



Probabilistic Inventory Planning for a Hardware Retailer: Safety Stock and Reorder Point Assessment

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ABSTRACT

This study examines the information required to apply a probabilistic inventory policy to 9 mm plain square bars at Toko Besi Sadarman, Gunungsitoli. The analysis uses the annual demand totals reported for 2022 and 2023, checks the internal consistency of the proposed inventory thresholds, and compares their assumptions with the cited case study. Annual demand increased from 4,319 to 4,621 units, equivalent to 6.99%. This change describes annual volume but does not establish daily demand variability or a probability distribution. The proposed safety stock of 79 units and reorder point of 206 units imply mean demand during replenishment lead time of 127 units. However, the daily demand series, lead-time observations, service target, and parameter estimates needed to reproduce these thresholds are unavailable in the supplied evidence. A continuous-review framework is therefore specified to separate order quantity, expected lead-time demand, and safety stock. The analysis identifies the records and performance measures required before implementation. The resulting framework can support inventory planning and staff learning, but neither an optimal stochastic policy nor realized cost savings can be established from the available data. Further validation requires consistent operating-day definitions, reliable transaction records, and out-of-sample policy evaluation.

Keywords: *inventory planning; economic order quantity; safety stock; reorder point; lead time*

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INTRODUCTION

Inventory decisions at a hardware retailer involve both the quantity ordered and the timing of replenishment. Ordering large batches can reduce the frequency of purchases while increasing the resources tied up in stock. The classical economic order quantity (EOQ) model formalizes this cost trade-off (Harris, 1913/1990). Safety stock addresses a different question: how much additional inventory is needed to buffer demand and supply uncertainty. Reviews of safety stock methods show that the appropriate formulation depends on the uncertainty represented and the operational setting (Barros et al., 2021; Gonçalves et al., 2020).

A probabilistic policy requires more information than an annual sales total. In particular, demand during replenishment lead time must be characterized using observations at a compatible time scale. Both parameter estimation and distributional assumptions affect safety stock calculations (Eppen & Martin, 1988). A normal approximation can also give misleading conclusions about the effects of lead-time variability (Chopra et al., 2004). Consequently, describing a policy as probabilistic does not by itself establish that its thresholds meet a stated service objective.

The present case concerns 9 mm plain square bars at Toko Besi Sadarman in Gunungsitoli. The supplied annual demand totals, 4,319 units in 2022 and 4,621 units in 2023, also appear in the published case study by Bu'ulolo et al. (2024). The analysis assesses whether the proposed safety stock of 79 units and reorder point of 206 units can be justified from the available evidence. Its objectives are to check numerical consistency, distinguish observed information from modeling assumptions, and specify a reproducible inventory-planning procedure. This is an analytical assessment; it does not report a completed community training intervention or an observed improvement in business performance.

METHODS

The analysis uses the annual demand totals and proposed thresholds supplied in the manuscript, together with the cited published study as a documentary comparison. No transaction-level dataset, supplier delivery log, or post-implementation observation series is available for this assessment. The methods therefore comprise descriptive arithmetic, a consistency check of the reported thresholds, and specification of a conditional continuous-review model. No fitted demand distribution or simulation experiment is claimed.

Annual demand change is calculated as the difference between the 2023 and 2022 totals divided by the 2022 total. This statistic measures growth in aggregate volume. It is not used to estimate daily variance, seasonality, forecast error, or the frequency of zero-demand periods. Those quantities require a time series. Supply chain forecasting research distinguishes forecasting choices from the operational decisions that they support (Syntetos et al., 2016).

Let D denote expected annual demand in units per year, S the incremental cost of placing one order, and h the annual holding cost per unit of average inventory. Under constant unit acquisition cost, instantaneous replenishment, and no shortages, the classical baseline order quantity is given by Equation (1).

$$Q_0 = \sqrt{\frac{2DS}{h}} \quad (1)$$

This EOQ baseline does not jointly optimize safety stock and shortage costs under uncertainty. A numerical value requires defensible estimates of S and h on consistent cost and time bases. Annual overhead divided by annual sales should not automatically be treated as the holding cost of one unit kept in inventory for a year. No new optimal order quantity is calculated here because the required cost basis is not established in the supplied evidence.

