JRSSEM 2026, Vol. 6, No. 1, August
E-ISSN: 2807 - 6311
P-ISSN: 2807 - 6494

Transmission Spare Parts Inventory Management Strategy Based on Poisson Demand Estimation and Inter-Warehouse Coordination Through Risk Pooling

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Keywords:
Spare Parts;
Poisson;
Risk Pooling;
Warehouse;
Transmission

Abstract

Spare parts inventory management, particularly for slow-moving transmission components, presents a significant challenge for utility companies due to unpredictable and infrequent demand patterns, high asset value, and the need to maintain operational reliability. Excessive inventory levels tie up substantial working capital, increase carrying costs, and elevate the risk of obsolescence, whereas insufficient stock availability may result in equipment downtime and service disruptions. This study aimed to optimize inventory management for slow-moving transmission spare parts by balancing operational reliability and inventory cost efficiency over a ten-year planning horizon. A Poisson-based forecasting approach, using equipment failure rates as the primary demand driver, was implemented. Additionally, three risk-pooling schemes (no risk pooling, full risk pooling, and partial risk pooling) were evaluated through simulation to assess fill rates, disruption response, and inventory holding costs. The Poisson-based approach reduced projected spare parts requirements by 36% and lowered ending inventory levels by 55% compared with the existing policy. The simulation results indicated that while no risk pooling provided higher fill rates and full risk pooling minimized holding costs, partial risk pooling achieved the optimal trade-off across key performance metrics. Implementing a Poisson-based demand model combined with partial risk pooling enables organizations to significantly reduce procurement expenditures and inventory holding costs without compromising operational reliability.

INTRODUCTION

Spare parts are essential components for ensuring the continuous operation of industrial equipment across various sectors, including manufacturing, energy, mining, transportation, and construction. They play a critical role in supporting equipment reliability and maintaining operational continuity. One of the most challenging categories in inventory management is slow-moving spare parts, which are characterized by infrequent usage, low and intermittent demand, and typically high asset value (Mouschoutzi & Ponis, 2022). Managing these items presents a significant challenge because organizations must maintain adequate stock levels despite uncertain demand patterns. According to the company's inventory monitoring reports for 2024–2025, the total value of spare parts inventory exceeded IDR 2.3 trillion. This condition indicates that a substantial amount of working capital remains tied up in inventory that has not generated optimal value for the company and may instead become a financial burden. Consequently, excessive slow-moving inventory may increase carrying costs, storage expenses, and the risk of obsolescence (Emar et al., 2021).

Several issues, including excessive warehouse space utilization, incomplete or damaged goods, and inventory obsolescence, have emerged due to the high value of spare parts inventory stored in the company's warehouses (Maziliauskis, 2021; Mor et al., 2021). The procurement of replacement parts is calculated at 2% of the acquisition value or the installed asset population in accordance with the company's inventory planning policy (İfraz et al., 2025). The company currently employs a decentralized warehouse management system (no risk pooling) as part of its inventory planning strategy, in which each regional warehouse independently plans, procures, and utilizes spare parts according to its own requirements. Although this strategy improves local responsiveness, it may also result in duplicate inventory, inefficient stock allocation, and higher total inventory costs across the warehouse network (Ahlsell et al., 2023).

Several studies have examined inventory management strategies for slow-moving spare parts. Mouschoutzi and Ponis (2022) conducted a comprehensive literature review on spare parts logistics management in the maritime industry, highlighting the challenges of demand uncertainty and the need for efficient inventory policies. Syntetos et al. (2011) analyzed demand distributions for spare parts and emphasized that Poisson-based approaches are particularly suitable for modeling intermittent and low-frequency demand patterns. Louit et al. (2011) developed optimization models for critical spare parts inventory using a reliability-based approach, demonstrating the effectiveness of probabilistic demand forecasting in reducing inventory costs. Berman et al. (2011) investigated the benefits of risk pooling in inventory management and concluded that inventory aggregation can significantly reduce demand variability and improve stock utilization. Silbermayr and Gerchak (2019) examined partial pooling strategies among independent firms, showing that cooperative pooling arrangements can enhance inventory efficiency while maintaining operational flexibility. Hafner et al. (2021) developed an evaluation model for cooperative inventory pooling systems, further supporting the applicability of risk pooling in spare parts management. More recently, Munyaka and Yadavalli (2022) conducted a systematic review of inventory management concepts and implementations, emphasizing the importance of selecting appropriate demand distributions and inventory policies to improve supply chain performance.

