Reslaj: Religion Education Social Laa Roiba Journal

Volume 8 Nomor 11 (2026) 993 – 1017 P-ISSN 2656-274x E-ISSN 2656-4691
DOI: 10.47476/reslaj.v8i11.13489

Optimizing Spare Parts Safety Stock: Integrating Demand Variability and Operational Criticality in Smelting Operation

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ABSTRACT

This quantitative study applies Monte Carlo simulation with 5,000 iterations to optimize inventory policies for Maintenance, Repair, and Operations (MRO) spare parts with intermittent demand at the Smelting & Refining Unit of PT Freeport Indonesia. Using 24 months of historical demand data (January 2024 to December 2025) extracted from the SAP ERP system, the study analyzes 45 critical Material Numbers (MN), consisting of 15 Mechanical, 15 Electrical, and 15 Instrumentation spare parts. The proposed approach integrates intermittent demand classification using the Average Demand Interval (ADI) and Coefficient of Variation Squared (CV^2), operational criticality assessment, and Monte Carlo simulation to determine optimal safety stock and reorder point values. The simulation reduced total safety stock from 261 units to 105 units, a reduction of 59.77%, while average safety stock decreased from 5.80 to 2.33 units per Material Number. The proposed policy achieved an average service level of 95.92% and an average stockout probability of 4.08% across the 45 Material Numbers. Under the assumed holding cost scenario, the reduction in safety stock was estimated to generate potential holding cost savings of USD 62,045.54. Overall, integrating intermittent demand classification, operational criticality, and Monte Carlo simulation provides a practical decision support framework for recalibrating SAP Material Requirements Planning (MRP) parameters to improve inventory efficiency and operational reliability in continuous process industries.

Keywords: *intermittent demand, Monte Carlo simulation, safety stock, SAP ERP, MRO spare parts.*

INTRODUCTION

The growth of mineral based manufacturing industries in Indonesia has encouraged smelting companies to strengthen competitiveness through effective, efficient, and sustainable supply chain management. Smelting production is characterized by continuous processes; therefore, production equipment reliability is a decisive factor in maintaining operational continuity. In this context, supply chain management focuses not only on raw material procurement but also on spare parts inventory management as a supporting component of continuous production. Supply chain management comprises a set of interrelated activities that integrate suppliers, production, warehousing, transportation, sellers, and users effectively and efficiently so that products can be delivered at the right time, in the right quantity, and to the right

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location while minimizing operating costs and meeting customer needs optimally (Jamaludin, 2021).

This study focuses on safety stock management for Maintenance, Repair, and Operations (MRO) spare parts in smelting operations that are continuous process, capital intensive, and highly dependent on equipment reliability. In such an environment, spare part availability is not merely a warehousing issue but an element of operational risk control: when a critical material is unavailable when needed, maintenance work may be delayed and equipment may be exposed to downtime.

The practical problem underlying this study is the simultaneous presence of two opposing conditions in spare parts management. On the one hand, some materials are held in relatively large quantities, tying up working capital, increasing holding costs, and exposing long stored items to deterioration. On the other hand, stockouts can still occur for materials required for maintenance activities. Stockouts of critical spare parts have consequences that extend beyond inventory shortages because they may delay work, prolong downtime, disrupt production schedules, reduce service level achievement, and potentially increase production losses. Thus, the central issue is not simply how many spare parts should be stored, but how to determine an inventory buffer that adequately protects operations without creating overstock.

As industrial operations become more complex, spare parts inventory management becomes increasingly challenging. Spare part availability must ensure operational continuity, while companies are simultaneously required to control inventory costs and avoid inefficient use of working capital. This creates a trade off between maintaining the required service level and minimizing total inventory costs. Adequate inventory is therefore essential because sound inventory management can support company performance, minimize inventory costs, and anticipate fluctuations in demand (Adelia & Mandala, 2021).

The problem becomes more complex when spare parts demand is intermittent. This demand pattern is characterized by irregular intervals between demand occurrences and by periods of zero demand. These characteristics reduce the accuracy of conventional forecasting methods that assume continuous demand. In addition, an imbalance between supply and demand can lead to both overstock and stockout conditions (Ariyanti et al., 2025). Both risks are costly. Overstock increases holding and inventory maintenance costs and ties up working capital, whereas stockouts of critical spare parts can halt production, increase downtime and lost production costs, and disrupt the achievement of operational targets (Nurdianto & Widiasih, 2025).

Inventory management in industrial operations is part of a wider material flow system. Stock decisions affect procurement, storage, distribution, and the ability of production units to obtain materials when needed. Effective supply chain management depends on coordination between procurement and distribution so that material flow

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supports operating requirements rather than creating unnecessary accumulation (Ardhi et al., 2026). Inventory positioning also needs to reflect the service requirement of the supply network, because stock placed at an unsuitable point may increase cost without improving availability (Duc et al., 2022). At warehouse level, inventory performance can be evaluated through turnover measures that indicate how efficiently materials move through storage (Hudori, 2017). Reliable inventory records also depend on clear material issue procedures, since physical stock movements must correspond with administrative records (Meyliawati & Suprianto, 2020). Warehouse management should connect receiving, storage, control, and release activities as one integrated process (Puteri et al., 2023). In a broader production context, inventory policy must balance availability, ordering decisions, and cost as part of supply chain planning (Silver et al., 2017). Cycle counting supports this control by checking inventory accuracy on a recurring basis rather than relying only on a complete physical count (Wardana & Sukmono, 2019). Just in Time control further shows that inventory can be kept lower when replenishment is synchronized with actual production needs (Zulkarnain & Marwan, 2025).

Classical inventory models remain useful because they provide a clear basis for deciding order quantity and review frequency. Under uncertain demand, Economic Order Quantity can be used to structure the relationship between ordering decisions and inventory cost (Abdallah et al., 2023). In spare parts settings, the same principle helps determine an order quantity that avoids excessive purchasing while still supporting maintenance needs (Balhaqi & Rosyada, 2022). Applications to raw material inventory likewise show the value of using systematic calculation rather than ordering based only on routine or intuition (Deftania et al., 2022). When the number of items is large, ABC analysis can separate materials according to their relative importance and can be combined with periodic review so that managerial attention is focused on the most influential items (Fikram, 2019). Statistical inventory control is also relevant when stock parameters need to be derived from observed demand rather than fixed assumptions (Perkasa et al., 2026). From a cost perspective, Economic Order Quantity seeks a balance between ordering cost and holding cost so that total inventory cost can be controlled (Ramadhana & Puspitasari, 2016). For inventories with several items and additional risks such as expiration, probabilistic models provide a more flexible basis because the decision must account for more than a single deterministic demand value (Zahira & Setyawan, 2026).