For the stochastic component, let daily demand have mean μ_d and variance σ_d^2 . Let L be replenishment lead time measured in nonnegative whole days, with mean $E(L)$ and variance

$\text{Var}(L)$. If daily demands are independent and identically distributed, and independent of L , total demand X_L over the random lead time has the moments in Equations (2) and (3).

$$E(X_L) = \mu_d E(L) \quad (2)$$

$$\text{Var}(X_L) = E(L) \sigma_d^2 + \mu_d^2 \text{Var}(L) \quad (3)$$

The assumptions are explicit: correlated demand, seasonality, supplier disruption, or dependence between demand and lead time can invalidate this representation. Forecast-error variance may also require separate estimation; alternative aggregation strategies can lead to different inventory performance (Babai et al., 2022). Monthly demand variability cannot simply be inserted into a daily lead-time formula without an appropriate conversion and justification.

Under an adequate normal approximation, a candidate safety stock and reorder point can be expressed by Equation (4), where z_α is the standard normal quantile associated with a chosen cycle service level α . Here σ_{XL} is the square root of $\text{Var}(X_L)$. The ceiling function rounds the reorder point upward to a whole unit.

$$SS = z_\alpha \sigma_{XL}, \quad r = [E(X_L) + SS] \quad (4)$$

A cycle service level describes the probability of avoiding a shortage over the relevant replenishment cycle. It is distinct from the fill rate, which concerns the fraction of demand satisfied immediately. Shortage expectations require their own calculation; Sondakh (2023) specifically examines derivation errors in a simple probabilistic inventory formulation. The present assessment does not choose a service target or infer it from the proposed safety stock.

In a continuous-review implementation, replenishment is triggered by inventory position, defined as on-hand stock plus stock on order minus backorders. An on-hand balance alone can prompt duplicate orders while replenishment is already in transit. Lost sales must be recorded separately if unmet demand is not backordered. The illustrative numerical check below uses a 365-day calendar only as a stated scenario; it is not a claim about the store's operating schedule.

RESULT AND DISCUSSION

Annual demand increased by 302 units, or 6.99%, between the two reported years. Table 1 separates these reported totals from the proposed control parameters. The increase provides a reason to review inventory planning, but two annual observations cannot establish high daily variance, nonlinear demand, or a suitable probability distribution.

Table 1. Reported demand and proposed inventory thresholds

Item	Value (units)	Interpretation
Annual demand, 2022	4,319	Reported annual total
Annual demand, 2023	4,621	Reported annual total
Annual increase	302	Calculated difference (6.99%)
Proposed safety stock	79	Parameter basis not supplied
Proposed reorder point	206	Parameter basis not supplied

Note. Annual totals and thresholds from the supplied manuscript; the percentage change is calculated here.

Figure 1 retains the annual demand comparison supplied with the manuscript. Its bars describe annual volume rather than the timing of individual customer requests. The same annual total could arise from a relatively steady sequence or from concentrated purchases, with different implications for replenishment risk.

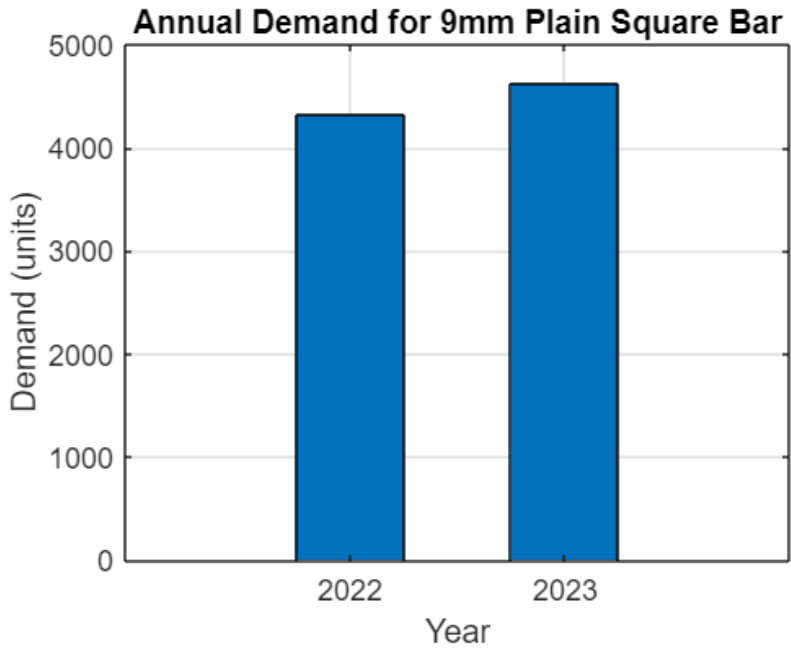


Figure 1. Annual demand for 9 mm plain square bars.

