DINASTI PUBLISHER
DIJEFA: Dinasti International Journal of Economics, Finance & Accounting
https://dinastipub.org/DIJEFA dinasti.info@gmail.com +62 811 7404 455
E-ISSN: 2721-303X
P-ISSN: 2721-3021

DOI: https://doi.org/10.38035/dijefa.v7i2

Forecast-Driven Spare-Parts Inventory Control in Coal-Mining Operations: An Integrated Operational–Financial Framework

Muhammad Candany[1*], Liane Okdinawati[2]
[1]Institut Teknologi Bandung, Bandung, Indonesia, muhammadcandany07@gmail.com
[2]Institut Teknologi Bandung, Bandung, Indonesia,

*Corresponding Author: muhammadcandany07@gmail.com[1]

Abstract: Coal-mining contractors face challenges in maintaining equipment availability while controlling spare-parts inventory costs. This study examines how PT Geobara Energy, a coal-mining contractor in Muara Enim, South Sumatra, can reduce critical spare-parts stockout exposure through an integrated forecasting and continuous-review inventory policy. Using operational and inventory data from 2023–2025, the study applies ABC classification, demand-pattern screening, item-specific forecasting selection, and EOQ–ROP–Safety Stock analysis. The results show that only 11 of 16 high-value spare parts were suitable for quantitative forecasting. Simpler forecasting methods, particularly Single Exponential Smoothing and Trend Analysis, outperformed complex seasonal models. The proposed EOQ-based policy reduced annual inventory cost from Rp124,291,519 to Rp49,375,014, representing a 60.3% reduction while maintaining replenishment protection for critical spare parts. The findings suggest that spare-parts inventory control should be managed as an integrated operational–financial governance system rather than merely as a warehouse activity.

Keywords: Critical Spare Parts, Demand Forecasting. Economic Order Quantity, Reorder Point, Safety Stock.

INTRODUCTION

Mining contractors operating in coal extraction depend heavily on the uninterrupted availability of heavy equipment as the primary driver of production. In this context, spare-parts readiness is no longer merely a warehouse responsibility but a strategic operational variable. When a critical spare part is unavailable, the affected machine enters Wait Part status, Mechanical Availability (MA) declines, production targets are disrupted, and revenue becomes exposed simultaneously. In coal-mining operations characterised by thin margins and high fixed-cost intensity, these operational disruptions can quickly generate substantial financial consequences.

Indonesia's coal industry provides an important context for this issue. The country possesses approximately 38.84 billion tonnes of proven coal reserves, while national production exceeded 700 million tonnes in 2024 (Ministry of Energy & Resources, 2024).

Despite this scale, the sector remains vulnerable to commodity-price volatility, regulatory changes, and pressures associated with the global energy transition. These conditions increase the need for operational efficiency and stricter cost control. Consequently, spare-parts management becomes a critical determinant of operational continuity and profitability rather than a purely administrative inventory activity.

Previous studies have consistently highlighted the complexity of spare-parts inventory management in capital-intensive industries. Kennedy et al. (2002) explained that stockout consequences in spare-parts systems are highly asymmetric because the operational loss caused by a missing critical component may exceed the value of the component itself. Axsater (2015) further argued that spare-parts inventory models must accommodate intermittent demand and asymmetric stockout penalties. In mining operations, Muniz et al. (2021) reported that 30–50 percent of maintenance expenditure is associated with spare-parts procurement and logistics, while Barabadi et al. (2021) demonstrated that heterogeneous mining environments frequently produce inefficient inventory planning and prolonged downtime. Similarly, Gölbaşı (2019) found that suboptimal spare-parts policies contribute directly to production losses. In the Indonesian context, Pardede & Vanany (2021) identified that unstructured inventory systems among mining contractors often create simultaneous overstocking and stockout conditions, increasing operational costs and destabilising production performance.

Although the literature provides extensive discussion on spare-parts management, a significant research gap remains. Existing studies commonly examine forecasting, inventory policy, maintenance planning, and financial implications as separate analytical domains. Forecasting studies indicate that no single forecasting model consistently outperforms others across all demand conditions, particularly when demand series are intermittent or highly volatile (Makridakis, Wheelwright, et al., 2020). Bacchetti & Saccani (2012) therefore emphasised the importance of demand classification before selecting forecasting methods, while Syntetos et al. (2016) argued that intermittent spare-parts demand requires item-specific forecasting approaches rather than uniform estimation procedures.

Recent studies suggest that integrating forecasting, maintenance information, and inventory planning can improve spare-parts decision-making. Van der Auweraer & Boute (2019) showed that maintenance-service information enhances spare-parts forecasting accuracy, whereas Zhu et al. (2020) demonstrated that maintenance-linked inventory policies reduce total operational costs compared with separated planning approaches. From a financial perspective, Pratama & Sari (2021) noted that operational policies in Indonesian coal mining generate direct cash-flow consequences that are often underestimated when spare-parts expenditure is viewed solely as inventory cost.

However, the literature still lacks an integrated framework that systematically connects demand screening, forecasting-model selection, and continuous-review inventory policy into a single operational-financial decision system. More specifically, limited research has examined how forecast outputs can be translated into EOQ, Reorder Point (ROP), and Safety Stock parameters while simultaneously evaluating their implications for equipment reliability and working-capital efficiency. This gap is particularly relevant for PT Geobara Energy because these inventory parameters determine both spare-parts availability and capital utilisation. EOQ defines economically optimal order quantities, Safety Stock provides protection against uncertainty, and ROP determines replenishment timing before stockout occurs. Together, these parameters form the analytical basis for reducing Wait Part exposure while maintaining inventory efficiency.

