Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

Inventory Management of Primary Transmission Equipments in an Electric Power Company: A Comparative Study of Continuous Review and Periodic Review Methods

Farhan Asyifa[1*], Suparno[2], Effi Latiffianti[3]
[1,2,3]Faculty of Industrial Technology & Systems Engineering, Institut Teknologi Sepuluh Nopember, Indonesia
Email: fasyifa@gmail.com

ABSTRACT

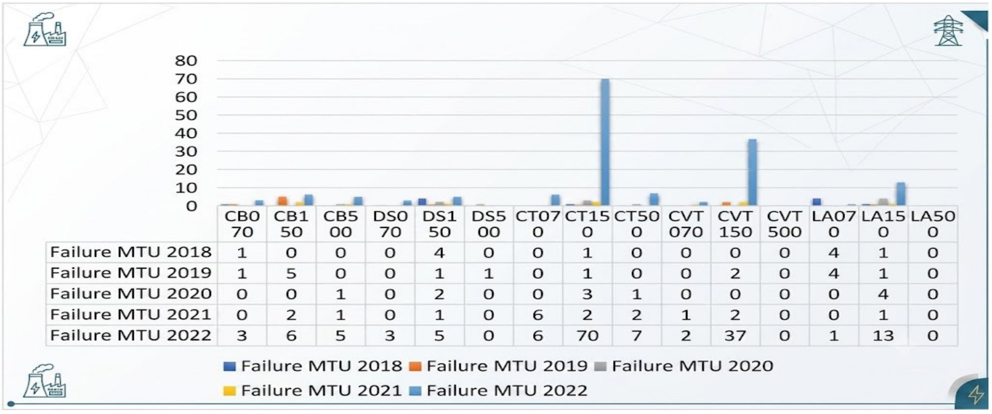
This study investigates the inventory management system of primary transmission equipment (MTU) in an electric power company and compares the effectiveness of continuous and periodic review methods. This study is motivated by a surge in the failure rate of critical components in 2022, as well as procurement demand patterns dominated by intermittent (98 items) and lumpy (56 items) characteristics with total procurement value above Rp 2.1 trillion. The methodology consists of material classification, combination of the ADI - CV and ABC methods, a calculation of inventory parameters through continuous review (s, Q) model for lumpy materials and periodic review (R, s, S) model for intermittent materials with a review interval (R) of six months, chosen to align with the company's semiannual stock opname policy, and validation using a Monte Carlo simulation on a sample of 20 MTUs from three main transmission units: UIT JBB, UIT JBT, and UIT JBM. The findings demonstrate that the current condition has reached a service level of 0.00% for all materials. The results of implementing the models show an increase in service levels to averages of 63.19% (UIT JBB), 69.31% (UIT JBT), and 66.21% (UIT JBM), with an overall service level of 68.82%. Service level standard deviations varied from 7.65% to 27.01% and depended on the material properties for inventory parameters. The study found that intermittent materials are better suited to a periodic review, while lumpy materials are more effectively managed with a continuous review. Furthermore, the Monte Carlo simulation is required to validate the parameters. The recommended policies are phased implementation beginning with the best-performing material (CVT150-RFQ 007, service level 76.13%), limited joint inventory for high-value items, and the creation of a real-time inventory information system.

Keywords: Continuous Review, Inventory Management, Periodic Review, Primary Transmission Equipments, Service Level.

INTRODUCTION

Electric power companies oversee complex assets in generation, transmission, and distribution. The Java-Bali power system is operated by three main transmission units—UIT JBB, UIT JBT, and UIT JBM—to improve reliability and operational efficiency (PT PLN (Persero), 2025). The firm applies condition-based maintenance through the Health Index (HI) to extend asset lifecycles. Nevertheless, data show a rise in MTU failures in 2022 (See Figure 1), especially CT150 and CVT150, suggesting collective asset aging or higher system loading.

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784



	CB070	CB150	CB500	DS070	DS150	DS500	CT070	CT150	CT500	CVT 070	CVT 150	CVT 500	LA070	LA150	LA500
Failure MTU 2018	1	0	0	0	4	0	0	1	0	0	0	0	4	1	0
Failure MTU 2019	1	5	0	0	1	1	0	1	0	0	2	0	4	1	0
Failure MTU 2020	0	0	1	0	2	0	0	3	1	0	0	0	0	4	0
Failure MTU 2021	0	2	1	0	1	0	6	2	2	1	2	0	0	1	0
Failure MTU 2022	3	6	5	3	5	0	6	70	7	2	37	0	1	13	0

Figure 1. Number of MTU Failures in the Electric Power Company in 2018–2022

The audit at UIT JBB revealed that a failure of the outdoor sealing end at the GIS Pondok Kelapa substation on 28 April 2020 triggered a chain of damage. No repairs had been made by the audit deadline due to the replacement material being out of stock, resulting in an extended outage whereby TLOD targets were breached. At issue was the absence of a documented material requirements planning system (including ABC analysis and safety-stock determination), which had been identified as an extreme-risk level in the 2021 UITJBB Risk Profile.

The current MTU inventory management system is basic and reactive, as orders are simply modified without establishing minimum or maximum limits while safety stock is completely ignored. The required demand is characterized as lumpy (56 MTU items) and intermittent (98 MTU items). Both demand types occur infrequently but exhibit high variability in size. A centralized Unit Price Contract (KHS) system is used to address this demand. From 2018 to 2024, the total procurement value exceeded Rp 2.186 trillion with inventory costs unevenly distributed across units.

Given these unique demand characteristics and the high stakes of stockouts for national grid reliability, we turned to the academic literature to see how similar problems have been tackled in other industries. Numerous previous studies have demonstrated the effectiveness of systematic approaches in manufacturing, mining, and electricity sectors. Through classification integration and Monte Carlo simulation, a study successfully reduced costs by 25.99% [1]. Another study achieved a 92% service level using continuous review [2]. Additionally, overstock issues were effectively addressed through periodic review [3]. However, no study has specifically investigated MTU in electric power companies with unique demand characteristics and critical impacts on national infrastructure. Specifically, no prior study has comparatively evaluated both Continuous Review and Periodic Review models with Monte Carlo validation for primary transmission equipment under intermittent and lumpy demand patterns, nor examined the trade-offs between individual and joint inventory strategies across geographically dispersed transmission units. Previous research within Indonesian electric power companies has primarily focused on distribution materials and general spare parts using single-model approaches without addressing the specific challenges of primary transmission equipment under mixed intermittent and lumpy demand patterns [2], [3]. Thus, this research fills that gap.