This study addressed the research gap in managing slow-moving transmission spare parts inventory within an electric utility company in Southeast Asia. The main contributions of this study were: (1) the development of a Poisson-based inventory planning model to estimate spare parts requirements under different confidence levels while minimizing inventory-related costs; (2) the evaluation of no risk pooling, full risk pooling, and partial risk pooling schemes through simulation; and (3) the formulation of an inventory management strategy that balances service performance, operational responsiveness, and cost efficiency based on trade-offs among alternative risk-pooling configurations.

This study aimed to optimize inventory management for slow-moving transmission spare parts by developing a Poisson-based forecasting model and evaluating alternative risk-pooling configurations to balance operational reliability and inventory cost efficiency. The findings provide several practical benefits. This study offers a practical and implementable inventory planning framework that enables organizations to reduce procurement expenditures and holding costs while maintaining acceptable service levels. The Poisson-based approach, which utilizes equipment failure rates as the primary demand driver, provides a simpler and more data-efficient alternative to complex probabilistic methods, making it particularly suitable for organizations with limited historical data. Furthermore, the comparative evaluation of no risk pooling, full risk pooling, and partial risk pooling schemes provides actionable insights for practitioners in selecting appropriate inventory strategies based on operational priorities, including cost minimization, service performance, or balanced trade-offs. The integration of Poisson-based demand estimation with risk-pooling strategies contributes to the existing body of knowledge by offering a comprehensive approach to managing slow-moving, high-value spare parts in capital-intensive industries, ultimately supporting operational reliability and financial sustainability.

RESEARCH METHOD

Overview of Inventory Management

Inventory management was a critical component of material management systems within logistics and supply chain operations. It was applied across various industries, including manufacturing, healthcare, humanitarian relief, environmental science, engineering, agriculture, and energy (Munyaka & Yadavalli, 2022). The primary objective of inventory management was to determine optimal inventory levels and compositions that supported customer service performance while improving organizational financial outcomes. Therefore, companies needed to establish an appropriate balance between inventory-related costs and service levels (Rădăşanu, 2016). Effective inventory management required continuous organizational efforts to improve system performance, particularly in addressing challenges arising from increasingly complex and globalized business environments.

Warehouse Material Classification and Management

Material classification plays a crucial role in inventory planning and management. The classification of materials significantly influences inventory control policies and decision-making processes. By implementing an appropriate material classification model, organizations can establish suitable inventory policies that help reduce lead times and improve the efficiency of spare parts management (Emar et al., 2021). In the spare parts management system of electric utility companies, spare parts are generally classified into five categories as follows:

- Strategic Category (Class A1): Spare parts with very high asset value and a very limited asset population.
- Strategic Category (Class A2): Spare parts with high asset value and a limited asset population.
- Critical Category (Class B1): Spare parts with relatively lower asset value and a large asset population.
- Critical Category (Class B2): Spare parts with significantly lower asset value and a very large asset population.
- Consumable Category (Class C): Frequently used items characterized by low asset value and the largest asset population

This study focuses on Strategic Category (Class A2) materials, specifically Current Transformers (CTs), for which the company applies an economic stock policy. Under this policy, spare parts procurement decisions are primarily determined by the availability of capital and the financial capacity of the company.

Poisson Distribution Model for Spare Parts Demand

The Poisson distribution is one of the discrete probability distributions that uses non-negative integers as random variables. It is commonly applied to estimate the probability of a given number of events occurring within a specified time interval, assuming that the events occur independently and at a known average rate. Selecting an appropriate demand distribution has a significant impact on inventory management performance, particularly in achieving the desired service level while maintaining cost efficiency (Syntetos et al., 2011). Stochastic inventory modeling based on the Poisson distribution has been widely used to predict random failure occurrences and corrective maintenance costs. This approach enables the estimation of unexpected costs arising from component failures that are not covered by scheduled or preventive maintenance activities (Andrzejczak et al., 2018). Furthermore, the Poisson distribution is particularly suitable for modeling low-frequency demand and randomly occurring spare parts requirements. Compared with the Weibull distribution, the Poisson approach is relatively simpler to implement and requires less detailed historical data, making it more practical for forecasting demand for slow-moving spare parts (Ugbosu & Apanapudor, 2024).

Poisson Distribution Model for Spare Parts Demand

The Poisson distribution can be used to represent the probability of various events occurring within a specified period. It is a flexible and widely applied probability distribution across multiple disciplines due to its ability to model the occurrence of discrete events. In the context of this study, the Poisson distribution is employed to represent the probability of transmission equipment failures, which serve as the basis for estimating spare parts requirements. The mathematical formulation of the Poisson distribution is expressed through its probability mass function (PMF), as shown in the following equation:

$$f(k, \lambda) = \frac{\lambda^k e^{-\lambda}}{k!}, k = 0, 1, 2 \ldots \tag{1}$$

where:

k = number of occurrences (non-negative integer: 0, 1, 2, ...)