PT Geobara Energy, a coal-mining contractor operating in Muara Enim, South Sumatra, provides a relevant case for examining this issue. The company relies heavily on Komatsu PC500 excavators, yet recurring Wait Part incidents have repeatedly reduced MA and disrupted revenue performance. Internal operational records indicate that monthly coal revenue from excavator EX-302 declined by approximately 25–30 percent whenever MA fell below 90 percent. In overburden operations, monthly revenue decreased to approximately Rp3.8–4.5 billion during June–July 2024 when excavator reliability deteriorated, but recovered to above Rp9.8 billion per month once MA exceeded 95 percent during September–October 2024. These records demonstrate that the relationship between spare-parts availability, equipment reliability, and financial performance is directly observable rather than merely theoretical.

Based on this background, the study addresses three research questions. First, which forecasting methods provide the most accurate demand estimates for forecast-feasible critical spare parts? Second, how can these forecast outputs be translated into EOQ, ROP, and Safety Stock parameters under a continuous-review policy? Third, what operational and financial implications emerge from implementing a forecast-driven replenishment policy compared with the company's existing reactive approach?

This study contributes to the literature in three ways. First, it provides empirical evidence regarding the integration of forecasting, inventory management, and financial performance within Indonesian coal-mining contractors, an operational environment characterised by high fixed costs, commodity-price volatility, and significant stockout consequences. Second, the study offers a comparative evaluation of simple and complex forecasting models applied to actual critical spare-parts demand data. The findings indicate that excessive model complexity may generate misleading inventory signals when demand patterns lack stable seasonal structures (Sinaga et al., 2024). Third, the study proposes an integrated analytical framework that links demand-pattern screening, forecasting-model selection, and continuous-review inventory policy into a unified operational-financial decision system. By integrating forecasting outputs with EOQ, ROP, and Safety Stock analysis, the framework addresses a gap in the literature where forecasting, inventory planning, and financial implications are often examined separately rather than as interconnected managerial decisions in capital-intensive mining operations.

METHOD

Research Design and Data Sources

This study employs a quantitative case-study design to examine the integration of forecasting, inventory policy, and financial interpretation within a single operational decision framework. A case-study approach was selected because the analysis requires contextual operational data that cannot be adequately captured through cross-sectional methods. In addition, the study aims to develop a practically implementable framework based on the actual planning environment of PT Geobara Energy, including its demand characteristics, operational constraints, and cost structure.

The study utilised internal operational data from PT Geobara Energy covering the period 2023–2025. The dataset included monthly spare-parts consumption records, inventory and replenishment histories, supplier lead-time information, equipment performance records (including Mechanical Availability, Wait Part hours, and downtime classifications), and inventory-related cost parameters. The analytical focus was placed on critical spare parts associated with Komatsu PC500 excavators and supporting loading equipment because these assets contributed most directly to recurring Wait Part incidents and MA deterioration.

Analytical Stages

The analytical procedure consisted of six sequential stages designed to form an integrated operational framework.

The first stage applied ABC classification to the company's top 30 spare parts in order to identify financially significant items. The second stage screened the top 16 ranked items based on observed historical demand behaviour. Items exhibiting excessively sparse, erratic, or event-driven demand were excluded from forecasting analysis to avoid generating misleading statistical estimates. This inclusion–exclusion procedure ensured that forecasting was applied only to forecast-feasible items.

The third stage conducted item-specific forecasting-model comparison using five candidate methods: Trend Analysis, Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Winters Exponential Smoothing, and Time-Series Decomposition. Model selection was based primarily on Mean Absolute Percentage Error (MAPE) and secondarily on Mean Absolute Deviation (MAD). Rather than applying a uniform model across all items, the study selected forecasting methods according to individual demand characteristics. SES was applied to relatively stable demand series, whereas Trend Analysis was used for items exhibiting persistent directional movement, consistent with forecasting principles proposed by Montgomery et al. (2015) and Hyndman and Hyndman & Athanasopoulos (2021).

The fourth stage translated forecast outputs into EOQ, Safety Stock, and Reorder Point (ROP) parameters under a continuous-review inventory policy. To ensure analytical consistency across all items, several operational assumptions were standardised, including 360 working days per year, a seven-day supplier lead time, an ordering cost of Rp1,000,000 per purchase order, and annual holding cost equal to 15 percent of unit cost.

The fifth stage evaluated the operational implications of the proposed policy, particularly its potential effect on spare-parts availability and Wait Part exposure. The sixth stage examined the financial implications through baseline-versus-proposed cost comparison, working-capital estimation, and procurement-budget simulation for 2026–2027.

Table 1. Mapping of Research Questions, Analytical Stages, and Expected Outputs

Research Question	Analytical Stage	Primary Method / Metric	Expected Output
RQ1	Critical-item identification, demand-pattern screening; forecasting model comparison	ABC analysis, MAPE, MAD, and item-specific model selection	Forecast-feasible items identified and best-fit model selected per item
RQ2	Inventory parameter design for forecast-feasible items	EOQ, Safety Stock, ROP under a continuous-review policy	Economically justified order quantity and explicit reorder trigger established for each item
RQ3	Baseline-versus-proposed comparison and managerial interpretation	Annual inventory-cost comparison, working-capital estimation, and forecast-based procurement simulation	Operational and financial implications of the proposed policy identified

Source: Author's methodological framework based on the research design and analytical procedures.

Core Equations and Continuous-Review Inventory Policy

Inventory control in this study follows a continuous-review logic, in which management determines both how much to order and when to reorder. For maintenance-critical spare parts, this distinction is operationally important because stockout may directly interrupt equipment readiness and trigger Wait Part downtime. The framework therefore centres on three interrelated parameters: Economic Order Quantity (EOQ), Safety Stock (SS), and Reorder Point (ROP). Together, these parameters translate forecast outputs into a practical replenishment rule that supports reliability while controlling inventory cost.