This research aims to: (1) determine the demand quantity, economic order quantity, reorder point, safety stock and maximum stock level in MTU; and (2) propose an inventory policy. The potential benefits for users include more accurate planning, a corporate policy reference based on data, and academic contributions derived from a comparative analysis of periodic review (PR) and continuous review (CR) methods in the electric-power sector. Additionally, this

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

study examines supply-chain processes to match the availability of materials with maintenance schedules, thereby minimizing downtime and optimizing costs.

METHODS

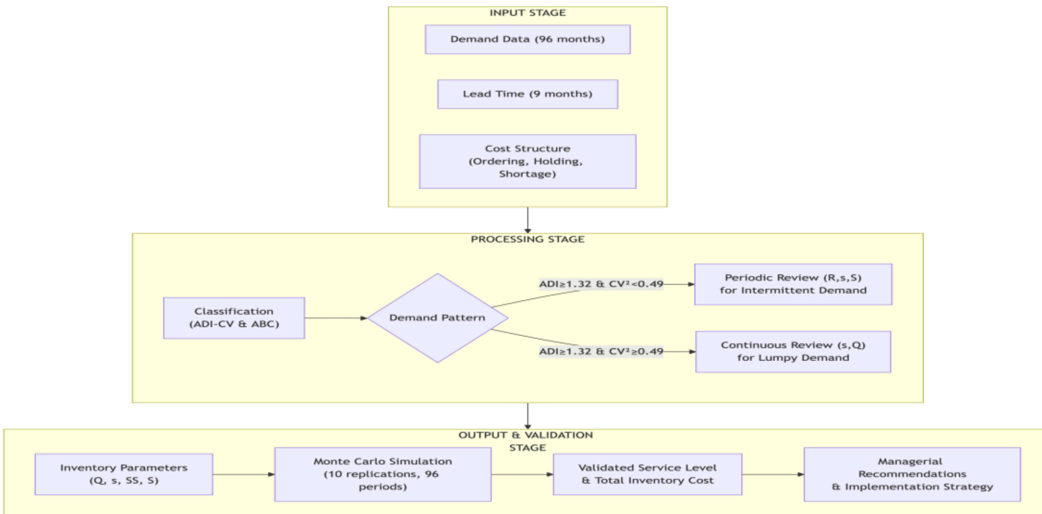


Figure 2. Research Framework

This study aims to determine optimal inventory parameters (demand quantity, EOQ, reorder point, safety stock, maximum stock) and to recommend improved inventory management policies for MTU in an electric power company [4], [5]. We built a three-stage research framework (see Figure 2) that connects what we start with (input), how we process it, and what we finally get as recommendations. This framework helped us keep the logic straight: demand characteristics drive model selection, and every result gets checked against uncertainty.

The framework began with an input stage, where three types of data were collected [6], [7]: (a) historical demand for MTU over 96 months (2018-2025), (b) a fixed procurement lead time of 9 months based on the company's unit price contract, and (c) cost structure, including ordering cost (IDR 1.5 million per order), holding cost (24% of unit value per year), and estimated shortage cost. A field study was also carried out to understand the actual operational practices [8]. In the processing stage, we first classified each MTU item using two complementary tools: ABC analysis to prioritize items by spending, and the ADI-CV method to identify demand patterns. Using the ADI-CV criteria [9], we distinguished intermittent demand ($ADI \geq 1.32$, $CV^2 < 0.49$) from lumpy demand ($ADI \geq 1.32$, $CV^2 \geq 0.49$) [10], [11]. Based on this distinction, we applied a periodic review (R, s, S) model to intermittent items and a continuous review (s, Q) model to lumpy ones [4], [12], [13]. The analysis was conducted separately for each transmission unit (UIT JBB, JBT, JBM) and also for a combined (joint) inventory scenario [14], [15] to evaluate whether demand pooling across regions could improve performance. The output and validation stage consisted of two parts. First, we calculated inventory parameters (order quantity Q, reorder point s, safety stock SS, and maximum stock S) using standard analytical formulas (Hadley-Within iteration for continuous review and revised power approximation for periodic review) [5], [16]. Because MTU demand is inherently unpredictable, we then ran a Monte Carlo simulation for every material [17], [18]. For each item, we built a probability distribution from the 96 months of historical demand, converted it into a cumulative distribution, and generated random demand values for another 96 periods. This

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

process was repeated 10 times (replications) to capture a range of possible outcomes. From each replication, we calculated total inventory cost (purchasing + ordering + holding) and service level [5], [19]; the results were then averaged across all 10 replications to obtain a more realistic performance estimate [20].

Finally, we compared three scenarios side by side: the existing reactive policy, the analytical model results, and the Monte Carlo simulation outcomes [1], [2]. The comparison focused on total inventory cost and service level [21]. Based on these comparisons, we discussed the strengths and weaknesses of each approach, as well as the practical implications for the company [22], [23]. This methodological design (combining ABC and ADI-CV classification, dual inventory models, and Monte Carlo validation) follows established best practices in modern inventory management for intermittent and lumpy demand [4], [5], [9]. The paper concludes by summarizing the main findings and offering concrete recommendations for both practitioners and future researchers [4], [24].

RESULTS AND DISCUSSION

Results

The data collection phase of this study started with a review of the MTU management system at the electric power company, which coordinates the Head Office, three Transmission Main Units (UIT JBB, UIT JBT, UIT JBM), and strategic suppliers, with a total procurement value exceeding IDR 2.185 trillion for the 2018-2024 period. The data gathered fell into three categories. First, MTU demand data were extracted from the Unit Price Contract (KHS) procurement records for 2018-2024, obtained separately from each of the three transmission main units. Figure 3, Demand Pattern of MTU CB150 – RFQ 004 at UIT JBB, depicts the demand for this material over 96 months (January 2018 to December 2025), showing low demand frequency in only 16 periods (≈16.7 % of the total periods) and high variability in quantity ranging from 1 to 13 units, with notable peaks in October 2023 (12 units), September 2024 (13 units), and April 2025 (10 units). Second, MTU lead-time data were assumed to be nine months according to the KHS contract terms, reflecting various activity phases, including production, the Factory Acceptance Test (FAT), export-import documentation for internationally sourced materials, and final delivery. Third, MTU procurement data contain four cost components: the purchasing cost (all-in cost from the KHS), the ordering cost (IDR 1,500,000 per order), the holding cost (24% per year of the sourcing costs as implemented by DSN), and shortage penalty costs, which comprise contract penalties and Energy Not Served (ENS) costs.