The two proposed thresholds imply expected demand during lead time of $206 - 79 = 127$ units. That identity is arithmetically consistent with the additive reorder-point structure, but it does not verify either input. Under the illustrative 365-day scenario, the 2023 daily mean would be $4,621/365 = 12.6603$ units. Expected lead-time demand of 127 units would then correspond to approximately 10.03 days. These calculations expose the missing assumption; they do not estimate actual supplier lead time.

For comparison, the cited study uses a fixed three-day lead time and reports safety stocks of 70 and 65 units, with reorder points of 106 and 104 units for 2022 and 2023, respectively (Bu'ulolo et al., 2024). These values do not reproduce the proposed pair of 79 and 206. They should not be substituted automatically, because their time-scale and rounding assumptions also require scrutiny. A fixed three-day lead time, the illustrative daily mean above, and safety stock of 79 units would instead yield a rounded reorder point of 117 units. This is a conditional consistency check, not an operating recommendation.

Figure 2 redraws the supplied inventory-depletion illustration using its plotted values. The trajectory crosses the proposed reorder threshold before reaching the safety stock line. However, no replenishment receipt, supplier delay, random demand generation, or repeated trial is represented. The figure illustrates threshold positions; it is not evidence that the policy prevents stockouts or achieves a particular service level.

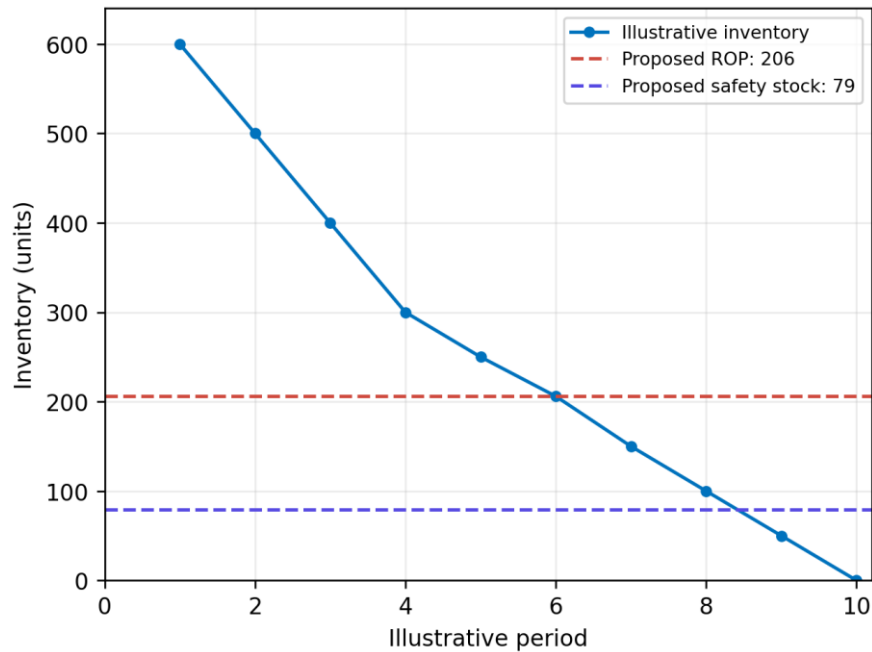


Figure 2. Illustrative depletion path redrawn from the supplied figure.

A suitable demand model must be chosen after inspecting a transaction series. Demand categorization can use the spacing between nonzero demands and variation in demand sizes (Syntetos et al., 2005). If intermittent demand is observed, separate estimation of occurrence intervals and demand sizes may be relevant (Croston, 1972), while the forecasting bias of candidate estimators also needs attention (Syntetos & Boylan, 2005). These are conditional methodological options. The annual totals in this case do not demonstrate intermittency and do not justify selecting any particular estimator.