Forecast accuracy was evaluated using Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD). MAPE was used as the primary indicator of relative forecast accuracy, while MAD served as a supporting measure of absolute forecast deviation:

$$\text{MAPE} = (1/n) \cdot \Sigma\, |At - Ft| / At \times 100$$

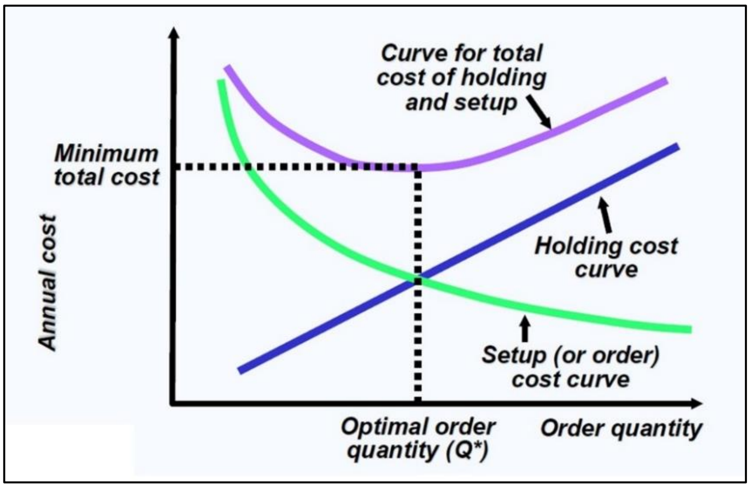
$$\text{MAD} = (1/n) \cdot \Sigma\, |At - Ft|$$

Where At is actual demand in period t, Ft is forecast demand in period t, and n is the number of observations.

The Economic Order Quantity model determines the order quantity that minimises the trade-off between annual ordering cost and annual holding cost (Silver et al., 2016; Fithri et al., 2019):

$Q^* = \sqrt{(2DS / H)}$

Where Q* is the optimal order quantity, D is annual demand, S is ordering cost per purchase order, and H is annual holding cost per unit. The EOQ logic reflects the trade-off between ordering cost and holding cost. Small order quantities increase ordering frequency, while large order quantities increase average inventory and holding cost. The optimal point is reached when these two opposing cost components are balanced, as illustrated in Figure 1.



Source: Adapted from Heizer et al. (2017), Prentice Hall (2008).
Figure 1. EOQ Cost Curves: Setup Cost, Holding Cost, and Total Inventory Cost

The total annual inventory cost under a given order quantity was calculated as:

$TC = (D / Q)S + (Q / 2)H$

Where TC is total annual inventory cost and Q is order quantity. This equation was used to compare the baseline monthly-replenishment scenario with the proposed EOQ-based continuous-review policy.

Safety Stock was used to provide a protective buffer against demand uncertainty during lead time. Under the assumption of constant lead time, it was calculated as:

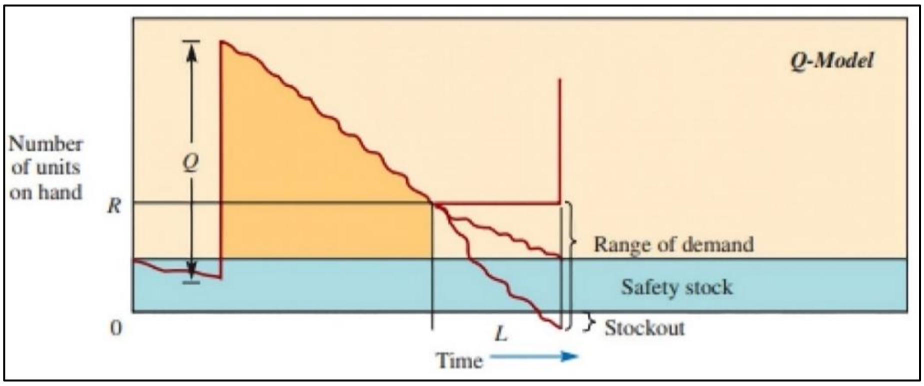
$SS = z \cdot \sigma d \cdot \sqrt{L}$

Where SS is safety stock, z is the service-level factor, σd is the standard deviation of daily demand, and L is lead time in days.

The Reorder Point was then calculated as:

$ROP = d \cdot L + SS$

Where ROP is the reorder point and d is average daily demand. This equation converts forecast information into an actionable procurement signal by triggering replenishment before on-hand inventory is exhausted during supplier lead time. The relationship among inventory level, reorder point, safety stock, and lead time under a continuous-review policy is illustrated in Figure 2.



Source: Jacobs & Chase (2018)

Figure 2. Continuous-Review Q-Model with Reorder Point, Safety Stock, and Lead Time

Ordering frequency was calculated to estimate how often each spare part should be replenished under the proposed policy:

$F = D / Q^*$

Where F is ordering frequency per year. This equation enabled comparison between the proposed EOQ-based replenishment frequency and the baseline assumption of 12 orders per year.

Baseline Definition and Validation Procedures

The baseline scenario represented the company's observed reactive replenishment policy, in which spare parts were replenished once per month, generating 12 purchase orders annually. Under this assumption, monthly order quantity equalled annual demand divided by 12, while average inventory equalled one-half of monthly replenishment quantity. Baseline annual inventory cost therefore consisted of annual ordering cost plus annual holding cost.

Several validation procedures were conducted to improve analytical reliability. These procedures included data consistency checks, duplicate-record verification, and missing-data identification across all operational records. Historical demand series were also inspected for outliers and structural irregularities prior to forecasting analysis. Finally, the resulting EOQ, Safety Stock, and ROP parameters were cross-checked against historical stock behaviour and recorded Wait Part incidents to ensure operational reasonableness.

This study is limited to a single-company case setting and assumes relatively stable supplier lead time conditions. Consequently, the findings should be interpreted within the operational context of PT Geobara Energy. Future research may extend the framework through stochastic inventory simulation, broader sensitivity analysis, and multi-company comparative datasets to improve external generalisability.