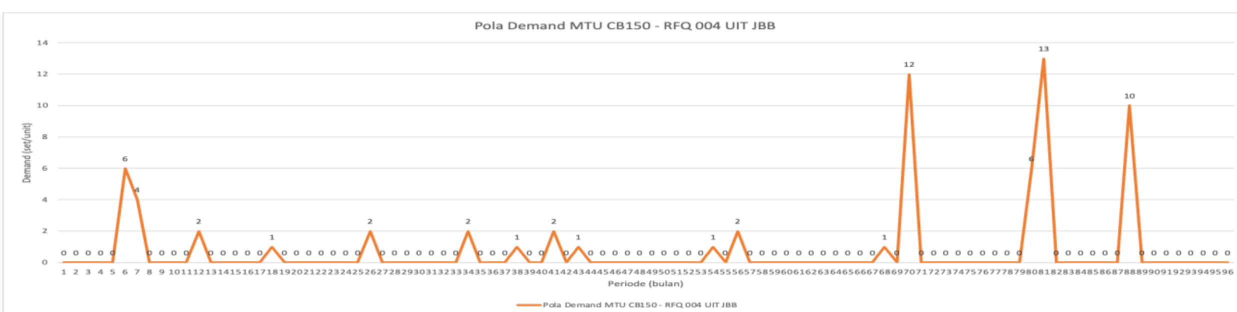


Figure 3. Demand Pattern of MTU CB150 - RFQ 004 at UIT JBB

Following the data collection, MTU classification was performed by two complementary methods: ABC analysis and the ADI-CV method [9], [10]. Table 1 presents the rationale behind the selection of MTU samples, which includes five items corresponding to each scenario (UIT JBB, UIT JBT, UIT JBM, and a combined scenario) for a total of 20 items. The selection was made following the ABC classification, where Class A and Class B items are

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

prioritized, as they make up the majority of both inventory costs and operational risks for the company [4], [25]. Table 1 lists each sample's characteristics, including ADI and CV values and its demand pattern (intermittent or lumpy). In the UIT JBB scenario, CB500-RFQ001 and CT500-RFQ001 are intermittent, whereas CB150-RFQ004, DS500-RFQ002, and CB150-RFQ009 are lumpy. Almost all samples in UIT JBT and the combined scenario are lumpy, except for CB500-RFQ001 in UIT JBM, which is intermittent. These demand, lead-time, cost, and classification data are used as the main inputs for later processing steps, such as existing inventory calculations, simulating continuous-review and periodic-review models, and Monte Carlo simulation.

Table 1. Selection of MTU Samples

No	MTU	Unit	Demand	Total Cost (IDR)	Persentase	Class	ADI	CV	Category
				UIT JBB					
1	CB500 - RFQ 001	Set/Unit	36	93.081.684.000	14,83%	A	10,7	0,3	Intermittent
2	CB150 - RFQ 004	Set/Unit	66	55.336.798.000	8,81%	A	6	0,9	Lumpy
3	CT500 - RFQ 001	Set/Unit	91	41.773.064.667	6,65%	B	10,7	0,4	Intermittent
4	DS500 - RFQ 002	Set/Unit	53	34.160.143.000	5,44%	B	8,73	0,5	Lumpy
5	CB150 - RFQ 009	Set/Unit	34	27.486.529.333	4,38%	B	19,2	0,6	Lumpy
				UIT JBT					
1	CB500 - RFQ 001	Set/Unit	72	186.821.016.000	19,74%	A	8	2,1	Lumpy
2	CB150 - RFQ 002	Set/Unit	174	98.489.974.000	10,41%	A	3,43	1,1	Lumpy
3	CT500 - RFQ 001	Set/Unit	79	36.548.849.667	3,86%	B	24	0,8	Lumpy
4	DS150 - RFQ 008	Set/Unit	143	29.930.281.333	3,16%	B	12	2,6	Lumpy
5	CVT150 - RFQ 002	Set/Unit	208	25.088.266.667	2,65%	B	7,38	0,9	Lumpy
				UIT JBM					
1	CT500 - RFQ 001	Set/Unit	137	64.401.028.500	7,89%	A	10,7	1,1	Lumpy
2	CB150 - RFQ 002	Set/Unit	95	54.169.332.500	6,64%	A	3	1	Lumpy
3	CB500 - RFQ 001	Set/Unit	18	47.040.462.000	5,77%	A	6,86	0,1	Intermittent
4	CB070 - RFQ 001	Set/Unit	76	37.422.210.000	4,59%	B	3,84	1,4	Lumpy
5	CVT150 - RFQ 007	Set/Unit	299	36.793.445.000	4,51%	B	8,73	0,9	Lumpy
				Gabungan UIT					
1	CB500 - RFQ 001	Set/Unit	126	64.401.028.500	13,71%	A	3,31	2,2	Lumpy
2	CB150 - RFQ 002	Set/Unit	290	54.169.332.500	6,88%	A	2	0,9	Lumpy
3	CT500 - RFQ 001	Set/Unit	307	47.040.462.000	5,96%	B	5,05	0,7	Lumpy
4	CB150 - RFQ 004	Set/Unit	104	37.422.210.000	3,66%	B	4,57	1,2	Lumpy
5	CVT150 - RFQ 002	Set/Unit	497	36.793.445.000	2,52%	B	2,53	1,1	Lumpy

MTU UIT JBB

Table 2 presents the existing inventory costs and service levels for MTU at UIT JBB. As shown in the table, all items have a service level of 0.00%, with holding costs below 1% of total costs. This confirms a reactive policy that lacks sufficient safety stock and results in every demand being unmet. For lumpy items (CB150-RFQ004, DS500-RFQ002, CB150-RFQ009), we applied the Continuous Review model. Table 3 lists the calculated parameters (Q, s, SS, S) for these materials. Using these parameters, the service level improved to between 36.36% and 68.75%, as detailed in Table 4. For intermittent items (CB500-RFQ001 and CT500-RFQ001), we used the Periodic Review system with a review period of six months (R = 6 months). Table 5 presents the parameters for this model. The resulting service levels, shown in Table 6, reached 88.89% for CB500-RFQ001 and 55.56% for CT500-RFQ001. To validate these analytical results, we performed a Monte Carlo simulation. Table 7 summarizes the simulation outcomes, showing average service levels ranging from 57.77% to 68.23% with standard deviations between 8.32% and 13.86%. This confirms that the proposed models are robust despite demand uncertainty. Overall, these results demonstrate that demand-based strategies (periodic review for intermittent items and continuous review for lumpy items) can significantly reduce stockouts at UIT JBB.