Safety stock is used as protection against uncertainty, while the reorder point indicates the inventory position at which replenishment should begin. These parameters should reflect the actual demand pattern, lead time, and service requirement of each item. Practical spare parts control shows that inventory levels need to be aligned with consumption and replenishment conditions so that stock is available without becoming excessive (Adelia & Mandala, 2021). Safety stock and reorder point optimization can

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reduce stockout exposure when both parameters are calculated from demand behavior instead of being set uniformly (Ariyanti et al., 2025). The use of minimum inventory and reorder point in pharmaceutical logistics likewise reflects the need to protect service continuity while limiting unnecessary stock (Darmayanti & Ayuningtyas, 2025). In periodic review systems, reorder levels must also consider service constraints because the time between reviews creates additional exposure to shortage (Donselaar et al., 2021). Continuous review provides a different logic because inventory position is monitored continuously and replenishment can be triggered as soon as the specified threshold is reached (Escalona et al., 2021). Forecast estimates influence this threshold, so changes in the observation window can affect both inventory requirements and reorder point calculations (Fahturohman et al., 2026). Lead time is equally important because a longer waiting period means that existing stock must cover demand for a longer interval before the next order arrives (Faizol et al., 2021). Order quantity and reorder timing should also be considered together, as shown by applications that combine Economic Order Quantity and reorder point within one inventory control process (Faleri et al., 2023). When procurement conditions are uncertain, safety stock provides an additional buffer to absorb differences between expected and actual material requirements (Nafi & Islami, 2025). Information systems can strengthen this control by linking stock records with safety stock and reorder point rules in daily distribution activities (Nugroho et al., 2025). The financial effect of keeping additional inventory can be expressed through holding cost, which converts stored units into an annual cost burden (Priharto, 2023). Service level based safety stock calculation also makes the desired degree of availability explicit, which is important when management must decide how much protection against stockout is acceptable (Sayang et al., 2022).

For MRO spare parts, inventory control cannot be separated from maintenance policy because the value of a spare part is closely related to the equipment function it protects. Life Cycle Cost analysis considers maintenance decisions over the useful life of equipment, so a maintenance policy should take into account not only immediate repair cost but also downtime and long term cost consequences (Aisya et al., 2018). In MRO planning, long lead times and irregular requirements make it necessary to define stock boundaries and material requirements more carefully. The combination of Material Requirements Planning and Min Max Inventory Control provides a way to plan required materials while also setting minimum and maximum stock limits to reduce shortage and excessive inventory (Anggaraini et al., 2025). When demand is uncertain, a deterministic calculation alone may not represent the range of possible inventory outcomes. Monte Carlo simulation can be combined with safety stock and reorder point calculations to evaluate spare parts availability under repeated demand scenarios (Farisan et al., 2025). Reliability information adds another layer to the decision because the probability of equipment failure influences how urgently a spare part may be required. Maintenance

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scheduling and spare parts optimization are therefore more useful when they are considered together rather than managed as separate activities (Nurdianto & Widiasih, 2025). Criticality analysis helps determine which components deserve stronger inventory protection by considering the consequences of failure across several attributes, not only the frequency of demand (Polenghi et al., 2022). Lead time also determines the period during which the inventory system must protect operations before replenishment arrives. Empirical work on procurement, lead time, and inventory shows that these factors are closely related to smooth operational activity (Pranata et al., 2025). For items that require close monitoring, a continuous review system can link forecasting results with safety stock and reorder point so that an order is triggered when inventory reaches a predetermined level (Rahmania et al., 2024). The logic of service parts control also extends beyond a single warehouse. The METRIC model shows that recoverable item inventory can be allocated across a multi echelon repair and supply network by considering expected backorders and system investment (Sherbrooke, 1968). This network perspective is relevant to critical spare parts because availability at one location may depend on repair and supply decisions made elsewhere. Operational readiness also depends on coordination between maintenance and procurement, since delays or mismatches in spare parts supply can weaken the ability of equipment to return to service when required (Widodo, 2025). Taken together, these studies support an inventory policy that combines demand behavior, maintenance need, lead time, criticality, and service requirements rather than relying on historical usage alone.

Intermittent demand is different from regular demand because periods with no consumption are mixed with occasional nonzero demand. This makes both the timing and size of future demand difficult to represent with a single average. Multivariate Support Vector Regression has been used to forecast intermittent spare parts demand in railway operations, showing that additional demand information can be incorporated when simple time series patterns are weak (Afghoni & Vanany, 2026). Forecast quality should also be considered together with inventory consequences, because a statistically acceptable forecast may still produce poor replenishment decisions if it is disconnected from stock control (Goltsos et al., 2022). ADI and CV provide a useful way to describe the interval between demand occurrences and the variability of demand size, allowing different demand states to be distinguished before a forecasting or inventory method is selected (Neu et al., 2024). Reviews of spare parts forecasting emphasize that intermittent demand requires methods designed for sparse and irregular observations rather than methods that assume continuous demand (Pinçe et al., 2021). Classification is important because different spare parts can show different combinations of demand frequency and variability even within the same operational environment (Ratnaningsih & Safirin, 2025). Forecasting should ultimately be linked with the stock keeping unit decision, since the purpose of the forecast is to support an appropriate inventory level

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for each item (Sfiris & Koulouriotis, 2025). Croston based approaches separate the estimation of demand size from the interval between demand occurrences, which is why they are often considered for spare parts with many zero demand periods (Simamora et al., 2019). The ADI and CV based categorization proposed by Syntetos et al. (2005) provides a structured basis for grouping demand patterns before selecting the forecasting method. Intermittent demand also creates a risk of obsolescence because a large buffer may remain unused for a long period, so forecasting decisions need to be connected with inventory aging and obsolescence considerations (Teunter et al., 2011). Alternative forecasting methods have also been proposed specifically for service parts with intermittent demand because conventional forecasts often respond poorly to long sequences of zero demand (Willemain et al., 2004). The practical value of a classification method therefore depends on whether the resulting categories help the inventory decision that follows, rather than on classification alone (Intermittent Demand Classifications: Is That What You Need?, n.d.).

Monte Carlo simulation is useful when inventory outcomes depend on uncertain variables that cannot be represented adequately by one fixed value. The method repeatedly samples possible values from a probability distribution and observes how the system responds across many trials. In inventory planning, simulation can be combined with a backorder policy to evaluate how stock behaves when demand varies from one period to another (Adadiah, 2026). The same logic has been used for prediction problems in which repeated random sampling represents uncertainty in future outcomes (Anggraini & Nurcahyo, 2021). For tire and oil inventory, Monte Carlo simulation has been applied to estimate demand and support inventory optimization under uncertain usage patterns (Augusto et al., 2024). Within a broader production system, simulation and quantitative optimization are useful because operating decisions are often influenced by several interacting constraints rather than a single deterministic factor (Noor et al., 2025). In the present study, this makes Monte Carlo simulation suitable for testing whether a proposed safety stock and reorder point can maintain the desired service level across repeated demand realizations.

Recent forecasting research also shows a growing use of data driven methods for inventory decisions. Regression, Support Vector methods, and neural networks can be used to model the relationship between historical data and required safety stock when the underlying pattern is difficult to capture with a simple formula (Churniawan et al., 2025). Forecast performance may also change when the demand regime changes, so comparisons between classical models and LSTM models need to consider whether the evaluation is conducted under comparable demand conditions (Kariman & Syahputri, 2026). In supply networks with service constraints, evolutionary computation can search for inventory combinations that satisfy service requirements while reducing cost across several echelons (Liu & Nishi, 2024). For intermittent demand, the quality of input

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features can be as important as model complexity because sparse demand contains limited direct information about future occurrences (Nathan et al., 2026). Stochastic programming offers another way to represent demand uncertainty by considering more than one possible future scenario when supply chain decisions are optimized (Sarange et al., 2024). These approaches do not remove the need for basic inventory logic, but they show how richer data and computational methods can support decisions when demand behavior becomes more complex.