RESULTS AND DISCUSSION

Operational Problem Characterisation and Critical-Item Identification

The initial analysis indicates that Wait Part exposure at PT Geobara Energy did not originate from a single inventory deficiency, but from a broader combination of reactive replenishment practices, the absence of explicit reorder parameters, fragmented operational monitoring, and limited coordination among Maintenance, Warehouse, Procurement, and Finance functions. This finding suggests that inventory improvement cannot rely solely on isolated stock calculations, but requires an integrated replenishment-governance approach capable of linking operational reliability with procurement discipline and financial control.

ABC classification results revealed a moderate concentration of inventory value. Category A represented 43.96 percent of total inventory value while accounting for only 20 percent of assessed items. Category B contributed 32.91 percent, whereas Category C accounted for the remaining 23.12 percent. Among the top 16 ranked items, representing 79.64 percent of total inventory value, demand-pattern screening identified 11 items as forecast-feasible and 5 items as unsuitable for routine time-series estimation. The excluded items exhibited sparse, highly irregular, batch-driven, or event-triggered demand patterns that weakened statistical reliability and reduced forecasting usefulness for operational planning. Consequently, these items were considered more appropriate for event-based procurement, preventive-maintenance linkage, inspection-driven ordering, or replacement-cycle planning.

Table 2. ABC Classification Summary and Demand-Pattern Screening Results

Step	Coverage	Result	Interpretation
ABC Classification	Top 30 spare parts	Category A = 43.96%; Category B = 32.91%; Category C = 23.12%	Inventory value is moderately concentrated, supports differentiated control intensity
Screening Focus	Top 16 ranked items (79.64% of total inventory value)	11 items forecast-feasible, 5 items excluded	Financial importance alone does not guarantee forecasting feasibility
Excluded Items	Injector, tip spike J-550, roller GP track single flange, tip spike 505-4114, segment	Excluded from routine time-series estimation	Demand was sparse, event-clustered, or failure-driven, better suited to event-based or inspection-linked procurement

Source: Author's analysis based on PT Geobara Energy internal inventory and operational data, 2023–2025.

To improve transparency in the screening process, Table 3 presents the demand characteristics, forecasting feasibility, and exclusion rationale for each high-value spare part. The results demonstrate that exclusion decisions were not driven by low operational importance, but by insufficient demand regularity for statistically meaningful forecasting. This finding reinforces the argument that high inventory value alone is insufficient to justify routine forecasting implementation. Forecasting feasibility also depends on the existence of a sufficiently stable and interpretable historical demand signal.

Table 3. ABC Classification Summary and Demand-Pattern Screening Results

(Rank)	Sparepart Item	ABC Category	Demand Pattern	Data Characteristics	Forecasting Feasibility	Justification
1	INJECTOR, 387-9434	A	Lumpy / Erratic	Many zero-demand months, very low frequency	No	Sparse demand reduces statistical validity and increases error
2	TIP SPIKE (J-550), 159-0550	A	Lumpy	Event-based usage, clustered consumption	No	Demand is driven by operational events, not time dependency
3	FILTER AIR PRIMARY, 496-9845	A	Intermittent	Some zero months but recurring demand	Yes	Forecastable using intermittent-demand methods (Croston-type)
4	ROLLER GP TRACK SINGLE FLANGE, 528-2933	A	Low-volume continuous	Low demand level, short and weak signal	No	Low-volume series yields unstable parameter estimation
5	TRACK ROLLER DOUBLE, 288-	A	Continuous	Stable monthly demand	Yes	Consistent consumption

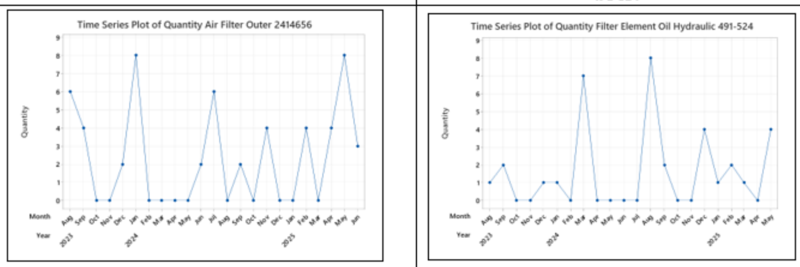
	0935/398-5218/120-5766					supports time-series forecasting
6	AIR FILTER OUTER, 2414656	A	Intermittent	Several zero months, recurring pattern	Yes	Feasible, but accuracy may be limited due to intermittency
7	CAB AIR FILTER, 2655428	B	Intermittent	Multiple zero months across years	Yes	Still usable for forecasting with intermittent models (limited accuracy)
8	BATTERY MF 12 V - 120 AH L	B	Continuous	Demand occurs in most months (2024–2025)	Yes	Adequate continuity for short-term forecasting evaluation
9	FILTER ELEMENT-FUEL, 570-1623/500-0480	B	Continuous	High and stable demand	Yes	Strong continuity enables reliable forecasting and MAPE analysis
10	FILTER ELEMENT-WTR SEP & FUEL, 500-0481	B	Continuous	Minimal zero-demand months	Yes	Regular demand improves predictability and reduces noise
11	FILTER ELEMENT OIL HYD, 491-5241/590-9787	B	Intermittent	Fluctuations with occasional zero months	Yes	Feasible only under intermittent-demand forecasting approaches
12	AIR FILTER INNER, 2414659	B	Continuous	Mostly continuous with rare gaps	Yes	Sufficient stability for conventional forecasting models
13	OIL FILTER ENGINE, 1742032/2022275/2625884	B	Continuous	Stable monthly demand across horizon	Yes	High continuity supports robust accuracy (MAPE/MAD)
14	TIP SPIKE, 505-4114	B	Lumpy (batch)	Very few observations; fixed batch demand	No	Sparse series prevents meaningful forecasting parameterization
15	SEGMENT, 173-0946/398-0972	B	Lumpy (batch)	Few occurrences; large batch quantity	No	Better controlled via maintenance planning / replacement cycles
16	FILTER HYDRAULIC, 126-1818/465-6506	C	Continuous	Demand exists every month; low variance	Yes	Low variance strengthens forecasting reliability

Source: Author's analysis based on PT Geobara Energy internal spare-parts inventory records and demand-pattern screening, 2023–2025.