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

Table 2. Existing Inventory Cost Calculation Results for UIT JBB

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	93.081.684.000	13.500.000	904.960.817	94.000.144.817	0,00%
2	CB150 - RFQ 004	55.336.798.000	24.000.000	469.524.347	55.830.322.347	0,00%
3	CT500 - RFQ 001	41.773.064.667	13.500.000	417.730.647	42.204.295.313	0,00%
4	DS500 - RFQ 002	34.160.143.000	16.500.000	341.601.430	34.518.244.430	0,00%
5	CB150 - RFQ 009	27.486.529.333	7.500.000	226.359.653	27.720.388.987	0,00%

Table 3. Calculation Parameters of the Continuous Review Model for UIT JBB

No	MTU	Q	s	SS	S
1	CB150 - RFQ 004	6	9	2	15
2	DS500 - RFQ 002	5	7	2	12
3	CB150 - RFQ 009	3	7	4	10

Table 4. Results of the Continuous Review Model for UIT JBB Inventory Cost Calculation

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB150 - RFQ 004	65.398.034.000	19.500.000	5.173.152.177	70.590.686.177	68,75%
2	DS500 - RFQ 002	41.894.515.000	19.500.000	2.919.725.430	44.833.740.430	36,36%
3	CB150 - RFQ 009	33.953.948.000	21.000.000	4.672.709.987	38.647.657.987	40,00%

Table 5. Calculation Parameters of the Periodic Review Model for UIT JBB

No	MTU	Q	s	SS
1	CB500 - RFQ 001	6	8	8
2	CT500 - RFQ 001	6	14	23

Table 6. Results of the Periodic Review Model for UIT JBB Inventory Cost Calculation

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	113.766.502.667	12.000.000	8.894.472.027	122.672.974.693	88,89%
2	CT500 - RFQ 001	52.331.092.000	7.500.000	4.751.112.300	57.089.704.300	55,56%

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

Table 7. Monte Carlo Simulation Results for the MTU at UIT JBB

MTU Type	CB500 - RFQ 001	CB150 - RFQ 004	CT500 - RFQ 001	DS500 - RFQ 002	CB150 - RFQ 009
Mean Purchasing Cost (IDR)	117.386.345.933	64.894.972.200	51.091.671.400	45.439.435.500	40.987.265.800
Std. Dev. Purchasing Cost (IDR)	35.498.059.106	12.196.295.037	6.275.662.748	9.661.995.277	10.630.127.790
Mean Ordering Cost (IDR)	12.300.000	19.350.000	9.450.000	21.150.000	25.350.000
Std. Dev. Ordering Cost (IDR)	3.224.903	3.636.619	1.589.025	4.497.221	6.574.572
Mean Holding Cost (IDR)	9.517.602.189	5.557.994.454	4.867.250.601	2.898.455.907	4.527.193.067
Std. Dev. Holding Cost (IDR)	2.742.755.531	1.289.814.695	592.521.584	593.396.885	653.688.474
Mean Total Inventory Cost (IDR)	126.916.248.122	70.472.316.654	55.968.372.001	48.359.041.407	45.539.808.867
Std. Dev. Total Inv. Cost (IDR)	33.064.606.099	11.662.162.237	5.823.534.493	9.245.414.710	10.216.905.690
Mean Service Level	68,23%	60,00%	63,29%	57,77%	66,66%
Std. Dev. Service Level	10,84%	10,74%	13,86%	8,32%	9,44%

MTU UIT JBT

Table 8 presents the existing inventory costs and service levels for MTU at UIT JBT. As shown, all materials have a lumpy demand pattern and a 0.00% service level under current conditions. The costliest item is CB500-RFQ001 (IDR 186.82 billion), while CB150-RFQ002 has the highest ordering cost (IDR 42 million). Because of its low demand frequency (ADI = 24), CT500-RFQ001 often ends up with zero inventory under the current policy. Unlike UIT JBB, where two different models were used, all lumpy materials at UIT JBT were managed with a single Continuous Review (s, Q) model. Table 9 lists the calculated parameters for each material. Among these, DS150-RFQ008 shows the highest parameter values (s = 32, SS = 18, Q = 14), which corresponds to its very high coefficient of variation (CV = 2.6). Using these parameters, service levels improved to between 50% and 75%, as detailed in Table 10. To validate these results, we ran a Monte Carlo simulation. Table 11 summarizes the simulation outcomes, with average service levels ranging from 62.47% to 76.19%. Notably, the simulation result for CB150-RFQ002 (76.19%) is considerably higher than its deterministic model result (67.86%). Interestingly, despite having the highest CV (see Table 8), DS150-RFQ008 also shows the lowest standard deviation in service level (6.96%). This suggests that the relatively large safety stock (SS = 18) stabilizes performance even under extreme demand variability.

Table 8. Existing Inventory Cost Calculation Results for UIT JBT

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	186.821.016.000	18.000.000	1.868.210.160	188.707.226.160	0,00%
2	CB150 - RFQ 002	98.489.974.000	42.000.000	984.899.740	99.516.873.740	0,00%
3	CT500 - RFQ 001	36.548.849.667	6.000.000	365.488.497	36.920.338.163	0,00%
4	DS150 - RFQ 008	29.930.281.333	12.000.000	299.302.813	30.241.584.147	0,00%
5	CVT150 - RFQ 002	25.088.266.667	19.500.000	250.882.667	25.358.649.333	0,00%

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

Table 9. Calculation Parameters of the Continuous Review Model for UIT JBT

No	MTU	Q	s	SS	S
1	CB500 - RFQ 001	8	12	4	20
2	CB150 - RFQ 002	12	22	5	34
3	CT500 - RFQ 001	8	18	10	26
4	DS150 - RFQ 008	14	32	18	46
5	CVT150 - RFQ 002	21	27	7	48

Table 10. Results of the Continuous Review Model for UIT JBT Inventory Cost Calculation

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	228.336.797.333	16.500.000	25.194.889.797	253.548.187.130	75,00%
2	CB150 - RFQ 002	115.471.004.000	25.500.000	6.090.529.427	121.587.033.427	67,86%
3	CT500 - RFQ 001	48.114.941.333	19.500.000	8.087.011.293	56.221.452.627	50,00%
4	DS150 - RFQ 008	38.093.085.333	19.500.000	5.680.474.373	43.793.059.707	62,50%
5	CVT150 - RFQ 002	30.395.400.000	18.000.000	2.674.071.500	33.087.471.500	61,54%