λ = average number of occurrences within a specified time interval (occurrences per unit time)

e = Euler's number, approximately equal to 2.718

This equation provides the probability that exactly (k) events will occur within a specified time interval, assuming that the events occur independently and at a known average rate. For example, if the average occurrence rate is three events per minute and the probability of the number of events occurring within a 20-minute interval is to be determined, the Poisson distribution can be applied with a parameter value of $\lambda = 20 \times 3 = 60$.

Furthermore, the Poisson distribution can be used to estimate the confidence level that the available spare units will be sufficient to replace failed units within a system. In other words, this formulation assists in determining the number of spare units required to ensure that the system continues to operate at a specified confidence level. Accordingly, the Poisson formulation can be expressed as follows:

$$CL \leq \sum_{k=0}^{S} \frac{(n\lambda R)^k e^{-(n\lambda R)}}{k!} \qquad (2)$$

For k = 0 to S,

where:

- n = number of units currently operating in the system (units)
- λ = average number of occurrences within a specified time interval (occurrences per unit time)
- e = Euler's number, approximately equal to 2.718
- R = average repair time (hours) or spare part Lead time from the material requisition process until the material becomes available in the warehouse (time period)
- CL = desired confidence level (%)
- S = minimum number of spare units required (units)
- k = number of spare units (units)

Transmission spare parts are maintained to restore equipment to its normal operating condition following failures or operational disturbances. When equipment failures occur, defective components are immediately replaced with new spare parts to ensure system continuity and reliability. In this context, it is assumed that whenever inventory is depleted, an emergency order can be placed to obtain the required spare part through expedited delivery, albeit at an additional cost.

According to previous research, a cost-based modeling approach has been developed for non-repairable spare parts components. This approach is designed to estimate the expected total cost over a specified planning horizon by considering several major cost elements (Louit et al., 2011). The primary cost components include the initial acquisition cost, emergency procurement cost, and the residual value of unused spare parts. These cost considerations are incorporated into the calculation of the expected total cost for each spare parts stocking decision, enabling the determination of the optimal number of spare units required. The expected total cost can be calculated using the following equation:

$$E(C_T) = (C_r - D_T)S + D_T\, E(N_T) + (C_e - D_T)\, E(N_T - S)_+ \qquad (3)$$

where:

- C_r = initial acquisition/regular cost (IDR)
- C_e = emergency cost (IDR)
- D_T = salvage value (IDR)
- T = time interval, assuming that a quantity of spare parts is purchased at the beginning of the interval (hours/days/months/years)

S = number of spare parts purchased at the beginning of the interval (units)

$E(N_T)$ = expected number of spare parts required during the time interval T, estimated based on the Poisson parameter (units)

$E(N_T\text{-}S)^+$ = number of spare units (units)

This approach accounts for the stochastic nature of spare parts demand over a specified time interval $T$by employing an appropriate probability distribution, such as the Poisson or normal distribution. The expected demand for spare parts, $E(N_T)$, is derived from the corresponding probability distribution. The expected number of spare part replacements that exceed the initial inventory level during the interval Tcan then be estimated using the following expression:

$$\begin{aligned} E(N_T - S)_+ &= \sum_{k>S}(k-S)\,P(N_T = k) = a\big(1 - P(N_T \le S-1)\big) - S(1 - P(N_T \le S)) \\ &= a\big(1 - P(N_T \le S-1)\big) - S(1 - P(N_T \le S)) \\ &= a\left(1 - \sum_{k=0}^{S-1} \frac{a^k}{k!} e^{-a}\right) - S\left(1 - \sum_{k=0}^{S} \frac{a^k}{k!} e^{-a}\right) \end{aligned} \quad (4)$$

where:

$P(N_T = k)$ = probability that the number of spare part replacements required during the time interval $T$is equal to k

a = Poisson parameter, obtained from $n \times \lambda \times R$ as defined in Equation (2)

Application of the Risk Pooling Concept in Spare Parts Inventory Management

Risk pooling in inventory management offers several advantages, including a reduction in demand variability at the pooled inventory location relative to the variability observed across individual stocking locations. Furthermore, inventory aggregation improves stock utilization and enhances inventory management efficiency, leading to lower overall inventory costs. Nevertheless, inventory costs may increase with greater demand uncertainty and variability (Berman et al., 2011). Previous studies have also demonstrated that risk pooling can mitigate spare parts obsolescence, thereby reducing waste and asset disposal costs associated with obsolete inventory (Yilmaz, 2025). This outcome is achieved through the redistribution and shared utilization of spare parts among organizations participating in a cooperative pooling arrangement, enabling surplus inventory in one organization to satisfy demand in another (Hafner et al., 2021). The study was conducted by comparing the existing inventory management policy without risk pooling against two alternative scenarios: complete risk pooling and partial risk pooling. The proposed formulations are adapted and simplified from an inventory pooling model that evaluates non-pooling, complete pooling, and partial pooling strategies within a system consisting of two independent retailers (Silbermayr & Gerchak, 2019). The underlying assumptions and model formulations are presented as follows:

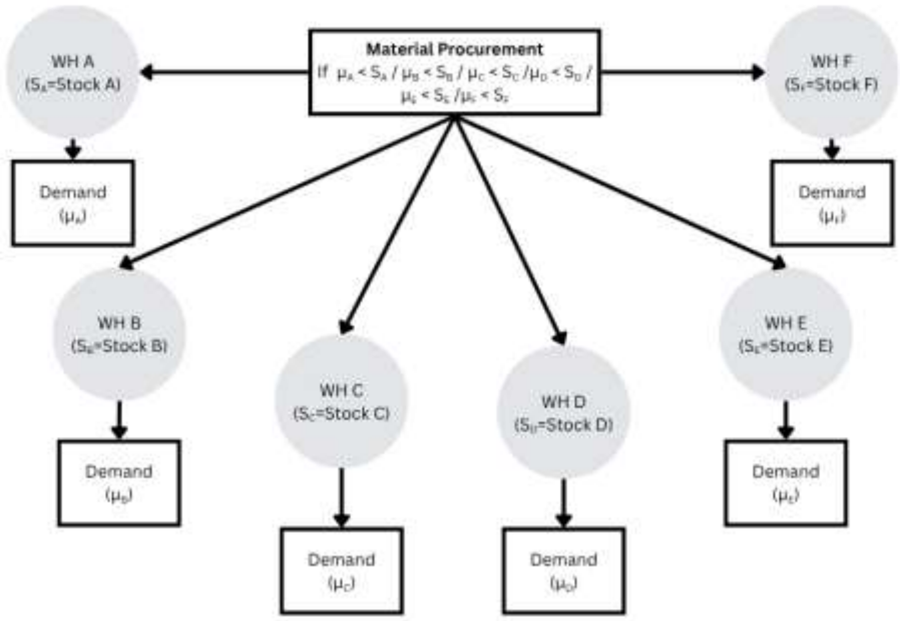

Figure 1. No risk pooling model

Source: Adapted from Silbermayr & Gerchak, 2019; modified by the authors

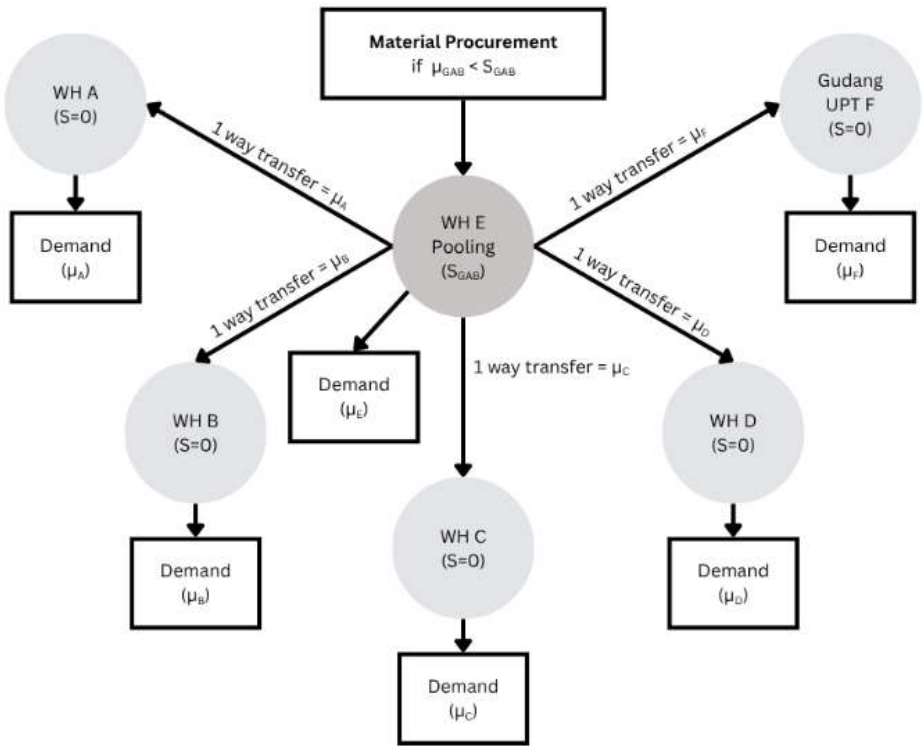

Figure 2. Full risk pooling model

Source: Adapted from Silbermayr & Gerchak, 2019; modified by the authors

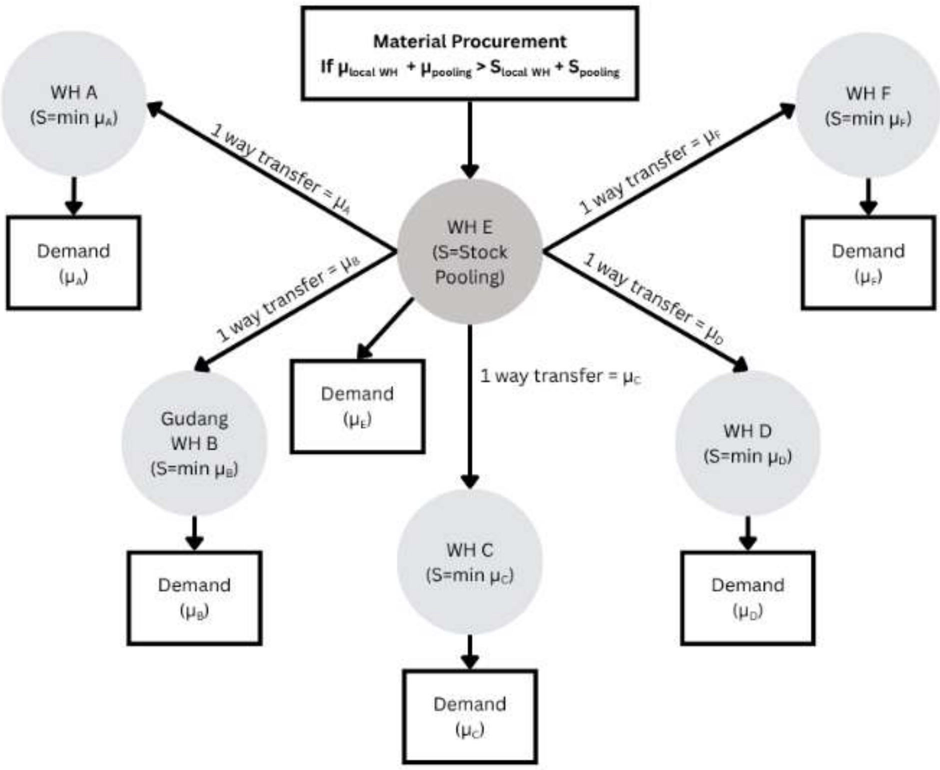

Figure 3. Partial risk pooling model

Source: Adapted from Silbermayr & Gerchak, 2019; modified by the authors

RESULTS AND DISCUSSION

The study adopted a systematic research methodology comprising six sequential phases: (1) quantitative data collection; (2) simulation of spare parts demand using a Poisson-based approach; (3) risk