Forecasting Results and Model Selection

For the 11 forecast-feasible items, simpler forecasting models generally outperformed more complex seasonal specifications. This result reflects the underlying demand characteristics of PT Geobara Energy's critical spare parts, which were dominated by intermittent consumption, recurring replacement intervals, and mild directional movement rather than stable seasonal cycles. The findings indicate that demand behaviour in mining spare-parts systems is operationally driven and often lacks the consistency required for advanced seasonal estimation models. Figure 3 presents representative demand patterns used to support the item-specific model-selection process.

Time Series Plot of Quantity Air Filter Outer 2414656	Time Series Plot of Quantity Filter Element Oil Hydraulic 491-524



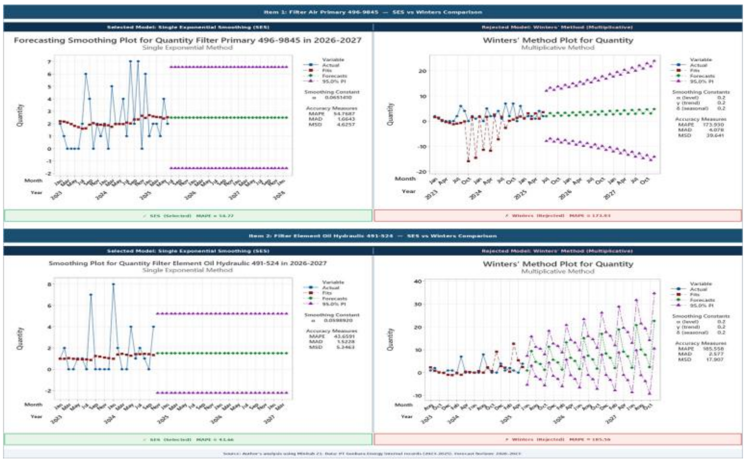
(a) Mild directional trend and intermittent positive demand suitable for trend-based forecasting.	(b) Intermittent and lumpy demand with multiple zero-demand months; SES selected as the forecast method.

Source: Author's analysis based on PT Geobara Energy internal spare-parts demand data, 2023–2025.
Figure 3. Comparative Time-Series Demand Patterns for Selected Spare Parts: (a) Air Filter Outer 2414656 and (b) Filter Element Oil Hydraulic 491-524

As shown in Figure 3, Air Filter Outer 2414656 exhibits mild directional movement with intermittent positive demand, whereas Filter Element Oil Hydraulic 491-524 displays intermittent and lumpy demand with several zero-demand periods. These contrasting patterns demonstrate that forecast-feasible spare parts still require different modelling treatments depending on the structure and continuity of the historical demand signal. Consequently, the results support item-specific forecasting selection rather than a uniform modelling approach across all spare parts.

Single Exponential Smoothing (SES) was selected for items whose demand fluctuated around a relatively stable level, including Filter Element Fuel 570-1653, Filter Element Oil Hydraulic 491-524, Oil Filter Engine 1742032, Track Roller Double 288-0935, Battery MF 12V–120 AH L, and Filter Element–Water Separator and Fuel 500-0481. Trend Analysis was selected for items exhibiting persistent directional movement, namely Air Filter Outer 2414656, Cab Air Filter 2655428, and Filter Hydraulic 126-1818.

The Winters model performed poorly in cases where stable seasonal structure was absent. For Filter Air Primary 496-9845, Winters produced a MAPE of 173.93 compared with 54.77 under SES. Similarly, for Filter Element Oil Hydraulic 491-524, Winters generated a MAPE of 185.56 compared with 43.66 under SES. These results indicate that imposing seasonal forecasting structures on non-seasonal spare-parts demand can produce unstable and operationally misleading forecasts. Figure 4 illustrates this contrast through side-by-side forecasting outputs for selected critical spare parts.



Source: Author's analysis using Minitab 21

Figure 4. Side-by-Side Minitab 21 Forecasting Output: Selected Model vs. Winters' Method for Two Critical Spare Parts at PT Geobara Energy (2023–2025). Item 1: Filter Air Primary 496-9845 — SES (MAPE = 54.77)

Figure 4 further confirms that SES produced more stable and operationally reasonable forecasting outputs, while Winters generated implausible and highly volatile estimates when genuine seasonality was absent. This finding reinforces the argument that forecasting accuracy in spare-parts environments depends more on demand-pattern compatibility than on model sophistication itself. The result is consistent with Makridakis, Spiliotis, et al. (2020), who argued that simpler forecasting models may outperform more complex approaches when the underlying demand structure is noisy, intermittent, or weakly seasonal.

While Figure 4 provides visual comparison for representative cases, the final model-selection decision must be evaluated across the complete set of forecast-feasible items. Table 4 therefore summarises the selected forecasting method, forecasting behaviour, key accuracy indicators, and projected demand for 2026–2027 for each retained spare part. These projected demand values subsequently became the operational basis for EOQ, Safety Stock, Reorder Point, and procurement-budget calculations in the inventory-policy stage.