Table 11. Monte Carlo Simulation Results for the MTU at UIT JBT

MTU Type	CB500 - RFQ 001	CB150 - RFQ 002	CT500 - RFQ 001	DS150 - RFQ 008	CVT150 - RFQ 002
Mean Purchasing Cost (IDR)	253.246.266.133	107.999.350.800	59.958.619.200	40.437.275.200	32.168.465.000
Std. Dev. Purchasing Cost (IDR)	71.774.157.128	23.627.441.999	20.332.006.336	14.140.904.253	11.011.779.819
Mean Ordering Cost (IDR)	18.300.000	23.400.000	24.300.000	20.700.000	19.050.000
Std. Dev. Ordering Cost (IDR)	5.186.521	5.108.816	8.240.146	7.238.784	6.521.120
Mean Holding Cost (IDR)	23.907.900.575	8.153.158.537	7.622.054.408	5.655.358.053	2.061.700.683
Std. Dev. Holding Cost (IDR)	4.241.901.467	2.408.127.345	2.060.500.664	637.415.876	707.360.518
Mean Total Inventory Cost (IDR)	277.172.466.709	116.175.909.337	67.604.973.608	46.113.333.253	34.249.215.683
Std. Dev. Total Inv. Cost (IDR)	67.960.231.425	23.293.798.545	20.318.086.888	13.894.557.143	10.365.279.898
Mean Service Level	71,33%	76,19%	66,16%	70,40%	62,47%
Std. Dev. Service Level	8,88%	9,14%	7,77%	6,96%	14,13%

MTU UIT JBM

Table 12 presents the existing inventory costs and service levels for MTU at UIT JBM. As shown, the current situation is alarming, with a 0.00% service level for all materials. CB150-RFQ002 has the highest ordering cost among the three units (IDR 48 million). Meanwhile, CB500-RFQ001, despite its investment value of IDR 47.04 billion, has a total demand of only 18 units over eight years, making it highly vulnerable to obsolescence. UIT JBM's approach is unique because it uses two inventory models. Four lumpy items were managed under Continuous Review, while one

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

intermittent item (CB500-RFQ001) was managed under Periodic Review. Table 13 lists the parameters for the Continuous Review model, and Table 15 shows the parameters for the Periodic Review model. The resulting service level improvements are presented in Tables 14 and 16. Under Continuous Review, CT500-RFQ001 reached 77.78%, and CB070-RFQ001 reached 72.00%, while CB150-RFQ002 only reached 40.63% (the lowest). Under Periodic Review, CB500-RFQ001 achieved only 14.29%. To validate these findings, we ran a Monte Carlo simulation. Table 17 summarizes the simulation outcomes, which revealed some surprising results. CVT150-RFQ007 achieved the highest service level (76.13%) while also yielding lower total cost (saving IDR 2.44 billion compared to the deterministic model). The service level for CB500-RFQ001 surged from 14.29% to 50.73%, but due to its very low demand frequency, its standard deviation remained extremely high (27.01%). Overall, service level variability at UIT JBM (standard deviations between 13.74% and 27.01%) is considerably greater than that of the other units. This likely reflects the geographical complexities of managing materials across East Java, Bali, and Madura.

Table 12. Existing Inventory Cost Calculation Results for UIT JBM

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CT500 - RFQ 001	64.401.028.500	13.500.000	644.010.285	65.058.538.785	0,00%
2	CB150 - RFQ 002	54.169.332.500	48.000.000	541.693.325	54.759.025.825	0,00%
3	CB500 - RFQ 001	47.040.462.000	21.000.000	470.404.620	47.531.866.620	0,00%
4	CB070 - RFQ 001	37.422.210.000	37.500.000	374.222.100	37.833.932.100	0,00%
5	CVT150 - RFQ 007	36.793.445.000	16.500.000	367.934.450	37.177.879.450	0,00%

Table 13. Calculation Parameters of the Continuous Review Model for UIT JBM

No	MTU	Q	s	SS	S
1	CT500 - RFQ 001	15	21	8	36
2	CB150 - RFQ 002	6	11	2	17
3	CB070 - RFQ 001	6	10	2	16
4	CVT150 - RFQ 007	26	45	16	71

Table 14. Results of the Continuous Review Model for UIT JBM Inventory Cost Calculation

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CT500 - RFQ 001	77.563.282.500	16.500.000	7.610.603.295	85.190.385.795	77,78%
2	CB150 - RFQ 002	61.581.978.000	27.000.000	3.233.053.845	64.842.031.845	40,63%
3	CB070 - RFQ 001	44.315.775.000	22.500.000	2.476.759.425	46.815.034.425	72,00%
4	CVT150 - RFQ 007	44.792.020.000	19.500.000	3.476.303.750	48.287.823.750	54,55%

Table 15. Calculation Parameters of the Periodic Review Model for UIT JBM

No	MTU	Q	s	SS
1	CB500 - RFQ 001	6	2	3

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

Table 16. Results of the Periodic Review Model for UIT JBM Inventory Cost Calculation

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	54.880.539.000	27.000.000	4.233.641.580	59.141.180.580	14,29%

Table 17. Monte Carlo Simulation Results for the MTU at UIT JBM

MTU Type	CT500 - RFQ 001	CB150 - RFQ 002	CB500 - RFQ 001	CB070 - RFQ 001	CVT150 - RFQ 007
Mean Purchasing Cost (IDR)	76.153.041.000	62.950.466.400	59.323.249.300	44.315.775.000	41.912.533.000
Std. Dev. Purchasing Cost (IDR)	19.324.825.827	15.060.282.372	21.866.665.346	10.234.289.850	12.294.584.282
Mean Ordering Cost (IDR)	16.200.000	27.600.000	15.750.000	22.500.000	19.650.000
Std. Dev. Ordering Cost (IDR)	4.110.961	6.603.030	3.889.087	5.196.152	5.764.113
Mean Holding Cost (IDR)	7.950.471.497	3.332.269.254	2.299.755.920	3.020.366.265	3.917.209.815
Std. Dev. Holding Cost (IDR)	806.644.532	1.008.428.350	1.512.189.474	633.390.699	622.016.227
Mean Total Inventory Cost (IDR)	84.119.712.497	66.310.335.654	61.638.755.220	47.358.641.265	45.849.392.815
Std. Dev. Total Inv. Cost (IDR)	18.868.132.379	14.158.982.047	20.391.453.865	9.690.474.267	11.800.297.768
Mean Service Level	64,36%	70,11%	50,73%	69,71%	76,13%
Std. Dev. Service Level	13,74%	16,99%	27,01%	14,08%	14,97%