Reliable inventory optimization also depends on the quality of operational data and on the ability to translate model outcomes into measurable business effects. Automated digital measurement illustrates how sensor based data can improve the consistency of physical estimates used in operational analysis (Antoniadis et al., 2025). Inventory decisions also need to be assessed in financial terms, because reducing stock is useful only when the relevant cost consequences are understood (Ginting et al., 2024). The wider adoption of Industry 4.0 technologies reinforces the role of integrated digital information in improving operational and delivery performance (Ribeiro et al., 2026). In the present study, these ideas are reflected in the use of SAP data and holding cost evaluation to support material specific inventory decisions.

RESEARCH METHODS

Priadana and Sunarsi (2021) describe quantitative research as an approach that uses measurable data and systematic analysis to examine empirical relationships and patterns. Consistent with this quantitative orientation, this study employs Monte Carlo simulation to evaluate safety stock policies for Maintenance, Repair, and Operations (MRO) spare parts at the Smelting & Refining Unit of PT Freeport Indonesia in Gresik. The unit of analysis is each MRO spare part stock keeping unit (SKU) characterized by intermittent demand and used to support maintenance of production equipment. Historical data were obtained from the SAP ERP system for a 24 month period, from January 2024 through December 2025, including demand history, zero demand frequency, lead time, inventory data, and operational criticality information.

RESULTS AND DISCUSSION

This study is based on secondary empirical data extracted from the SAP Enterprise Resource Planning (ERP) system at the Smelting & Refining Unit of PT Freeport Indonesia. After data cleansing, the existing inventory management condition indicated inefficient allocation of working capital caused by a uniform, one size fits all inventory policy. Logistics management tended to determine safety stock and reorder points from historical averages of material movements without accounting for differences in demand variability across materials. This approach resulted in inventory accumulation for several components while stockout risk remained present for critical materials because of uncertain demand fluctuations.

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The study analyzes 45 Material Numbers (MN) that exhibit intermittent demand and high criticality, comprising 15 Mechanical, 15 Electrical, and 15 Instrumentation spare parts. All 45 MN were retained in the calculations and optimization. To improve readability, the article presents detailed results for only five representative materials from each discipline, consisting of five Mechanical, five Electrical, and five Instrumentation items, giving a total of 15 displayed MN rather than all 45. The five examples in each discipline were selected to represent different lead times, ADI and CV^2 values, criticality, and safety stock outcomes. Accordingly, the sample tables illustrate the pattern of results, while aggregate statistics continue to be calculated from all 45 MN.

The Monte Carlo simulation shows that optimization not only adjusts safety stock values but also produces more efficient reorder point (ROP) recommendations. ROP is calculated from average demand during lead time plus safety stock, so changes in safety stock directly affect the reorder threshold. Overall, optimization across the 45 materials produced generally lower ROP values while maintaining the minimum target service level of 95% and a low stockout probability for critical materials.

Mechanical Material Optimization Results

Table 1. Mechanical Material Inventory Simulation Parameters and Results

No. / Material No.	Material Description	Demand Profile	Lead Time / Target SL	Existing Policy	Monte Carlo Policy
1 40851841	BEARING:ROLLER;SPHERICAL;HI TEMP MAIN SHAFT	Avg: 1.45 SD: 1.12 CV^2: 0.420 ADI: 1.38 Class: Intermittent Z: 1.6449	90 days 95.00%	SS: 6 ROP: 10 SL: 95% Holding cost: USD 2,386.37	SS: 3 ROP: 7 SL: 95.20% Holding cost: USD 1,193.18
2 40851850	SEAL:OIL;LIP;V RING 120MM FEEDER PUMP	Avg: 1.15 SD: 0.98 CV^2: 0.460 ADI: 1.42 Class: Intermittent Z: 1.6449	70 days 95.00%	SS: 4 ROP: 7 SL: 95% Holding cost: USD 1,590.91	SS: 2 ROP: 5 SL: 94.60% Holding cost: USD 795.46

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No. / Material No.	Material Description	Demand Profile	Lead Time / Target SL	Existing Policy	Monte Carlo Policy
3 40851919	COUPLING:FLEXIBLE;MOTOR TO PUMP REFINING	Avg: 1.14 SD: 0.96 CV^2: 0.470 ADI: 1.47 Class: Intermittent Z: 1.6449	62 days 95.00%	SS: 4 ROP: 6 SL: 95% Holding cost: USD 1,590.91	SS: 2 ROP: 4 SL: 94.30% Holding cost: USD 795.46
4 40851921	SPROCKET:ROLLER CHAIN;HARDENED STEEL FLUID	Avg: 1.44 SD: 1.10 CV^2: 0.420 ADI: 1.35 Class: Intermittent Z: 1.6449	72 days 95.00%	SS: 5 ROP: 8 SL: 95% Holding cost: USD 1,988.64	SS: 2 ROP: 5 SL: 95.80% Holding cost: USD 795.46
5 40851922	CHAIN:ROLLER;LINK 1.5 INCH PITCH CONVEYOR	Avg: 1.55 SD: 1.16 CV^2: 0.430 ADI: 1.33 Class: Intermittent Z: 1.6449	98 days 95.00%	SS: 7 ROP: 12 SL: 95% Holding cost: USD 2,784.09	SS: 3 ROP: 8 SL: 97.00% Holding cost: USD 1,193.18

Source: Research data processing results.

Based on the optimization results for the 15 Mechanical materials classified as highly critical intermittent demand items, all materials showed lower safety stock and reorder point values than under the company's existing condition. Nevertheless, most materials continued to achieve the target service level of at least 95%, while a small number were slightly below the target but still exhibited low stockout probabilities. These results indicate that Monte Carlo simulation can produce a more efficient inventory policy without compromising material availability reliability. The proposed policy can therefore reduce excess inventory while maintaining operational continuity.

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Electrical Material Optimization Results

Table 2. Electrical Material Inventory Simulation Parameters and Results

No. / Material No.	Material Description	Demand Profile	Lead Time / Target SL	Existing Policy	Monte Carlo Policy
1 40851885	MOTOR:ELEC;AC; 3 PHASE;45KW INDUCTION HEAVY	Avg: 1.15 SD: 0.98 CV^2: 0.460 ADI: 1.42 Class: Intermittent Z: 1.6449	70 days 95.00%	SS: 4 ROP: 7 SL: 95% Holding cost: USD 1,590.91	SS: 2 ROP: 5 SL: 94.60% Holding cost: USD 795.46
2 40851890	CONTACTOR:MAG ;3 POLE;100A;24VDC COIL SWITCH	Avg: 1.35 SD: 1.04 CV^2: 0.430 ADI: 1.39 Class: Intermittent Z: 1.6449	85 days 95.00%	SS: 6 ROP: 9 SL: 95% Holding cost: USD 2,386.37	SS: 2 ROP: 6 SL: 95.70% Holding cost: USD 795.46
3 40851895	RELAY:OVERLOAD;THERMAL;ADJ 50 70A OVRHEAT	Avg: 1.65 SD: 1.18 CV^2: 0.450 ADI: 1.33 Class: Intermittent Z: 1.6449	115 days 95.00%	SS: 8 ROP: 14 SL: 95% Holding cost: USD 3,181.82	SS: 3 ROP: 9 SL: 98.20% Holding cost: USD 1,193.18
4 40851900	FUSE:CARTRIDGE; HIGH VOLT;20A CERAMIC FUSE	Avg: 1.25 SD: 1.00 CV^2: 0.440 ADI: 1.41 Class: Intermittent Z: 1.6449	95 days 95.00%	SS: 6 ROP: 10 SL: 95% Holding cost: USD 2,386.37	SS: 2 ROP: 6 SL: 96.00% Holding cost: USD 795.46

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No. / Material No.	Material Description	Demand Profile	Lead Time / Target SL	Existing Policy	Monte Carlo Policy
5 40851908	CABLE:POWER;3 CORE;16MM2 ARMOURED XLPE SYS	Avg: 1.62 SD: 1.16 CV^2: 0.430 ADI: 1.33 Class: Intermittent Z: 1.6449	125 days 95.00%	SS: 9 ROP: 15 SL: 95% Holding cost: USD 3,579.55	SS: 4 ROP: 10 SL: 98.80% Holding cost: USD 1,590.91

Source: Research data processing results.