pooling simulation; (4) data analysis and interpretation; (5) verification and validation of the results; and (6) formulation of conclusions and recommendations. Figure 4 illustrates the overall research framework and the complete research pipeline implemented in this study.

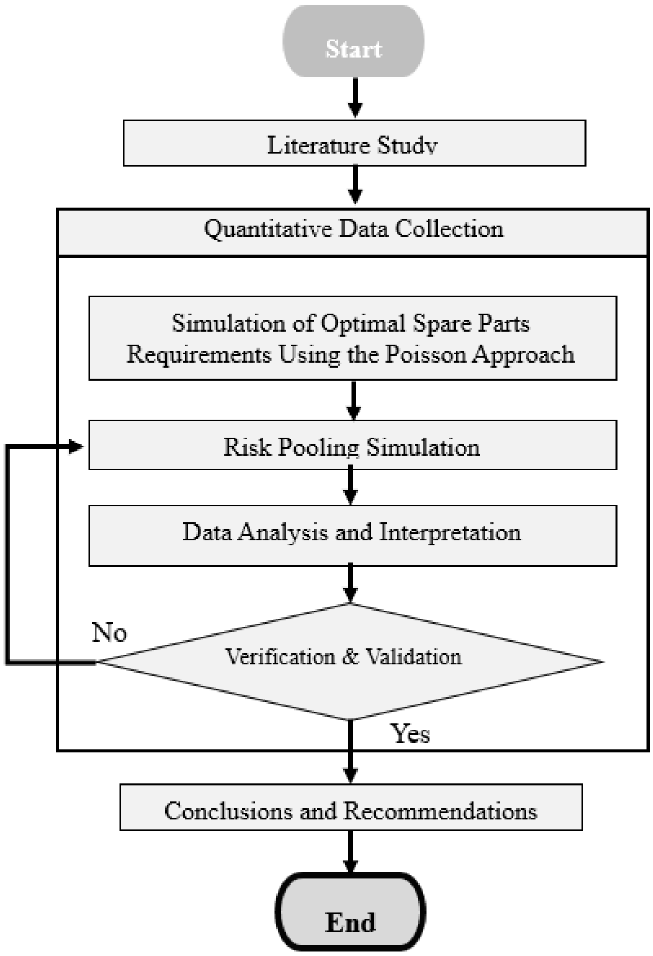

Figure 4. Research Workflow Diagram

Source: Authors' documentation, 2024

Data Collection

Data collection was conducted to obtain information on spare parts inventory levels, spare parts consumption over a seven-year period, the population of installed equipment, and cost-related data associated with spare parts. The collected data are presented in Table 1.