MTU UIT (The combined scenario)

The combined scenario was designed to evaluate whether risk pooling through a joint inventory system could reduce demand variability and improve overall service levels across the three transmission units. Table 18 presents the existing inventory costs and service levels for the combined scenario of the three units (UIT JBB, JBT, JBM). As shown, the accumulated inventory problem is severe, with very high procurement values (CB500-RFQ001 alone reaches IDR 327.34 billion). Nevertheless, all materials still have a 0.00% service level and holding costs below 1% of total costs. This indicates that simply aggregating demand without a proper control system only magnifies the failure. In this combined scenario, we used the Continuous Review model exclusively, because after aggregation all materials became lumpy. Table 19 lists the calculated parameters, which vary widely across items. For example, CVT150-RFQ002, which has the highest aggregate demand (497 units), has Q = 35 and s = 52, whereas CB150-RFQ004 (the lowest demand) has Q = 8. Using these parameters, service levels improved dramatically, ranging from 47.92% to 84.21%, as detailed in Table 20. However, the Monte Carlo validation revealed several critical corrections. Table 21 summarizes the simulation outcomes. The service level for CT500-RFQ001 dropped from 84.21% (deterministic) to 65.41% (simulation), confirming that analytical models tend to overpredict performance for materials with a medium coefficient of variation. In contrast, CB150-RFQ004 achieved the highest simulated service level (72.38%) with a small model-simulation gap of only +5.71%, making it the most stable candidate for implementation. Similarly, CB150-RFQ002 showed a strong performance gain, rising from 47.92% (deterministic) to 71.82% (simulation). Notably, the service-level standard deviations in the combined setting (ranging from 8.95% to 14.13%) are much smaller than those in the separate management approaches, where UIT JBM reached a standard

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

deviation of 27.01%. This suggests that pooling risk through a joint inventory decision helps stabilize performance across units.

Table 18. Existing Inventory Cost Calculation Results for UIT

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	327.335.302.000	43.500.000	3.247.374.028	330.626.176.028	0,00%
2	CB150 - RFQ 002	164.348.042.778	72.000.000	1.643.480.428	166.063.523.206	0,00%
3	CT500 - RFQ 001	142.424.343.944	28.500.000	1.424.243.439	143.877.087.384	0,00%
4	CB150 - RFQ 004	87.488.896.444	31.500.000	790.765.026	88.311.161.470	0,00%
5	CVT150 - RFQ 002	60.155.057.667	57.000.000	555.556.770	60.767.614.437	0,00%

Table 19. Calculation Parameters of the Continuous Review Model for UIT

No	MTU	Q	s	SS	S
1	CB500 - RFQ 001	9	17	5	26
2	CB150 - RFQ 002	19	30	2	49
3	CT500 - RFQ 001	21	39	10	60
4	CB150 - RFQ 004	8	13	3	21
5	CVT150 - RFQ 002	35	52	5	87

Table 20. Results of the Continuous Review Model for UIT Inventory Cost Calculation

No	MTU	Purchasing Cost (IDR)	Ordering Cost (IDR)	Holding Cost (IDR)	Total Inventory Cost (IDR)	Service Level
1	CB500 - RFQ 001	374.097.488.000	24.000.000	23.485.008.969	397.606.496.969	75,86%
2	CB150 - RFQ 002	183.049.716.611	25.500.000	6.964.956.709	190.040.173.321	47,92%
3	CT500 - RFQ 001	165.620.491.167	25.500.000	11.097.036.831	176.743.027.998	84,21%
4	CB150 - RFQ 004	100.948.726.667	22.500.000	6.973.874.534	107.945.101.201	66,67%
5	CVT150 - RFQ 002	67.780.346.667	24.000.000	3.376.913.700	71.181.260.367	68,42%

Table 21. Monte Carlo Simulation Results for the MTU at UIT

MTU Type	CB500 - RFQ 001	CB150 - RFQ 002	CT500 - RFQ 001	CB150 - RFQ 004	CVT150 - RFQ 002
Mean Purchasing Cost (IDR)	360.068.832.200	180.896.190.533	172.440.158.450	105.659.667.244	69.898.482.500
Std. Dev. Purchasing Cost (IDR)	105.833.708.147	23.699.660.754	41.346.180.818	35.334.724.834	10.614.187.917
Mean Ordering Cost (IDR)	23.100.000	25.200.000	26.550.000	23.550.000	24.750.000

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

MTU Type	CB500 - RFQ 001	CB150 - RFQ 002	CT500 - RFQ 001	CB150 - RFQ 004	CVT150 - RFQ 002
Std. Dev. Ordering Cost (IDR)	6.789.698	3.301.515	6.365.925	7.875.595	3.758.324
Mean Holding Cost (IDR)	29.397.827.599	7.399.062.229	13.692.685.705	6.581.015.739	2.798.844.172
Std. Dev. Holding Cost (IDR)	6.027.054.031	1.518.236.719	10.793.604.911	2.187.510.175	736.948.214
Mean Total Inventory Cost (IDR)	389.489.759.799	188.320.452.763	186.159.394.155	112.264.232.984	72.722.076.672
Std. Dev. Total Inv. Cost (IDR)	100.691.194.564	22.428.247.077	47.182.672.655	33.320.433.791	9.954.487.851
Mean Service Level	71,48%	71,82%	65,41%	72,38%	63,00%
Std. Dev. Service Level	14,13%	10,39%	8,95%	11,49%	11,43%

Discussion

As shown in Tables 2, 8, 12, and 18, the existing inventory condition across all units consistently showed a 0.00% service level, with holding costs below 1% of total costs [6]. This confirms the absence of safety stock and a purely reactive policy. At UIT JBB (Table 2), intermittent materials (CB500, CT500) were managed using the Periodic Review model (R = 6 months), while lumpy materials (CB150-004, DS500, CB150-009) employed the Continuous Review model using the Hadley-Within iteration method [4], [16]. Monte Carlo simulation (Table 7) yielded an average service level of 63.19% [5], [19]. An interesting phenomenon occurred for CT500 material (Table 6 vs Table 7): Monte Carlo simulation (63.29%) produced a higher result than the deterministic model (55.56%) with lower costs, showing that simulation effectively captures demand uncertainty [10]. The DS500 material (Table 4 vs Table 7), with CV = 0.5 at the classification boundary between erratic and lumpy, exhibited the largest positive gap (+21.41%). This gap was calculated as the difference between the Monte Carlo service level (57.77% from Table 7) and the deterministic model service level (36.36% from Table 4), i.e., (simulation result − model result). A positive gap indicates that the simulation outperformed the deterministic prediction, which we attribute to the model's sensitivity at the classification boundary. This finding indicates that materials at classification boundaries require validation through simulation [9].

