Alkahtani, 2022).

Scenario Analysis without False Cost Precision

Scenario	Orders/year	Implied lot size (t/order)	Reduction in order events vs. 594	Interpretive role
S4	4	3,428.61	99.33%	Near the reported EOQ-implied frequency
S6	6	2,285.74	98.99%	Low-frequency reference case
S7	7	1,959.20	98.82%	Source-reported frequency benchmark
S8	8	1,714.30	98.65%	Moderate low-frequency case
S12	12	1,142.87	97.98%	Monthly replenishment reference

Table 3. Replenishment-Frequency Scenarios Based on Recomputed Annual Volume

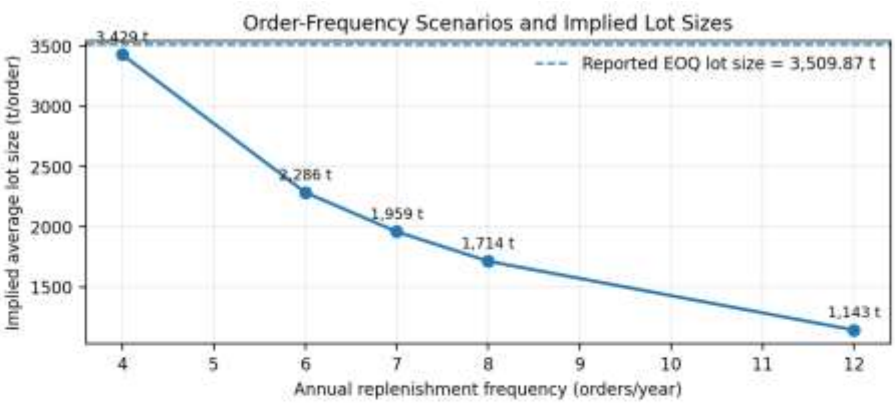

Figure 4. Order-Frequency Scenarios and Implied Average Lot Sizes

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The scenario analysis deliberately separates what can be computed from what cannot. With annual volume fixed at 13,714.42 tons, four annual replenishments imply an average lot of 3,428.61 tons, close to the source-reported EOQ quantity. Twelve annual replenishments imply 1,142.87 tons per order. Every scenario represents a reduction of more than 97% in order events relative to the reported 594, which immediately raises an operational question: whether the reported frequency counts purchase orders, truck movements, delivery tickets, partial unloading events, or another transactional unit. A credible implementation decision requires this unit to be defined explicitly.

Large reductions in transaction count may lower order-processing workload, but they simultaneously increase shipment size, cycle stock, space requirement, and exposure to quality or handling constraints. Classical EOQ treats these trade-offs through S and H, while stochastic and advanced inventory models add demand variability, lead time, service level, shortage cost, and dynamic information (Ralfs & Kiesmüller, 2022; Perez et al., 2021). In a bulk fertilizer context, supplier dispatch constraints, silo or warehouse capacity, material compatibility, production campaigns, and inbound transport scheduling may all bind before a mathematically convenient lot size can be adopted.

The high monthly variability observed in the source data also limits a literal constant-demand interpretation. Research on inventory optimization and supply-chain resilience shows that policy performance is sensitive to demand variance, lead time, shipping frequency, and disruption exposure (Chinello et al., 2020; Ivanov, 2020; Kamalahmadi et al., 2022). Accordingly, EOQ should be used here as a deterministic benchmark, not as the final operational policy. If daily consumption, lead-time distributions, and service targets become available, the next methodological step should be a continuous-review (Q,R) or stochastic simulation framework rather than further refinement of a static annual EOQ alone.

Digitalization, Resilience, and an Implementation Roadmap

The revised findings do not reduce the managerial relevance of the case. They redirect it. The immediate priority is not to adopt the previously reported 3,509.87-ton lot size, but to improve the data architecture that determines whether any lot-size recommendation is valid. A digital inventory system should capture actual production issues or consumption, purchase-order creation, delivery events, lead time, supplier identity, truck or shipment size, warehouse balance, stockout events, and cost-center information at a consistent timestamp and unit of measure. Digital-twin and digitalization research indicates that visibility and integrated data can strengthen responsive inventory decisions and supply-chain resilience (Ivanov & Dolgui, 2021; Maheshwari & Kamble, 2022; Shi et al., 2023; Zhao et al., 2023).