Table 1. Current Transformer (CT) Spare Parts Inventory Data at Each Warehouse

Tabel 1: Data Material & Gudang

Type of Material	Warehouse	Regular cost	Stock	Population	Failure in 7 years
Current Transformer (CT)	WH A	169.261.880	0	471	33
	WH B	169.261.880	3	786	41
	WH C	169.261.880	125	1122	95
	WH D	169.261.880	20	981	129
	WH E	169.261.880	9	1026	51
	WH F	169.261.880	18		

Regular cost, Cr	169.261.880
Emergency cost, Ce	225.682.507
Salvage value, DT	167.146.107
Confident level	99%

Source: Company data processed by the authors, 2024

Spare Parts Requirement Estimation Using the Poisson Distribution

The spare parts requirement estimation was carried out through three calculation stages. First, the required quantity was estimated using the Poisson distribution. Second, the Poisson-based estimation was refined by incorporating a minimum-cost criterion. Third, a normalization process was performed to scale the results obtained from the previous two calculations, using the highest scale value as the reference. To illustrate the calculation procedure, a case study involving a current transformer (CT) at Warehouse A (WH A) is presented as follows.

- The first step was to calculate the failure rate.
  Failure Rate (λ) = Number of Failures/(n x T)
  = 33/(471 x 7)
  = 0,010
- The second step was to determine the Poisson parameter.
  The Poisson parameter was calculated by considering the installed equipment population (n) and the procurement lead time (R).

  Poisson Parameter = n×λ×R
  = 471 × 0,010 × 0,5
  = 2,3571
- The third step was to estimate the spare parts requirement.
  The spare parts requirement was estimated using the Poisson distribution based on a confidence level (probability of occurrence) of 99%.
  By applying Equation (2), the results shown in Table 2 were obtained.

Table 2. Poisson-Based Estimation Results Using the Confidence Level Approach

Spare (k*)	P_indv	P_Cumulative	%P
0	0,09469	0,09469	9,47
1	0,22320	0,31789	31,79
2	0,26306	0,58094	58,09
3	0,20669	0,78763	78,76
4	0,12180	0,90943	90,94
5	0,05742	0,96685	96,68
6	0,02256	0,98941	98,94
7	**0,00760**	**0,99700**	**99,70**
8	0,00224	0,99924	99,92
9	0,00059	0,99983	99,98
10	0,00014	0,99996	100,00
11	0,00003	0,99999	100,00
12	0,00001	1,00000	100,00
13	0,00000	1,00000	100,00
14	0,00000	1,00000	100,00
15	0,00000	1,00000	100,00
16	0,00000	1,00000	100,00

Max	100,00
Min	9,47
Target	99,00
Selected spares	7,00

Source: Authors' calculation based on company data, 2024

Based on Table 2, the projected spare parts requirement at a 99% confidence level indicates an expected material demand (k) of 7 units. Meanwhile, the minimum probability value is 8.82%, corresponding to $k = 0$units, whereas the cumulative probability reaches 100% for $k > 10$ units.

The next stage, which is still based on the Poisson approach, involved estimating spare parts requirements using the minimum-cost criterion. By applying Equations (3) and (4), and incorporating the initial acquisition cost of the spare part, the emergency procurement cost, and the salvage value of unused inventory remaining in the warehouse, the following results were obtained.

Table 3. Poisson-Based Estimation Results Using the Minimum Cost Approach

Cr	169.261.880
Ce	225.682.507
DT	167.146.107

Spare (S)	**(Cr-DT)S**	**DT(E(NT)**	**(Ce-DT)E(NT-S)+**	**Sum, E (CT)**
0	-	393.987.251	137.978.658	531.965.909
1	2.115.774	393.987.251	84.985.091	481.088.116
2	4.231.547	393.987.251	45.056.777	443.275.575
3	6.347.321	393.987.251	20.526.795	420.861.366
4	8.463.094	393.987.251	8.095.502	410.545.847
5	**10.578.868**	**393.987.251**	**2.793.795**	**407.359.913**
6	12.694.641	393.987.251	853.177	407.535.069
7	14.810.415	393.987.251	232.988	409.030.654
8	16.926.188	393.987.251	57.433	410.970.872
9	19.041.962	393.987.251	12.886	413.042.098
10	21.157.735	393.987.251	2.651	415.147.637
11	23.273.509	393.987.251	503	417.261.263
12	25.389.282	393.987.251	89	419.376.622
13	27.505.056	393.987.251	15	421.492.321
14	29.620.829	393.987.251	2	423.608.082
15	31.736.603	393.987.251	0	425.723.854
16	33.852.376	393.987.251	0	427.839.627