The optimization results for the 15 Electrical materials show a pattern similar to that observed for the Mechanical group. All materials experienced reductions in safety stock and reorder point compared with the existing condition, while most continued to meet the target service level of at least 95%. Materials that were slightly below the target still had low stockout probabilities, indicating that the associated operational risk remained acceptable. These findings show that the Monte Carlo simulation approach can improve inventory management efficiency while maintaining the service level required by operations.

Instrumentation Material Optimization Results

Table 3. Instrumentation Material Inventory Simulation Parameters and Results

No. / Material No.	Material Description	Demand Profile	Lead Time / Target SL	Existing Policy	Monte Carlo Policy
1 40851903	SENSOR:PROXIMITY;INDUCTIVE;M30 SHEAR PINS	Avg: 1.40 SD: 1.06 CV^2: 0.420 ADI: 1.37 Class: Intermittent Z: 1.6449	65 days 95.00%	SS: 5 ROP: 8 SL: 95% Holding cost: USD 1,988.64	SS: 2 ROP: 5 SL: 95.10% Holding cost: USD 795.46

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No. / Material No.	Material Description	Demand Profile	Lead Time / Target SL	Existing Policy	Monte Carlo Policy
2 40851904	SENSOR:TEMPERATURE;RTD PT100;150MM FURNACE	Avg: 1.48 SD: 1.10 CV^2: 0.430 ADI: 1.34 Class: Intermittent Z: 1.6449	90 days 95.00%	SS: 6 ROP: 10 SL: 95% Holding cost: USD 2,386.37	SS: 3 ROP: 7 SL: 96.30% Holding cost: USD 1,193.18
3 40851905	TRANSMITTER:PRESSURE;0 10 BAR;4 20MA LINE	Avg: 1.72 SD: 1.20 CV^2: 0.450 ADI: 1.33 Class: Intermittent Z: 1.6449	105 days 95.00%	SS: 8 ROP: 14 SL: 95% Holding cost: USD 3,181.82	SS: 3 ROP: 9 SL: 98.50% Holding cost: USD 1,193.18
4 40851912	INVERTER:VFD;15KW;VECTOR CONTROL FAN SYS	Avg: 1.42 SD: 1.15 CV^2: 0.410 ADI: 1.36 Class: Intermittent Z: 1.6449	70 days 95.00%	SS: 5 ROP: 8 SL: 95% Holding cost: USD 1,988.64	SS: 2 ROP: 5 SL: 95.50% Holding cost: USD 795.46
5 40851913	PLC:MODULE;I/O ANALOG;8 CHANNEL BALANCING	Avg: 1.52 SD: 1.18 CV^2: 0.440 ADI: 1.33 Class: Intermittent Z: 1.6449	95 days 95.00%	SS: 7 ROP: 11 SL: 95% Holding cost: USD 2,784.09	SS: 3 ROP: 8 SL: 96.80% Holding cost: USD 1,193.18

Source: Research data processing results.

For the Instrumentation group, the optimization results show that all materials experienced reductions in safety stock and reorder point values compared with the

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previous inventory policy. All displayed materials also achieved service levels above the minimum 95% target with relatively low stockout probabilities. These findings indicate that Monte Carlo simulation can generate a more efficient inventory policy without reducing the availability of critical materials, thereby supporting operational continuity.

Comparison of the Existing Policy and the Monte Carlo Model

Table 4. Comparison of the Company's Existing Condition and Monte Carlo Simulation Results

Parameter	Company's Existing Condition	Monte Carlo Simulation Results
Inventory control approach	Safety stock and ROP are determined from historical averages using a uniform one size fits all policy.	Safety stock and ROP are calculated using ADI, CV^2, lead time, criticality, and Monte Carlo simulation.
Safety Stock	Relatively higher.	Lower and tailored to each material's characteristics.
Reorder Point (ROP)	Uses the company's existing parameters.	Lower for most materials without reducing service level.
Service Level	Not yet evaluated using probabilistic simulation.	95.00% to 99.70%, based on simulation results.
Stockout Probability	Not quantitatively measured.	0.30% to 5.70%.
Inventory Efficiency	Overstock remains for several materials.	More efficient inventory while maintaining low stockout risk.

Source: Research data processing results.

Comparison of the company's existing condition with the Monte Carlo simulation results in Table 4 shows that the proposed model produces a more efficient inventory policy. Under the existing condition, safety stock and reorder points are determined using a relatively uniform approach and therefore do not fully reflect the demand characteristics of each material. After optimization using ADI and CV^2 classification, criticality, and Monte Carlo simulation, most materials experienced reductions in safety stock and reorder point without compromising the company's target service level. These results indicate that a stochastic simulation based approach can reduce excess inventory while preserving operational continuity through consistently low stockout probabilities.

Analysis of the 45 Material Numbers (MN) shows that each material has a distinct demand profile based on Average Demand Interval (ADI), Coefficient of Variation Squared (CV^2), lead time, and operational criticality. These differences produce different

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safety stock and reorder point (ROP) requirements for each material. A Monte Carlo simulation with 5,000 iterations generated safety stock and ROP combinations that were more efficient than the company's existing inventory policy. Most materials showed lower safety stock and ROP values without reducing the system's ability to meet demand during lead time. In addition, the materials maintained service levels consistent with the company's target (≥95%) with low stockout probabilities.

These findings indicate that the previous inventory policy employed relatively large buffers because it did not explicitly account for the demand characteristics of individual materials. By using the empirical probability distribution of demand over 24 months, the Monte Carlo simulation produced inventory estimates that better reflected actual conditions. Consequently, reducing safety stock did not weaken inventory protection; rather, it reduced excess inventory that did not provide a meaningful additional service level benefit. Lower safety stock and ROP values for most materials also reduced holding costs, making the proposed policy more efficient than the existing condition.

Conceptually, ADI, CV^2, lead time, and operational criticality are the principal factors influencing safety stock and ROP requirements. Materials with higher ADI values have less frequent demand and therefore do not necessarily require large safety stocks when demand variability is low. Conversely, materials with higher CV^2 values or longer lead times require larger buffers to maintain the target service level. Highly critical materials are also prioritized for higher service levels to minimize the risk of operational disruption caused by stockouts.