A practical implementation sequence follows from the analysis. First, define the transaction unit behind the reported 594 events. Second, separate material purchase cost from fixed replenishment cost. Third, estimate annual holding cost per ton using finance and warehouse data. Fourth, collect actual brown-clay consumption rather than relying on procurement volume as a demand proxy. Fifth, estimate empirical supplier lead times and define a target service level. Sixth, test several feasible lot-size and reorder policies through simulation or controlled operational trials. This sequence creates an auditable bridge from cost accounting to inventory optimization.

Sustainability considerations also support a broader policy perspective. Larger, less frequent orders may reduce administrative and transport setup activity but can increase inventory capital and warehouse exposure; smaller orders may improve flexibility but increase transaction intensity. Recent production-inventory studies increasingly integrate environmental and operational objectives rather than optimizing cost in isolation (Konstantaras et al., 2021; Daryanto & Setyanto, 2023; Nobil et al., 2023). For fertilizer manufacturing, a mature policy should therefore evaluate cost, service continuity, transport efficiency, storage constraints, and resilience jointly.

Theoretical Contribution and Limitations

The principal contribution is a model-validation framework for applied EOQ research. The framework requires four gates before a savings claim is accepted: semantic validity of D, S, and H; arithmetic consistency of source data; identity consistency between Q and N; and comparability of the cost base across current and proposed policies. This sequence is simple enough for industrial case studies but addresses a recurring weakness in formula-based inventory papers, where mathematically precise outputs can conceal economically inconsistent inputs.

The study is limited by the data available in the source manuscript. Monthly procurement is available, but actual production consumption, inventory balances, verified fixed ordering cost, annual holding cost per ton, lead-time observations, storage-capacity constraints, and service-level data are not. The original ROP value therefore cannot be independently reproduced, and a new monetary EOQ optimum is intentionally not claimed. The analysis should be interpreted as a rigorous reassessment and decision-readiness audit rather than a substitute for transaction-level industrial data.

CONCLUSION

This study remakes the brown-clay inventory case at PT Pupuk Kujang into a model-validation and scenario-analysis study rather than a conventional EOQ calculation exercise. The reconstructed 2023 dataset contains 13,714.42 tons of procurement across 594 reported replenishment events, with substantial monthly variability in both volume and order frequency. The key finding is methodological: the expenditure labeled as "ordering cost" behaves almost exactly as a variable Rp16,000-per-ton procurement cost and therefore does not satisfy the fixed per-order cost definition required by classical EOQ. The reported storage cost is also insufficiently parameterized to derive an annual holding cost per ton. These cost-semantics problems invalidate a direct reproduction of the claimed monetary optimum. A second consistency test shows that the published EOQ quantity of 3,509.87 tons implies approximately 3.91 orders per year, whereas the manuscript reports seven; a seven-order policy would instead imply 1,959.20 tons per order. Consequently, the previously reported reduction from Rp230.71 million to Rp3.61 million should not be interpreted as a validated 98.4% saving because the baseline and EOQ figures do not use comparable cost bases. Scenario analysis demonstrates that four to twelve annual replenishments would imply average lots ranging from 3,428.61 to 1,142.87 tons, but none can be ranked economically until fixed ordering cost, holding cost, actual consumption, lead time, storage capacity, and service-level requirements are verified. The paper therefore recommends a data-first implementation pathway: standardize transaction definitions, separate procurement and inventory-control costs, capture consumption and lead-time data digitally, estimate defensible cost parameters, and then evaluate EOQ or more advanced stochastic policies. The broader

contribution is a reproducible four-gate validation framework that improves the credibility of applied inventory optimization by ensuring that data meaning, arithmetic consistency, model identities, and cost comparability are established before optimization claims are made.

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