Max	531.965.909
Min	407.359.913
Selected spares	**5**

Source: Authors' calculation based on company data, 2024

Based on Table 3, the spare parts requirement projection obtained using the cost-minimization approach indicates that the lowest expected cost is achieved with an inventory level of 5 units. The minimum expected cost is IDR 407.359.913, corresponding to a spare parts requirement of 5 units, whereas the maximum expected cost is IDR 531.965.909 when no spare parts inventory is procured.

Two Poisson-based estimation results were obtained, namely the projection based on the confidence level criterion and the projection based on the minimum expected cost criterion. The two approaches yielded different results, corresponding to inventory levels of 7 units and 5 units, respectively. Therefore, a scale normalization procedure was applied to integrate the outcomes of both approaches by selecting the highest normalized scale value. This procedure was intended to identify the optimal inventory level that simultaneously achieves a high confidence level and the lowest expected cost.

To perform the scale normalization, the minimum and maximum values obtained from the first and second calculation stages were required. The normalization process was conducted using the following equation:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

where:

X' = Normalized value

X = Observed data value

Xmin = Minimum value of the dataset

Xmax = Maximum value of the dataset

Based on the calculation results, the largest gap between the two normalized scales can be identified, indicating that the selected spare parts requirement represents the most appropriate inventory level by simultaneously considering both a high confidence level and the lowest expected cost. The scale normalization results for various spare parts inventory scenarios are presented in Table 4, while the corresponding graphical representation is shown in the figure below.

Table 4. Min–Max Scale Normalization Results

Spare	Poisson	Min. Cost	Optimization
0	0,00000	1,00000	-1,000
1	0,24654	0,59169	-0,345
2	0,53711	0,28823	0,249
3	0,76542	0,10835	0,657
4	0,89996	0,02557	0,874
5	0,96338	0,00000	0,963
6	**0,98830**	**0,00141**	**0,987**
7	0,99669	0,01341	0,983
8	0,99916	0,02898	0,970
9	0,99981	0,04560	0,954
10	0,99996	0,06250	0,937
11	0,99999	0,07946	0,921
12	1,00000	0,09644	0,904
13	1,00000	0,11342	0,887
14	1,00000	0,13040	0,870
15	1,00000	0,14738	0,853
16	1,00000	0,16436	0,836

Target Value	0,987
Selected spares	6

Source: Authors' calculation, 2024

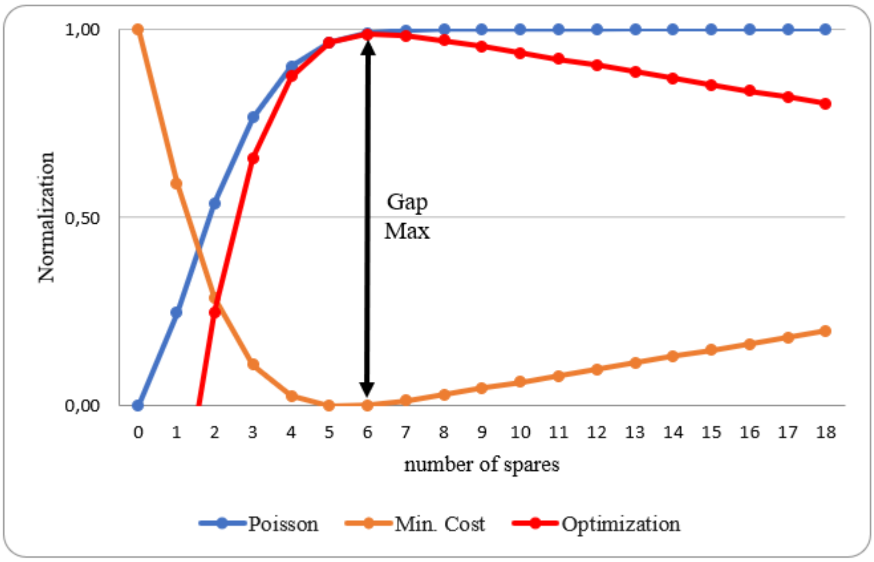

Figure 5. Scale Normalization Graph

Source: Authors' calculation and analysis, 2024

The calculation procedure was subsequently applied to the remaining warehouse locations following the same sequence of steps described previously. The results of the calculations are presented in Table 5.