The effect of lead-time uncertainty also depends on the model and cost structure. Song (1994) analyzes such effects in a stochastic single-item model and shows why blanket claims about optimal inventory levels are unsafe. Here, adding an unspecified buffer to annual demand cannot replace an estimate of lead-time demand uncertainty. The distributional warning raised by Chopra et al. (2004) is particularly relevant when a normal approximation is used without diagnostic checks.

Reliable inventory records are a prerequisite for applying any threshold. Empirical work documents differences between recorded and physical inventory and the importance of inventory auditing practices (DeHoratius & Raman, 2008). Operational errors and labor conditions can also affect record accuracy (Chuang & Oliva, 2015). Evidence linking record inaccuracy with store-level performance reinforces the need to reconcile balances before evaluating a replenishment rule (Shabani et al., 2021). These studies motivate a data-quality check; they do not establish that the same errors or effects occurred at Sadarman.

Imperfect records also change the information available to an inventory controller. Mersereau (2013) examines replenishment when physical inventory is imperfectly observed, demonstrating that such uncertainty is a substantive modeling issue. For this case, daily records should distinguish sales, customer requests that could not be fulfilled, purchase orders, receipts, adjustments, and physical counts. Supplier order quantities should not be treated as an interchangeable demand series: order batching and other mechanisms can distort demand signals along a supply chain (Lee et al., 1997).

Table 2 specifies the evidence needed to evaluate the proposed policy. The existing ordering practice and a proposed policy should be assessed over comparable conditions. A data-based rule may improve consistency, but the direction and magnitude of its effect on costs and service remain empirical questions.

Table 2. Evidence needed to evaluate an inventory policy

Dimension	Measure or record	Status in this assessment
Order quantity	Ordering cost; holding cost; order size	No validated stochastic optimum
Ordering trigger		Threshold basis incomplete
Stock availability	Inventory position; service target	No measured policy effect
Supplier performance	Unfilled requests; demand served	Lead-time distribution
Cost performance	Order and receipt dates	unavailable
	Comparable ordering, holding and shortage costs	No demonstrated cost saving

Note. This table specifies an evaluation framework; it does not report intervention results.

A subsequent evaluation should report both inventory outcomes and the resources required to obtain them. Performance-measurement research supports selecting explicit metrics instead of relying on broad assertions of efficiency (Gunasekaran et al., 2001). Forecast accuracy alone is also insufficient: research on temporal aggregation evaluates forecasts through their stock-control consequences (Babai et al., 2012). In this case, a policy comparison should use the same demand and lead-time inputs, document initial inventory and outstanding orders, and state how unmet demand is treated.

For practical use, the store could first reconcile its opening balance, record transactions consistently, and review supplier order-to-receipt intervals. Candidate parameters could then be estimated on an initial data window and evaluated on later observations. A simulation, if used, would need stated distributions, dependence assumptions, replication settings, and uncertainty intervals. These steps are proposed future work; no resulting cost reduction or service improvement is reported in this assessment.

The analysis has a limited but useful application to community-oriented business support. A worksheet separating order quantity, inventory position, and safety stock could help staff understand the decision process. Its educational or economic benefit would need to be assessed through an actual activity with defined participants, procedures, and outcome measures. The present article supplies an analytical basis for such work and does not claim that training, adoption, or sustained operational improvement has already occurred.

CONCLUSION

The available annual totals establish a 6.99% increase in demand, but they do not establish the daily demand or lead-time distributions needed for a probabilistic inventory policy. The proposed safety stock of 79 units and reorder point of 206 units imply expected lead-time demand of 127 units; their underlying parameter estimates remain unavailable. Consequently, these thresholds cannot yet be treated as validated operating settings, and neither an optimal order quantity nor realized savings can be inferred.

A defensible implementation requires consistent time units, marginal ordering and holding costs, reliable inventory records, an explicit service objective, and a documented treatment

of unmet demand. The proposed continuous-review framework makes those requirements transparent. Further work should estimate the policy from transaction and delivery records and evaluate its cost and service performance before recommending adoption.

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