The first finding from UIT JBT (Tables 8–11) was that lumpy items with very high variability (CV ≥ 2.6) predominated, where the continuous review model was applied to each sample [12]. The average Monte Carlo service level (Table 11) across all three units was the highest among units, reaching 69.31% [13]. Material DS150 (Table 11), which had the largest safety stock (SS = 18) and the highest CV at 2.6, exhibited a service level of 70.40% with the smallest standard deviation (6.96%). This confirms that a high safety stock is capable of mitigating extreme variability [5]. UIT JBM (Tables 12–17), on the other hand, showed the greatest performance variability, with service level standard deviations between 13.74% and 27.01% (Table 17), which we attribute to its extensive geographic coverage from East Java to Madura [15]. The intermittent CB500 material in JBM (ADI = 6.86; CV = 0.1) showed an anomaly (Table 16 vs Table 17): the Periodic Review model achieved only 14.29%, whereas Monte Carlo simulation reached 50.73%, indicating that fixed review intervals are inappropriate for materials with very low demand frequency [4].

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

This massive discrepancy suggests that the static assumptions in the conventional periodic model are not adaptive enough to extremely rare demand patterns. Therefore, before implementing this policy, the company should consider a more dynamic review interval, for example, adjusting R based on the time since the last demand occurrence rather than sticking to a fixed six-month cycle. CVT150 material (Table 17) attained the highest service level at JBM (76.13%) and was the sole material whose simulation costs were lower than the deterministic model, yielding savings of IDR 2.44 billion [20].

Aggregating the three units (Tables 18–21) converted all demand patterns into lumpy forms, yielding an average Monte Carlo service level of 68.82% and reduced variability, with standard deviations between 8.95% and 14.13% (Table 21). This supports the effectiveness of risk pooling via joint inventory [14], [21]. The CB500 material (Table 21), which has the highest coefficient of variation (CV = 2.2), reached a service level of 71.48% even though its total cost standard deviation was large (IDR 100.69 billion), illustrating that demand aggregation benefits very high-value materials [25]. CB150-004 (Table 21) obtained the highest service level in the combined scenario (72.38%) and the smallest model-simulation gap (+5.71%), making it a top candidate for implementation. In contrast, CT500 (Table 20 vs Table 21) displayed the highest deterministic service level (84.21%) but the simulation result was only 65.41% (gap of –18.80%), suggesting that analytical models tend to overestimate performance for materials with CV = 0.7 [11]. CVT150 (Table 21), which has the largest total demand (497 units), achieved the lowest cost increase (17.1%) and is therefore the most suitable candidate for joint inventory [4].

Looking across the units (Tables 2–21), UIT JBB had the greatest pattern diversity, combining intermittent and lumpy patterns; UIT JBT was mainly characterized by extreme lumpy patterns, with a coefficient of variation up to 2.6; and UIT JBM displayed the largest performance variability, with a service level standard deviation reaching 27.01%. All units had similar baseline conditions: a 0.00% service level and holding costs below 1% of total costs [6]. Following the implementation of the proposed models, UIT JBT achieved the highest average service level at 69.31%, followed by JBM at 66.21% and JBB at 63.19% [24]. Given the high unit prices of MTU (often exceeding IDR 1 billion per item) and the substantial increase in holding costs required to push service levels higher, we consider these figures a reasonable trade-off. Raising service level to 95% would demand a disproportionate cost increase (estimated at 200–300%), which may not be justifiable for many MTU items. In practice, the electric power company faces real constraints: warehouse space is limited, and the national electricity procurement budget cannot absorb an indefinite increase in holding costs. Moreover, a service level in the range of 65–70% is considered sufficient for MTU, as it balances operational availability with financial feasibility. Pushing beyond this range would require either a significant expansion of storage capacity or a reallocation of funds from other critical programs. The combined scenario demonstrated the effectiveness of joint inventory, achieving an average service level of 68.82% and more controlled variability.

Based on these findings, we offer the following strategic recommendations: (a) use ADI-CV classification for selecting the appropriate model [9], [10]; (b) start implementation gradually with the best-performing materials, such as CVT150-007 JBM (76.13%) and Combined CB150-004 (72.38%); (c) limit joint inventory to very high-value materials (>IDR 1 billion) with ADI > 6; (d) establish a demand recording system that distinguishes the causes of demand; (e) apply Croston/SBA forecasting methods to materials with ADI > 1.32 [4]; and (f) deploy real-time inventory information systems that integrate asset tracking [12]. By critically examining anomalies (such as the overestimation bias of deterministic models for medium-CV items and the stabilizing effect of large safety stocks under extreme lumpy demand), this discussion contributes to a more nuanced understanding of how inventory theory applies to critical infrastructure assets in a real-world setting.

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

CONCLUSION

This research successfully identified MTU inventory parameters by analyzing demand pattern characteristics across 20 samples from three transmission main units and a combined scenario. Intermittent materials (ADI ≥ 1.32; CV^2 < 0.49) were managed using a Periodic Review model with a fixed six-month review interval. This interval follows the company's semiannual stock opname policy. However, our simulation results (e.g., CB500-RFQ001 in JBM, Table 17) showed that this interval is too long for items with extremely low demand frequency (ADI > 6), leading to suboptimal service levels. Meanwhile, lumpy materials (ADI ≥ 1.32; CV^2 ≥ 0.49) were managed with a Continuous Review model, which proved more robust. Applying these two models raised service levels from 0 % under the current system to averages of 63.19 % (UIT JBB), 69.31 % (UIT JBT), 66.21 % (UIT JBM), and 68.82 % (combined scenario), but also increased total inventory costs by 14 % to 64 %. This increase mainly came from holding costs, which were previously below 1% of total costs. Despite the sharp rise in holding costs, the reduction in shortage costs (avoiding prolonged outages and multimillion-dollar losses from Energy Not Served) makes the trade-off economically justifiable for critical MTU. Unit-level precision of model performance was inconsistent; for instance, CB500 at UIT JBM yielded the greatest variability (standard deviation of 27.01%) because a periodic review model is inappropriate for very low demand frequencies. In contrast, the combined inventory approach proved effective, reducing variability to a range of 8.95%–14.13% and achieving an overall service level of 68.82%. Thus, the conclusion aligns with the original objectives: determining optimal inventory parameters and proposing actionable managerial policies to overcome the root cause of existing stockout failures. Based on these findings, this study advises that, for optimal model selection, an ADI-CV classification should be utilized. Furthermore, policy changes should be implemented gradually, prioritizing the best-performing materials, and policies for items with high CV values should always be validated through a Monte Carlo simulation.