Validation of Simulation Results

Monte Carlo Simulation Validation

Validation was conducted to evaluate the stability of the optimization results obtained through Monte Carlo simulation. The validation results indicate that the materials generally achieved the company's target service level of at least 95%; a small number of displayed materials were slightly below the target but remained within an acceptable range because their stockout probabilities were low. These results show that the resulting safety stock and ROP combinations can provide a consistent service level while keeping inventory shortage risk within an acceptable range.

Overall, the validation results demonstrate that the Monte Carlo simulation model can generate stable and implementable inventory policy recommendations for spare parts with intermittent demand characteristics. This empirical probability distribution approach improves inventory efficiency while also supporting operational continuity by maintaining service levels in line with the company's target.

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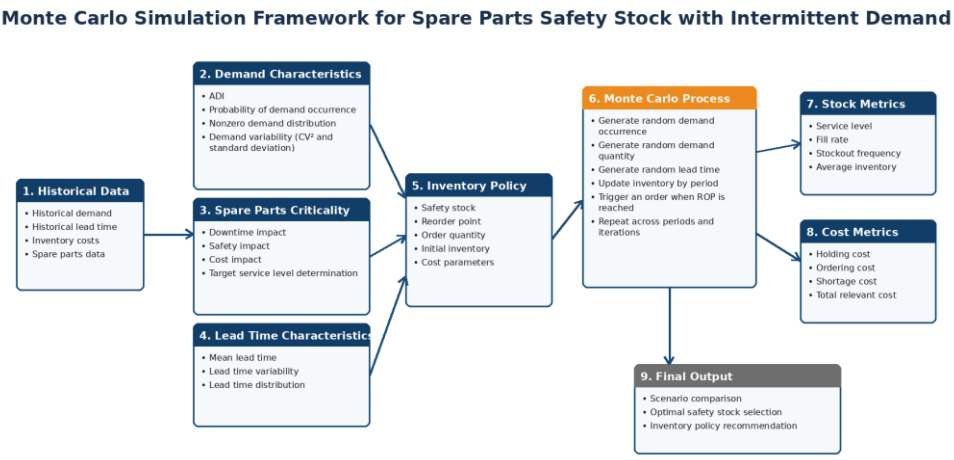


Figure 1. Monte Carlo Simulation Framework

The Monte Carlo simulation begins with the collection of historical data, including demand, lead time, inventory costs, and the characteristics of each Material Number (MN). Intermittent demand characteristics are then analyzed using ADI, CV^2, demand occurrence probability, and demand distributions to identify material demand patterns. The analysis proceeds to the assessment of criticality and lead time variation, which form the basis for setting inventory policy parameters such as safety stock, reorder point (ROP), order quantity, and target service level. The simulation generates random demand and lead time realizations from empirical distributions, updates inventory levels, and triggers replenishment when inventory reaches the ROP. Simulation performance is evaluated using service level, stockout probability, average inventory, and inventory cost, after which the results are compared with the existing PT Freeport Indonesia policy to identify a more efficient inventory policy recommendation.

Table 5. Evaluation Matrix and Comparison of the Existing Policy and Monte Carlo Model

Evaluation Metric	Existing Policy	Monte Carlo Model	Difference / Efficiency	Model Evaluation Conclusion
Total Safety Stock (SS)	261 units	105 units	−156 units (−59.77%)	The Monte Carlo model removes excess inventory (overstocking) associated with overly

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Evaluation Metric	Existing Policy	Monte Carlo Model	Difference / Efficiency	Model Evaluation Conclusion
				conservative analytical assumptions.
Total Reorder Point (ROP)	436 units	291 units	−145 units (−33.26%)	The reorder threshold becomes more precise, reducing the amount of capital tied up in stored materials.
Average Service Level (SL)	81.00%	95.92% (verified)	+14.92%	The model demonstrates that a smaller inventory buffer can still support the required availability target.
Average Stockout Probability	Not measured stochastically	4.08%	Risk quantified	The company gains quantitative visibility into stockout risk for each Material Number.

Source: Research data processing results.

Discussion Based on the Research Questions

Based on the processed data for 45 Material Numbers (MN), the safety stock under the existing policy was compared with the safety stock produced by Monte Carlo optimization. This comparison was used to identify changes in safety stock requirements for each material and to evaluate the reduction in inventory after implementation of the proposed policy. The aggregate comparison is presented below.

Table 6. Existing and Monte Carlo Inventory Parameters

Parameter	Value
Number of Material Numbers	45 MN
Total Existing Safety Stock	261 units
Total Proposed Safety Stock (Monte Carlo)	105 units
Average Existing Safety Stock	261 / 45 = 5.80 units

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Average Proposed Safety Stock	105 / 45 = 2.33 units
Reduction in Safety Stock	261 – 105 = 156 units
Percentage Reduction in Safety Stock	(156 / 261) × 100% = 59.77%
Total Existing ROP	436 units
Total Proposed ROP	291 units
Reduction in ROP	145 units = 33.26%
Average Proposed Service Level	95.92%
Average Stockout Probability	4.08%

Source: Research data processing results.

To provide an overall view of the change in safety stock across the 45 Material Numbers, the values for each material were aggregated. The aggregation sums the existing and Monte Carlo safety stock values and calculates their averages and percentage reduction. The cost parameters underlying the estimated USD 62,045.54 saving are presented in Table 7.

Table 7. Existing and Monte Carlo Holding Cost Parameters

Parameter	Value
Holding Cost Rate	20% per year
Implied Average Unit Value	USD 1,988.64 per unit
Safety Stock Difference	156 units
Estimated Holding Cost per Unit	USD 1,988.64 × 20% = USD 397.728/unit/year

Source: Research data processing results.

Existing vs. Proposed Calculation

Existing: 261 × USD 1,988.64 × 20% = USD 103,808.64
Proposed: 105 × USD 1,988.64 × 20% = USD 41,763.10
Estimated savings: USD 103,808.64 − USD 41,763.10 ≈ USD 62,045.54
Equivalently, the savings can be calculated from the 156 units of safety stock released: 156 × USD 397.7278 ≈ USD 62,045.54.

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Intermittent Demand Characteristics and Research Question 1

The first research question concerns the demand characteristics of the 45 Material Numbers based on ADI and CV^2. The results show that all analyzed materials exhibit intermittent demand characteristics, with ADI values of approximately 1.37 to 1.58 across the three disciplines. Differences in ADI and CV^2 across materials indicate that demand frequency and variability are not uniform. This finding confirms that a one size fits all inventory policy is inappropriate because different materials have different uncertainty profiles.

Lead Time, Criticality, and Research Question 2

The second research question addresses the influence of lead time, demand variability, and operational criticality on safety stock and ROP requirements. Materials with longer lead times generally require larger buffers when combined with uncertain demand. Conversely, materials with shorter lead times and lower demand variability can be managed with smaller safety stocks. Criticality is an important differentiator because all analyzed materials are critical spare parts; therefore, the consequences of stockout are considered more serious than holding costs alone. This pattern is consistent with Sherbrooke's (1968) view that spare parts control should account for operational consequences.

Effectiveness of Monte Carlo Simulation and Research Question 3

The third research question examines the extent to which Monte Carlo simulation generates safety stock and ROP policies that meet the target service level while reducing stockout risk. Using 5,000 iterations and empirical distributions derived from historical data, the model produces a measurable service level for each Material Number. In aggregate, the average service level reached 95.92% and the average stockout probability was 4.08%. Total safety stock decreased from 261 units to 105 units, while total ROP decreased from 436 units to 291 units. These results show that the inventory buffer can be reduced without eliminating its protective function against demand uncertainty.