Table 4. Selected Forecasting Methods, Error Metrics, and Forecast Demand 2026–2027

Spare Part Item	Selected Method	Key Error Metric	Forecast Behaviour	Forecast Demand (pcs)	
				2026	2027
Air Filter Outer 2414656	Trend Analysis	MAPE 40.26; MAD 2.25	Gradually increasing	35.80	39.64
Filter Air Primary 496-9845	SES	α=0.065; MAPE 54.77	Stable / level-based	29.76	29.76
Filter Element Fuel 570-1653	SES	α=0.623; MAPE 34.65	Recurring, responsive	72.36	72.36
Filter Element Oil Hydraulic 491-524	SES	α=0.060; MAPE 43.66	Recurring, smoothed	17.88	17.88
Oil Filter Engine 1742032	SES	α=0.067; MAPE 35.46	Stable recurring	60.12	60.12
Cab Air Filter 2655428	Trend Analysis	MAPE 42.08; MAD 0.97	Gradually decreasing	10.57	4.70
Battery MF 12V–120 AH L	SES	α=0.200	Level, moderate resp.	41.64	41.64
Filter Hydraulic 126-1818	Trend Analysis	MAPE 33.57; MAD 0.46	Gradually increasing	26.18	29.64
Filter Elem.–Wtr Sep & Fuel 500-0481	SES	α=0.655; MAPE 50.13	Responsive level	15.84	15.84

Source: Author's analysis based on PT Geobara Energy internal spare-parts demand data and forecasting model comparison, 2023–2025.

The results in Table 4 confirm that model selection was driven primarily by demand behaviour rather than analytical complexity. SES was consistently selected for items characterised by stable or recurring level-based demand, whereas Trend Analysis was preferred for items exhibiting directional movement over time. Operationally, these findings demonstrate that forecasting discipline in spare-parts management should prioritise demand-pattern suitability and decision usefulness rather than methodological sophistication alone. More importantly, the resulting demand forecasts provided the analytical foundation for the subsequent EOQ, Safety Stock, ROP, and procurement-budget analysis, thereby linking forecasting accuracy directly with operational reliability and working-capital planning.

Inventory Policy Design: EOQ, Safety Stock, and Reorder Point

The selected forecasting outputs were subsequently translated into a continuous-review replenishment policy for the ten critical spare parts retained in the final analysis. The resulting EOQ–ROP framework generated economically justified order quantities alongside operationally interpretable replenishment triggers. Although the annual demand volumes of several items remained relatively modest, the proposed Safety Stock and Reorder Point values were still differentiated according to demand intensity and variability rather than imposed uniformly across all spare parts. This distinction is operationally important because it prevents unnecessary stock accumulation while still maintaining minimum protection against Wait Part exposure and unexpected replenishment delays.

The reorder-point hierarchy reflects the underlying demand structure of the selected items. Oil Filter Engine 1742032, which recorded the highest annual demand volume at 84 units, produced the highest rounded ROP value of 6. Filter Element Fuel 570-1653 and Filter Air Primary 496-9845 followed with ROP values of 5 and 4 respectively. In contrast, lower-volume items such as Cab Air Filter 2655428, Filter Element–WTR SEP & Fuel 500-0481, and Track Roller Double 288-0935 were maintained at ROP values of 2. These lower reorder thresholds indicate that replenishment protection can still be maintained without creating excessive inventory commitment for relatively slow-moving items.

Table 5. Continuous-Review Inventory Parameters for the Selected Critical Spare Parts

Spare Part Item	Annual Demand (pcs)	Safety Stock (pcs)	ROP (unrounded)	ROP (rounded)	Note
Air Filter Outer 2414656	38.4	2	2.75	3	–
Filter Air Primary 496-9845	51.6	3	4.00	4	–
Filter Element Fuel 570-1653	72.0	3	4.40	5	–
Filter Element Oil Hydraulic 491-524	18.0	1	1.35	2	–
Oil Filter Engine 1742032	84.0	4	5.63	6	Highest ROP
Cab Air Filter 2655428	10.8	1	1.21	2	–
Battery MF 12V–120 AH L	42.0	2	2.82	3	–
Filter Hydraulic 126-1818	27.6	2	2.54	3	–
Filter Elem.–WTR SEP & Fuel 500-0481	17.88	1	1.35	2	–
Track Roller Double 288-0935	15.84	1	1.31	2	MAPE 10.79

Source: Author’s calculation based on PT Geobara Energy internal spare-parts demand, lead-time, inventory, and cost data, 2023–2025.

The results in Table 5 demonstrate that forecasting becomes operationally meaningful only after being translated into explicit replenishment parameters. EOQ determines economically efficient order quantities, while Safety Stock and ROP establish the timing of replenishment before inventory depletion occurs during supplier lead time. Together, these parameters transform forecast outputs into a structured and auditable replenishment-control mechanism capable of improving coordination among Warehouse, Procurement, Maintenance, and Finance functions.

More importantly, the proposed continuous-review framework does not merely minimise inventory cost. Operationally, the framework strengthens spare-parts readiness and reduces vulnerability to unplanned downtime by ensuring that replenishment decisions are driven by explicit inventory signals rather than reactive purchasing behaviour. From a financial perspective, this also improves working-capital discipline because inventory commitment is linked directly to observed demand behaviour and operational usage patterns rather than subjective estimation or emergency procurement practices.

Operational Implications: Wait Part Exposure and Equipment Reliability

The proposed inventory policy addresses spare-parts readiness through its most operationally significant mechanism: the process by which spare-parts unavailability translates directly into lost operating hours and declining equipment availability. Wait Part was identified as the dominant contributor to downtime across the observed excavator units, indicating that delayed spare-parts availability, rather than mechanical failure alone, became the primary source of Mechanical Availability (MA) deterioration during the study period. This finding suggests that operational disruption in mining environments is often driven not only by asset failure itself, but by the organisation's ability to respond rapidly through effective spare-parts replenishment and procurement coordination.

Although equipment reliability is also influenced by maintenance quality, operator behaviour, and asset condition, spare-parts readiness remains a necessary enabling condition for operational recovery following maintenance events. Without the required component, maintenance activity cannot restore equipment uptime regardless of technical capability. From an operational-resilience perspective, this indicates that spare-parts availability functions as a buffering mechanism that reduces vulnerability to prolonged downtime during unexpected maintenance events or supply delays.