The electric power company must rapidly transform its MTU inventory management into a data-driven, proactive model utilizing usage-based segmentation, beginning with the immediate implementation of the highest-performing items, namely CVT150-007 JBM and the combined CB150-004. Furthermore, establishing a Demand Tracking Record (DTR) system should be the company's primary objective to identify demand sources; subsequently, the Croston or Syntetos-Boylan Approximation (SBA) method should be applied to items with an Average Demand Interval (ADI) greater than 1.32. Appropriate warehouse space must be allocated for safety stock, given that current safety-stock costs represent only 1% of total inventory costs. The company should also develop real-time inventory information systems integrated with asset-tracking capabilities. However, limited joint inventory should be applied only to high-value items exceeding IDR 1 billion that exhibit low demand frequencies (ADI > 6), while decentralized stocking must be retained for emergency items, such as circuit breakers (CB) and current transformers (CT). This article contributes to the fields of operations management, industrial engineering, and critical infrastructure asset management by providing a comparative, simulation-validated inventory framework for primary transmission equipment in a national electricity system. Future studies should develop hybrid models for borderline intermittent-lumpy items, investigate lead-time uncertainty, and incorporate reliability factors and optimization algorithms, particularly since stock-point locations vary across different geographical conditions in the Java-Bali region. Finally, future research should examine material-transfer costs associated with risk pooling and joint inventory systems.

Prozima : Vol. 10, No. 1, June 2026, 73-87
E. ISSN. 2541-5115
Journal Homepage: http://ojs.umsida.ac.id/index.php/prozima
DOI Link: http://doi.org/10.21070/prozima.v10i1.1784
Article DOI: http://doi.org/10.21070/prozima.10i1.1784

REFERENCES

[1] D. Ermawanto, “Pengelolaan Spare Parts Inventory dengan Metode Continuous Review, Periodic Review dan Reliability di Warehouse PT. XYZ,” Institut Teknologi Sepuluh Nopember, Surabaya, 2020.
[2] M. Rizma, “Peramalan dan Pengendalian Persediaan Material pada Industri Distribusi Listrik,” Institut Teknologi Sepuluh Nopember, 2023.
[3] W. F. Riskianto, “Pengendalian Persediaan Consumable Material dan Spare Part pada Sistem Transmisi Tenaga Listrik,” Institut Teknologi Sepuluh Nopember, Surabaya, 2021.
[4] E. A. Silver, D. F. Pyke, and D. J. Thomas, Inventory and Production Management in Supply Chain, 4th ed. CRC Press, 2017.
[5] R. J. Tersine, Principles of Inventory and Materials Management, 4th ed. Prentice Hall, 1994.
[6] W. J. Kennedy, J. W. Patterson, and L. D. Fredendall, “An Overview of Recent Literature on Spare Parts Inventories,” Int. J. Production Economics, vol. 76, pp. 201–215, 2002.
[7] D. Waters, Inventory Control and Management, 2nd ed. John Wiley & Sons, 2003.
[8] R. M. Monczka, R. B. Handfield, L. C. Giunipero, and J. L. Patterson, Purchasing and Supply Chain Management, 4th ed. South-Western Cengage Learning, 2009.
[9] A. A. Ghobbar and C. H. Friend, “Evaluation of Forecasting Methods for Intermittent Parts Demand in the Field of Aviation: A Predictive Model,” Comput. Oper. Res., vol. 30, pp. 2097–2114, 2003.
[10] A. A. Syntetos and J. E. Boylan, “The Accuracy of Intermittent Demand Estimates,” Int. J. Forecast., vol. 21, no. 2, pp. 303–314, Apr. 2005.
[11] R. H. Teunter, A. A. Syntetos, and M. Z. Babai, “Intermittent Demand: Linking Forecasting to Inventory Obsolescence,” Eur. J. Oper. Res., vol. 214, no. 3, pp. 606–615, 2011, doi: 10.1016/j.ejor.2011.05.018.
[12] S. Axsäter, Inventory Control, 3rd ed. Springer International Publishing, 2015.
[13] P. H. Zipkin, Foundations of Inventory Management. McGraw-Hill, 2000.
[14] R. J. I. Basten and G. J. van Houtum, “System-Oriented Inventory Models for Spare Parts,” Elsevier Science B.V., 2014, doi: 10.1016/j.sorms.2014.05.002.
[15] D. Simchi-Levi, P. Kaminsky, and E. Simchi-Levi, Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies. McGraw-Hill Education, 2000.
[16] G. Hadley and T. M. Whitin, Analysis of Inventory Systems. Prentice-Hall, 1963.
[17] G. S. Fishman, Monte Carlo: Concepts, Algorithms, and Applications. Springer Science & Business Media, 2013.
[18] W. D. Kelton, R. P. Sadowski, and N. B. Zupick, Simulation with Arena, 6th ed. McGraw-Hill Education, 2015.
[19] A. M. Law, Simulation Modeling and Analysis. McGraw-Hill Education, 2015.
[20] R. Y. Rubinstein and D. P. Kroese, Simulation and the Monte Carlo Method. Wiley, 2017.
[21] S. Chopra and P. Meindl, Supply Chain Management: Strategy, Planning, and Operation. Pearson, 2016.
[22] S. Cavalieri, M. Garetti, M. MacChi, and R. Pinto, “A Decision-Making Framework for Managing Maintenance Spare Parts,” Production Planning and Control, vol. 19, no. 4, pp. 379–396, Jun. 2008.
[23] J. Huiskonen, “Maintenance Spare Parts Logistics: Special Characteristics and Strategic Choices,” Int. J. Production Economics, vol. 71, pp. 125–133, 2001.
[24] F. R. Jacobs and R. B. Chase, Operations and Supply Chain Management, 15th ed. McGraw-Hill Education, 2018.
[25] S. Nahmias and T. L. Olsen, Production and Operations Analysis, 7th ed. Waveland Press, 2022.