Inventory Efficiency and Operational Risk: Research Question 4

The fourth research question concerns the effect of the simulation based policy on inventory efficiency and operational risk. A 59.77% reduction in safety stock and a 33.26% reduction in ROP indicate a substantial decrease in capital tied up in inventory. At the same time, the target service level was maintained for most materials and stockout risk became quantifiable. These findings demonstrate a more measurable trade off between holding cost and the risk of material shortages. The practical contribution of the study lies in developing a material specific policy for each Material Number, so inventory decisions are no longer based solely on historical averages but jointly consider demand pattern, lead time, criticality, and stockout probability.

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CONCLUSION

This study developed a safety stock and reorder point optimization model for Maintenance, Repair, and Operations (MRO) spare parts in smelting operations by integrating intermittent demand classification based on Average Demand Interval (ADI) and Coefficient of Variation Squared (CV^2), operational criticality analysis, and Monte Carlo simulation. The proposed approach accommodates irregular intermittent demand and therefore produces a more adaptive inventory policy than a conventional one size fits all approach.

The results show that optimization across 45 Material Numbers reduced safety stock and reorder point values for most materials without compromising the company's service level. The materials generally maintained service levels consistent with the company's target (≥95%) with low stockout probabilities, thereby preserving the availability of critical spare parts needed for operational continuity. In addition to improving inventory system reliability, the reduction in safety stock indicates potential gains in working capital efficiency through lower overstock and holding costs.

The Monte Carlo simulation begins with historical data on demand, lead time, inventory costs, and the characteristics of each Material Number (MN). Analysis of the 45 Material Numbers 15 Mechanical, 15 Electrical, and 15 Instrumentation items shows that each material has distinct demand characteristics, lead time variation, and inventory risk levels. These differences are reflected in ADI, CV^2, demand occurrence probability, demand distribution, and procurement lead time. All materials in the study are categorized as Critical and therefore require high inventory availability to support continuous operations. Each Material Number was consequently evaluated individually through Monte Carlo simulation to estimate inventory requirements that reflect its actual conditions. During simulation, demand and lead time were generated randomly from empirical distributions, inventory levels were updated at each iteration, and potential stockout events were evaluated. The results show that Safety Stock and Reorder Point (ROP) requirements differ across Material Numbers because they are influenced by the combined effects of demand patterns, lead time variation, and material criticality. Thus, the Monte Carlo approach provides material specific recommendations that better reflect the conditions of each critical spare part. The analysis of all 45 Material Numbers therefore provides a basis for a more adaptive inventory policy that maintains material availability in line with the target service level while reducing stockout risk.

In practical terms, the proposed model can support decisions on safety stock and reorder points in continuous process industries characterized by stochastic demand and high material criticality. Future studies should incorporate stochastic lead time variation, dynamic changes in demand patterns, and optimization methods based on artificial intelligence or machine learning to improve the accuracy of inventory policy recommendations.

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DOI: 10.47476/reslaj.v8i11.13489

REFERENCES

Abdallah, B. N., Khairani, N. F., & Muqimuddin, M. (2023). Analisis Kuantitas Pemesanan Beras Dengan Mempertimbangkan Ketidakpastian Permintaan Menggunakan Metode Economic Order Quantity. Jurnal Optimasi Teknik Industri (JOTI), 5(2), 72. https://doi.org/10.30998/joti.v5i2.19125

Adadiah, A. A. (2026). Analisis Persediaan dengan Metode Simulasi Monte Carlo dan Model P Backorder Produk Ascorbic Acid di PT X. Jurnal Logic: Logistics & Supply Chain Center, 4(2), 96–106. https://doi.org/10.33197/jlscc.v4i2.3148

Adelia, N. M. J. & Mandala, K. (2021). Analisis Pengendalian Persediaan Suku Cadang Sparepart pada Bengkel Piaggio Vespa Nusa Dua. E Jurnal Manajemen Universitas Udayana, 10(9), 866. https://doi.org/10.24843/EJMUNUD.2021.v10.i09.p02

Afghoni, S. A. & Vanany, I. (2026). Multivariat Support Vector Regression untuk Peramalan Permintaan Suku Cadang Intermittent pada Industri Perkeretaapian. MALCOM: Indonesian Journal of Machine Learning and Computer Science, 6(2), 810–820.

Aisya, P., Budiasih, E., & Alhilman, J. (2018). Penentuan Optimasi Sistem Perawatan Pada Mesin Casting Line 37 Dengan Menggunakan Metode Life Cycle Cost (LCC) Di Pt Xyz. Journal Industrial Servicess, 4(1), 32–37. https://doi.org/10.36055/jiss.v4i1.4086

Anggaraini, D. D. F., Priyana, E. D., & Purwanto, P. (2025). Analisis Pegendalian Persediaan Material Maintenance, Repair Operations (MRO) Dengan Metode Material Requirement Planning (MRP) dan Metode Min Max Inventory Control. Jurnal Teknologi dan Manajemen Industri Terapan, 3(I), 1743–1753. https://doi.org/10.55826/jtmit.v4i4.1313

Anggraini, S. D. & Nurcahyo, G. W. (2021). Prediksi Peningkatan Jumlah Pelanggan dengan Simulasi Monte Carlo. Jurnal Informatika Ekonomi Bisnis, 95–100. https://doi.org/10.37034/infeb.v3i3.92

Antoniadis, K., Gitas, I. Z., Georgopoulos, N., Grammenos, A., & Stavrakoudis, D. (2025). Automated roundwood volume estimation using mobile LiDAR data and circle fitting methods. Remote Sensing Applications: Society and Environment, 40, 101785. https://doi.org/10.1016/j.rsase.2025.101785

Ardhi, S., Gunawan, T. P., Sugiono, J. P., & Sri Deviyanti, I. G. A. (2026). Analisis Manajemen Rantai Pasok dalam Mendukung Efektkvitas Pengadaan Bahan Baku dan Distribusi Produk pada Industri Kuliner Dapoer Widya. Jurnal Informatika dan Teknik Elektro Terapan, 14(2). https://doi.org/10.23960/jitet.v14i2.9326

Volume 8 Nomor 11 (2026) 993 – 1017 P-ISSN 2656-274x E-ISSN 2656-4691
DOI: 10.47476/reslaj.v8i11.13489

Ariyanti, G. I., Ramadhan, S. C. R., & Hartati, V. (2025). Optimasi Safety Stock dan Reorder Point untuk Mengurangi Stockout Produk Jadi di PT XYZ. Jurnal Logic: Logistics & Supply Chain Center, 4(1), 12–19. https://doi.org/10.33197/jlscc.v4i1.3003

Augusto, H., Anestesia Purba, A., & Aprillia, H. (2024). Monte Carlo Simulation for Tire and Oil Inventory Optimization at PT X. Jurnal Sains dan Teknologi Industri, 21(2), 373. https://doi.org/10.24014/sitekin.v21i2.31204

Balhaqi, M. H. & Rosyada, Z. F. (2022). Analisis Pengendalian Persediaan Material SUku Cadang Standar pada Pesawat NC 212l dengan Metode EOQ Studi Kasus: PT Dirgantara Indonesia. Industrial Engineering Online Jurnal, 11(4), 1–8.