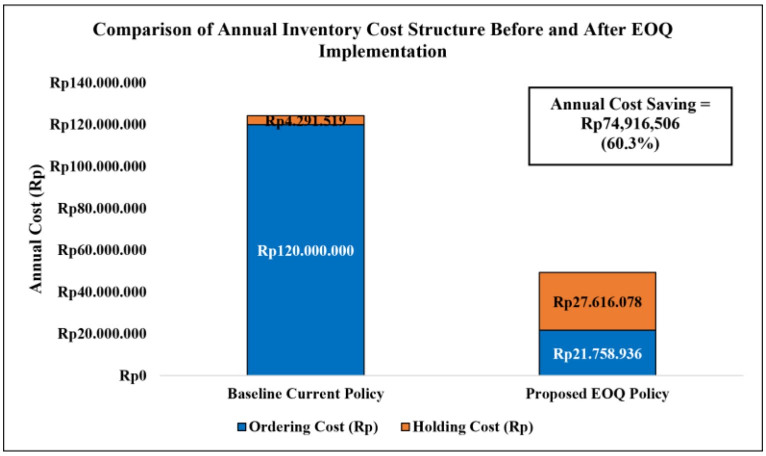
The observed relationship between MA and revenue further demonstrates the financial significance of spare-parts readiness. Periods of declining MA consistently coincided with weaker revenue performance in both coal extraction and overburden operations. The magnitude of this relationship indicates that the economic value of a structured spare-parts policy extends beyond inventory-cost efficiency and into direct revenue protection. In this context, the proposed forecast-driven replenishment framework reduces the probability of stockout during critical operating periods and thereby helps preserve production continuity and revenue stability.

An additional operational benefit of the proposed framework lies in its effect on cross-functional coordination. When reorder thresholds and replenishment parameters are explicitly documented, Maintenance, Warehouse, Procurement, and Finance functions can coordinate around a shared planning logic rather than responding independently to stockout emergencies. This strengthens planning discipline, improves procurement visibility, and reduces reliance on ad hoc emergency purchasing practices that frequently increase operational uncertainty and procurement inefficiency.

More broadly, the findings also suggest that inventory policy in mining operations should not be interpreted solely as a warehouse-control mechanism. Instead, explicit reorder logic contributes to supply-chain responsiveness, operational predictability, and working-capital governance by aligning replenishment timing with observed demand behaviour and maintenance requirements. In this sense, the proposed framework supports not only inventory optimisation but also broader operational stability within capital-intensive mining environments.

Financial Implications and Managerial Value

The financial outcome represents one of the most concrete managerial contributions of this study. Under the baseline reactive replenishment scenario, where each selected spare part is replenished once per month, the total annual inventory cost for the ten selected items reached Rp124,291,519. Under the proposed EOQ-based continuous-review policy, using identical cost assumptions, total annual inventory cost decreased to Rp49,375,014. This represents a potential annual saving of Rp74,916,506, equivalent to a 60.3 percent reduction in inventory-related cost.



Source: Author's analysis using Minitab 21

Figure 5. Comparison of Annual Inventory Cost Before and After EOQ Implementation

Figure 5 illustrates the cost reduction achieved by replacing fixed monthly replenishment with a forecast-driven EOQ-based policy. The largest per-item savings were generated by Filter Element–WTR Separator and Fuel 500-0481 at 77.6 percent, Cab Air Filter 2655428 at 74.0 percent, Filter Element Fuel 570-1653 at 68.7 percent, and Filter Hydraulic 126-1818 at 67.4 percent. These differences indicate that the financial impact of inventory optimisation is highly item-specific and depends on the interaction among demand intensity, unit price, ordering cost, and holding cost structure.

From a working-capital perspective, the proposed policy requires approximately Rp173.8 million in average inventory commitment across the ten selected spare parts. Forecast-based procurement simulations further indicate that annual procurement budgets remain below Rp0.6 billion in both 2026 and 2027, while annual inventory-policy costs remain relatively stable at approximately Rp44–45 million. These findings suggest that operational spare-parts protection can be maintained through structured and predictable financial commitment rather than through reactive and potentially volatile purchasing behaviour.

Table 6. Annual Inventory Cost Comparison: Baseline Scenario vs. Proposed EOQ-Based Policy

Comparison Element	Baseline Scenario (Current Policy)	Proposed EOQ-Based Policy	Interpretation
Replenishment logic	Monthly replenishment (12 orders/year per item)	Continuous review: EOQ lot size triggered at ROP	Reactive ordering replaced with explicit, economically justified replenishment discipline
Total annual inventory cost	Rp124,291,519	Rp49,375,014	Potential savings = Rp74,916,506 (60.3%)

Average working-capital commitment	Not optimised	Approx. Rp173.8 million (proposed policy)	Capital commitment is controlled relative to revenue scale protected by improved MA
Forecast-based procurement budget	Not structured as forward-looking budget	2026: Rp577,737,556; 2027: Rp578,890,875	Procurement becomes budgetable and compatible with proactive liquidity planning
Annual policy cost	Not explicitly separated	2026: Rp44,602,038; 2027: Rp44,177,538	Annual policy cost remains stable and manageable across planning periods
Largest per-item savings	–	Filter Elem.–WTR Sep & Fuel: 77.6%; Cab Air Filter: 74.0%	EOQ benefit varies with the interaction of demand volume, unit price, and cost structure

Source: Author's calculation based on PT Geobara Energy internal cost data and EOQ-based inventory policy simulation, 2023–2027.

Taken together, the results demonstrate that the value of integrating forecasting with inventory policy extends beyond inventory-cost reduction alone. The proposed framework converts forecast outputs into economically justified order quantities, explicit reorder thresholds, quantified safety buffers, and structured procurement budgets capable of supporting both operational reliability and financial predictability.