Churniawan, A. D., Lusiani, T., Wurijanto, T., Sutanto, T., Anindita, D., & Arnandy, A. (2025). Analisis Optimalisasi Safety Stock dengan Metode Regresi Linear Support Vector dan Neural Network. Jurnal Ilmiah Scroll: Jendela Teknologi Informasi, 13(2), 1–4. https://journal.univ45sby.ac.id/index.php/SCROLL/article/view/8

Darmayanti, N. P. D. U. & Ayuningtyas, D. (2025). Analisis Implementasi Persediaan Minimum dan Reorder Point dalam Pengendalian Logistik Farmasi: Literature Review. Syntax Literate ; Jurnal Ilmiah Indonesia, 10(6). https://doi.org/10.36418/syntax literate.v10i6.59912

Deftania, A., Meri, M., & Linda, R. (2022). Analisis pengendalian persediaan bahan baku dengan metode economic order quantity. UNES Journal of Scientech Research, 7(1), 35–45.

Donselaar, K. V., Broekmeulen, R., & Kok, T. D. (2021). Heuristics for setting reorder levels in periodic review inventory systems with an aggregate service constraint. International Journal of Production Economics, 237, 108137. https://doi.org/10.1016/j.ijpe.2021.108137

Duc, N. T. T., Tai, P. D., & Buddhakulsomsiri, J. (2022). Inventory Positioning in Supply Chain Network: A Service Oriented Approach. IEEE Access, 10, 92986–93002. https://doi.org/10.1109/ACCESS.2022.3202906

Escalona, P., Araya, D., Simpson, E., Ramirez, M., & Stegmaier, R. (2021). on the shortage control in a continuous review (Q,r) inventory policy using αL service level. RAIRO Operations Research, 55(5), 2785–2806. https://doi.org/10.1051/ro/2021125

Fahturohman, R. F., Nugroho, B., & Puspaningrum, E. Y. (2026). Weighted Moving Average Berbasis Variasi Window untuk Optimasi Persediaan dan Reorder Point Fiber Optik. Jutisi: Jurnal Ilmiah Teknik Informatika dan Sistem Informasi, 15(2), 502–511.

Faizol, A., Sari, N. P., Aini, C. F. N., & Nafiah, U. (2021). Pengaruh Ketepatan Waktu Tunggu Pemesanan Dalam Penerapan Metode Reorder Point Terhadap Terciptanya

Volume 8 Nomor 11 (2026) 993 – 1017 P-ISSN 2656-274x E-ISSN 2656-4691
DOI: 10.47476/reslaj.v8i11.13489

Kelancaran Manajemen Persediaan Bahan Baku Dan Kepuasan Pelanggan.. Journal of Economics and Policy Studies (JEPS), 2(1), 20–31.

Faleri, F., Sudarmaningtyas, P., & Hananto, V. R. (2023). Penerapan Metode Economic Order Quantity dan Reorder Point Pada Aplikasi Pengelolaan Persediaan Fumigasi. Journal of Applied Computer Science and Technology, 4(2), 131–140. https://doi.org/10.52158/jacost.v4i2.532

Farisan, F., Purba, A. A., & Arham Pratikno, F. (2025). Analysis of Spare Parts Inventory Planning for Machinery with Monte Carlo Simulation, Reorder Point, and Safety Stock. Jurnal Sains dan Teknologi Industri, 22(2), 240. https://doi.org/10.24014/sitekin.v22i2.36921

Fikram, M. N. (2019). Optimasi Persediaan Bahan Baku Dengan Analisis ABC dan Periodic Review PT XYZ. Jurnal Optimasi Teknik Industri (JOTI), 1(2), 21–25. https://doi.org/10.30998/joti.v1i2.3850

Ginting, A. P., Gaol, R. L., Waruwu, G. K., & Pasaribu, D. (2024). Analysis of Relevant Costs in Making Decisions to Accept or Reject Special Orders at Puncak Berastagi Resto. Seminar Nasional Manajemen dan Akuntansi, 2, 242–249.

Goltsos, T. E., Syntetos, A. A., Glock, C. H., & Ioannou, G. (2022). Inventory – forecasting: Mind the gap. European Journal of Operational Research, 299(2), 397–419. https://doi.org/10.1016/j.ejor.2021.07.040

Hudori, M. (2017). Pengukuran kinerja persediaan di gudang bahan baku menggunakan turn over ratio (TOR) pada industri manufaktur. Jurnal Citra Widya Edukasi, 9(3), 239–248.

Intermittent demand classifications: is that what you need?. (n.d.).

Jamaludin, M. (2021). Desain Sistem Informasi Manajemen Rantai Pasok pada PT "ABCD" Bandung Jawa Barat Indonesia. Jurnal Administrasi Bisnis, 10(2), 143–154. https://doi.org/10.14710/jab.v10i2.36302

Kariman, D. & Syahputri, N. (2026). Regime Aware Forecasting of Customer Water Consumption: Segmented Evaluation, Fair Benchmarking, and Significance Testing for Classical and LSTM Models. Bayanika Journal of Artificial Intelligence and Data Science, 1(1), 13–24. https://bayanika.org/index.php/bjaids/article/view/3

Liu, Z. & Nishi, T. (2024). Data driven evolutionary computation for service constrained inventory optimization in multi echelon supply chains. Complex & Intelligent Systems, 10(1), 825–846. https://doi.org/10.1007/s40747 023 01179 0

Volume 8 Nomor 11 (2026) 993 – 1017 P-ISSN 2656-274x E-ISSN 2656-4691
DOI: 10.47476/reslaj.v8i11.13489

Meyliawati, M. & Suprianto, E. (2020). Tinjauan SIstem Prosedur Pengeluaran Material C212 di Gudang Manajemen Persediaan PT.X. Jurnal Industri Elektro dan Penerbangan, 6(1), 17–23.

Nafi, N. A. & Islami, M. C. P. A. (2025). Analisis Perhitungan Dalam Optimalisasi Manajemen Inventori Pada Pengadaan Bahan Baku dengan Metode Safety Stock di PT ABC. Jurnal Serambi Engineering, 10(1), 12106 – 12119. https://jse.serambimekkah.id/index.php/jse/article/view/682

Nathan, B. S., Aravinth, P. M., Reddy, B. V. S., Sastry, C. C., Salunkhe, S., & Cep, R. (2026). Primacy of feature engineering over architectural complexity for intermittent demand forecasting. Scientific Reports, 16(1), 4792. https://doi.org/10.1038/s41598 026 35197 y

Neu, Z., Hicks, B., & Gopsill, J. (2024). Operating minimally intelligent agent based manufacturing systems across the Average demand Interval – coefficient of variation (ADI CV) demand state space. Production & Manufacturing Research, 12(1), 2323479. https://doi.org/10.1080/21693277.2024.2323479

Noor, Z., Rantererung, C. L., Kusdiah, Y., Kasnawati, K., & Buku, A. (2025). Optimasi Sistem Produksi. Arsy Media. https://books.google.co.id/books?id=tmPEQAAQBAJ

Nugroho, A., Setiaji, P., Setiaji, P., Nugraha, F., & Setiawan, A. (2025). Sistem Informasi Pengelolaan Stok dan Distribusi LPG 3Kg di PT Gasindo dengan Safety Stock & Reorder Point. JURNAL UNITEK, 18(1), 23–35. https://doi.org/10.52072/unitek.v18i1.1248

Nurdianto, D. & Widiasih, W. (2025). Analisis Keandalan Dan Penjadwalan Pemeliharaan Mesin Line Corrugated Dan Flexo Serta Optimasi Persediaan Sparepart Di Perusahahan Pembuatan Karton Box. Journal of Manufacturing in Industrial Engineering & Technology, 4(2), 103–114. https://doi.org/10.30651/mine tech.v4i2.29245

Perkasa, S. A., Nugraha, A. E., & Sa'adah, N. (2026). Analisis Pengendalian Persediaan Bahan Baku Pasir dan Split Menggunakan Metode Statistical Inventory Control pada Industri Beton Ready Mix. Factory Jurnal Industri, Manajemen dan Rekayasa Sistem Industri, 4(3), 361–369. https://doi.org/10.56211/factory.v4i3.1524

Pinçe, Ç., Turrini, L., & Meissner, J. (2021). Intermittent demand forecasting for spare parts: A Critical review. Omega, 105, 102513. https://doi.org/10.1016/j.omega.2021.102513

Polenghi, A., Roda, I., Macchi, M., & Pozzetti, A. (2022). An ontological modelling of multi attribute criticality analysis to guide Prognostics and Health Management program

Volume 8 Nomor 11 (2026) 993 – 1017 P-ISSN 2656-274x E-ISSN 2656-4691
DOI: 10.47476/reslaj.v8i11.13489

development. Autonomous Intelligent Systems, 2(1), 2. https://doi.org/10.1007/s43684 022 00021 7

Pranata, W. A., Ramadhan, R. R., & Ayuda, F. (2025). Pengaruh Pengadaan Barang, Waktu Tunggu (Lead Time) dan Persediaan Barang Terhadap Kelancaran Operasional pada Outlet Kunyit Restaurant di Prime Park Hotel Pekanbaru. Jurnal Ilmiah Mahasiswa Merdeka EMBA, 5(2), 894–905.

Priadana, S. & Sunarsi, D. (2021). Metode Penelitian Kuantitatif. Pascal Books.

Priharto, S. (2023). Rumus dan Contoh Perhitungan Holding Cost.

Puteri, M. A., Zabina, M. P., & Triputra, E. (2023). Telaah Sistem Manajemen Pergudangan dalam Berbagai Metode Inventory. Riset Sains dan Teknologi Kelautan, 6(1), 40–46. https://doi.org/10.62012/sensistek.v6i1.24246

Rahmania, R. A., Indriani, N., & Wulandari, C. P. (2024). Optimizing Spare Parts Inventory Management of Truck Dealer Services using Forecasting Methods and Continuous Review System Approach. Journal of Advanced Technology and Multidiscipline, 3(2), 60–65. https://doi.org/10.20473/jatm.v3i2.66530

Ramadhana, F. & Puspitasari, N. B. (2016). Analisis Usulan Penentuan Optimal Ordering Cost Cover Engine YA40003084 untuk Minimasi Total Inventory Cost dengan Metode Economic Order Quantity (EQQ). Industrial Engineering Online Jurnal, 5(4), 1–7.

Ratnaningsih, L. & Safirin, M. T. (2025). Strategi Pengklasifikasian dan Peramalan untuk Mengidentifikasi Permintaan Sparepart Bearing di PT Semen Indonesia (Persero). Jurnal Serambi Engineering(1), 12608–12620.

Ribeiro, A. C. E., Facin, A. L. F., & Silva, M. T. D. (2026). Tecnologias habilitadoras da Indústria 4.0 e desempenho de entregas: Estudo de casos no setor alimentício. Exacta, 24, 1. https://doi.org/10.5585/2026.25876

Sarange, A. D., Ingale, K. Y., & Patil, P. V. (2024). Data Driven Two Stage Stochastic Programming for Pharmaceutical Supply Chain Optimization under Demand Uncertainty. International Journal of Drug Delivery Technology, 16(19). https://impactfactor.org/PDF/IJDDT/16/IJDDT,Vol16,Issue19s,Article11.pdf

Sayang, E. S., Setyawan, H. B., & Lemantara, J. (2022). Rancang Bangun Aplikasi Pengendalian Persediaan Bahan Baku Berbasis Website Menggunakan Metode Safety Stock dengan Perhitungan Service Level pada CV Dwi Teknik. JSIKA, 11(1), 61–72.

Volume 8 Nomor 11 (2026) 993 – 1017 P-ISSN 2656-274x E-ISSN 2656-4691
DOI: 10.47476/reslaj.v8i11.13489

Sfiris, D. S. & Koulouriotis, D. E. (2025). A New Approach to Forecast Intermittent Demand and Stock Keeping Unit Level Optimization for Spare Parts Management. Applied Sciences, 15(22), 12030. https://doi.org/10.3390/app152212030

Sherbrooke, C. C. (1968). Metric: A Multi Echelon Technique for Recoverable Item Control. Operations Research, 16(1), 122–141. https://doi.org/10.1287/opre.16.1.122

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2017). Inventory and Production Management in Supply Chains. CRC Press.

Simamora, Y. K., Puspita, E., & Herryanto, N. (2019). Peramalan Jumlah Permintaan Spare Part LCV Bushing Struthbar dengan Menggunakan Metode Croston dan Metode Syntetos Boylan Approximation. Jurnal EurekaMatika, 7(1), 47–57.

Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. Journal of the Operational Research Society, 56(5), 495–503. https://doi.org/10.1057/palgrave.jors.2601841

Teunter, R. H., Syntetos, A. A., & Babai, M. Z. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. European Journal of Operational Research, 214(3).

Wardana, M. R. & Sukmono, Y. (2019). Perancangan Cycle Inventory Policy Menggunakan Metode Cycle Counting Pada Gudang Pt. Badak Ngl. Prosiding Seminar Nasional Rekayasa Tropis, 2(1), 78–87.

Widodo, W. (2025). Analisis Critical Factor Integrasi Sistem Perbaikan dan Pemeliharaan pada Pengadaan Paket Suku Cadang dalam Mendukung Operasional KRI. Jurnal Penelitian Inovatif, 5(4), 3029–3042. https://doi.org/10.54082/jupin.1921

Willemain, T. R., Smart, C. N., & Schwarz, H. F. (2004). A new approach to forecasting intermittent demand for service parts inventories. International Journal of Forecasting, 20(3), 375–387. https://doi.org/10.1016/S0169 2070(03)00013 X

Zahira, A. D. & Setyawan, E. B. (2026). Implementasi Model Persediaan Multi Item Probabilistik erbasis Kadaluwarsa untuk Menurunkan Total Biaya pada Industri FMCG. Jurnal Ilmiah Teknik Industri, 13(3), 163–174. https://doi.org/10.24912/jitiuntar.v13i3.37281

Zulkarnain, M. & Marwan, M. (2025). Implementasi Metode Just In Time Dalam Pengendalian Persediaan Bahan Baku Kayu Pada Produksi Furniture di CV. Berkat Jaya Baru. Prosiding Seminar Nasional Multi Disiplin Ilmu (Senadimu), 2(1), 352–363.