For PT Geobara Energy, the proposed policy improves budgeting discipline, strengthens procurement planning visibility, and reduces exposure to emergency purchasing practices associated with Wait Part incidents. More importantly, the findings indicate that spare-parts inventory policy in capital-intensive mining operations functions not merely as a warehouse-control mechanism, but as a form of operational-financial risk management aimed at protecting equipment availability and stabilising production revenue.

From a broader operations-management perspective, these findings also suggest that inventory optimisation contributes directly to operational resilience and working-capital governance. By aligning replenishment decisions with observed demand behaviour and maintenance requirements, the proposed framework improves supply continuity while maintaining manageable financial commitment under uncertain operating conditions.

CONCLUSION

This study demonstrates that spare-parts problems at PT Geobara Energy are more effectively addressed through an integrated operational-financial planning framework rather than through reactive procurement practices or routine monthly replenishment. By linking forecasting, inventory policy, and financial interpretation within a single decision system, the study provides a structured approach for translating spare-parts demand into operationally and financially meaningful replenishment policy.

The findings show that demand-pattern screening is essential before forecasting implementation. Among the 16 high-value spare parts analysed, only 11 displayed demand characteristics suitable for quantitative forecasting, while the remaining items were more appropriately managed through event-based or maintenance-linked planning approaches. The study also found that simpler forecasting methods, particularly Single Exponential Smoothing and Trend Analysis, consistently outperformed more complex seasonal models because the observed demand patterns lacked stable seasonality.

When translated into an EOQ-based continuous-review policy with explicit Reorder Point and Safety Stock parameters, the proposed framework reduced annual inventory cost from Rp124,291,519 to Rp49,375,014, representing a 60.3 percent reduction while maintaining replenishment protection for critical spare parts. The results further indicate that the value of spare-parts readiness extends beyond inventory efficiency, as reduced Wait Part exposure contributes directly to improved Mechanical Availability, operational continuity, and revenue protection.

Overall, the study supports the conclusion that spare-parts inventory control in coal-mining operations should be managed as an integrated operational-financial governance system rather than as a routine warehouse activity. For mining contractors operating in volatile and margin-sensitive environments, sustainable operational performance depends not only on analytical capability, but also on the managerial discipline to implement structured and data-driven replenishment planning.

REFERENCES

Axsater, S. (2015). *Inventory Control* (3rd ed.). Springer.

Bacchetti, A., & Saccani, N. (2012). Spare parts classification and demand forecasting for stock control: Investigating the gap between research and practice. *Omega*, *40*(6), 722–737. https://doi.org/10.1016/j.omega.2011.06.008

Barabadi, R., Ataei, M., Khalokakaie, R., & Nouri Qarahasanlou, A. (2021). Spare-part management in a heterogeneous environment. *PLOS ONE*, *16*(3), e0247650. https://doi.org/10.1371/journal.pone.0247650

Fithri, P., Hasan, A., & Asri, F. M. (2019). Analysis of inventory control by using economic order quantity model – a case study in PT Semen Padang. *Jurnal Optimasi Sistem Industri*, *18*(2), 116–124. https://doi.org/10.25077/josi.v18.n2.p116-124.2019

Gölbaşı, O. (2019). Effect of Spare Parts Policy on Equipment Production Loss in Mining. In *Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection - MPES 2018* (Vol. 17, Number 4, pp. 489–496). Springer International Publishing. https://doi.org/10.1007/978-3-319-99220-4_41

Heizer, J., Render, B., & Munson, C. (2017). *Operations Management: Sustainability and Supply Chain Management* (12th ed.). Pearson.

Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice* (3rd ed.). OTexts.

Jacobs, F. R., & Chase, R. B. (2018). *Operations and Supply Chain Management* (15th ed.). McGraw-Hill Education.

Kennedy, W. J., Wayne Patterson, J., & Fredendall, L. D. (2002). An overview of recent literature on spare parts inventories. *International Journal of Production Economics*, *76*(2), 201–215. https://doi.org/10.1016/S0925-5273(01)00174-8

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The M4 competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting*, *36*(1), 54–74.

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (2020). *Forecasting: Methods and Applications* (5th ed.). Wiley.

Ministry of Energy, & Resources, M. (2024). *Minerba One Data Indonesia (MODI): National Coal Production and DMO 2024*.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015). *Introduction to Time Series Analysis and Forecasting* (2nd ed.). Wiley.

Muniz, L. R., Conceição, S. V., Rodrigues, L. F., de Freitas Almeida, J. F., & Affonso, T. B. (2021). Spare parts inventory management: a new hybrid approach. *The International Journal of Logistics Management*, *32*(1), 40–67. https://doi.org/10.1108/IJLM-12-2019-0361

Pardede, S. R., & Vanany, I. (2021). Analysis and control for heavy equipment spare parts inventory in the nickel mining industry. *IPTEK Journal of Proceedings Series*, *0*(6), 478.

Pratama, R., & Sari, N. (2021). Cash flow impact of operational policies in Indonesian coal mining. *Asian Journal of Business and Accounting*, *14*(1), 133–152.

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2016). *Inventory and Production Management in Supply Chains* (4th ed.). CRC Press. https://doi.org/10.1201/9781315374406

Sinaga, P. T., Siahaan, A. R., & Tambunan, M. (2024). Building supply chain resilience in Indonesia's coal industry. *Journal of Energy Logistics*, *5*(1), 33–50.

Van der Auweraer, S., & Boute, R. (2019). Forecasting spare part demand using service maintenance information. *International Journal of Production Economics*, *213*, 138–149. https://doi.org/10.1016/j.ijpe.2019.03.015

Zhu, S., Jaarsveld, W. van, & Dekker, R. (2020). Spare parts inventory control based on maintenance planning. *Reliability Engineering & System Safety*, *193*, 106600. https://doi.org/10.1016/j.ress.2019.106600