Table 5. Recapitulation of Current Transformer (CT) Spare Parts Demand Projections

Material Type	Warehouse	Poisson-Based Estimation (Confidence Level Approach)	Poisson-Based Estimation (Minimum Cost Approach)	Min-Max Scale Normalization
Current Transformer (CT)	WH A	7	5	6
	WH B	8	6	7
	WH C	14	12	14
	WH D	17	15	18
	WH E	9	7	9
	WH F	18	8	17

Source: Authors' calculation based on company data, 2024

Comparing Company Policy Projections and Poisson Projections on The Impact of Inventory Management

Based on the projected spare parts requirements obtained from the Poisson calculations, warehouse operation simulations were subsequently conducted to evaluate and compare warehouse-related costs and fill rates resulting from the implementation of the company's existing 2% inventory policy and the proposed Poisson-based approach. The demand pattern was conditioned using historical consumption data. For illustrative purposes, the warehouse operation simulation presented below uses the Current Transformer (CT) inventory at Warehouse A (WH A) as a case study.

Table 6. Warehouse Operation Simulation for Current Transformer (CT) Spare Parts Projection at WH A

WH A

Company Policy

Periode	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Demand		0	3	0	0	15	15	0	3	0	12	**48**
Procurement		10	10	10	10	10	10	10	10	10	10	**100**
inventory	0	10	17	27	37	32	27	37	44	54	52	**337**

Poisson Approach

Periode	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Demand		0	3	0	0	15	15	0	3	0	12	**48**
Procurement		6	6	6	6	6	6	6	6	6	6	**60**
inventory	0	6	9	15	21	12	3	9	12	18	12	**117**

Source: Authors' simulation results, 2024

Based on the simulation and calculation results, the projected requirement for Current Transformer (CT) spare parts using the Poisson-based approach was lower than the projection derived from the company's policy of maintaining inventory equivalent to 2% of the installed equipment population. In Warehouse A, which was selected as the representative sample, the projected spare parts requirement decreased by approximately 40%. Furthermore, the average reduction in projected spare parts requirements across Warehouses A to F was approximately 36%. However, the average fill rate achieved under the Poisson-based approach was approximately 5% lower than that obtained under the 2% inventory policy. Therefore, in this case study, the Poisson-based projection provided cost advantages at the expense of a slight reduction in service performance as measured by the fill rate. Furthermore, the projected inventory balance at the end of the tenth year was substantially lower under the Poisson-based approach than under the 2% policy, with an average inventory reduction of approximately 55%. This finding indicates that the Poisson-based projection can effectively reduce the risk of excess inventory accumulation and improve inventory utilization by minimizing the amount of unused spare parts.

Simulation of No Risk Pooling, Full Risk Pooling, and Partial Risk Pooling Models over a Ten-Year Period

The simulation model requires demand projections over a ten-year planning horizon. In this study, the demand projections were generated using the Monte Carlo simulation method. This method was selected because it estimates future demand based on the probability of occurrence of events within a given period and randomly projects these occurrences into subsequent periods. Monte Carlo simulation is particularly suitable for representing uncertain and highly variable demand patterns, as it relies on the probability distribution derived from historical data (Alawiyah, 2026).

The simulation of the three risk pooling schemes was conducted using Current Transformer (CT) spare parts as the case study. The selection of the pooling warehouse was based on considerations of power system vulnerability and the magnitude of power loss resulting from equipment failures that could lead to service interruptions. In aggregate, the operational zone located near Warehouse E (WH E) exhibits the highest level of system vulnerability, with the greatest estimated power loss under an N–1 contingency condition. To ensure a fair comparison among the three inventory models, the spare parts inventory levels were adjusted to maintain the same total stock quantity across all simulation scenarios. The data used for the simulation setup are presented as follows.

Table 7. Ten-Year Demand Forecasting Through Monte Carlo Simulation

Type of Material	Warehouse	Stock (without RP)	Stock (Full RP)	Stock (Partial RP)	Demand Projection in 10 years									
					1	2	3	4	5	6	7	8	9	10
Current Transformer (CT)	WH A	17		6	0	3	0	0	15	15	0	3	0	12
	WH B	20		7	0	0	4	0	31	6	4	4	0	6
	WH C	39		14	0	19	17	19	5	0	15	22	0	22
	WH D	51		18	0	3	10	17	17	3	18	0	18	0
	WH E	25	200	138	22	0	8	3	3	22	3	3	12	3
	WH F	48		17	116	0	5	5	0	0	0	15	5	

Source: Authors' Monte Carlo simulation results, 2024

Furthermore, to ensure that each inventory model incurred a relatively comparable holding cost, inventory replenishment was performed whenever a stockout occurred, with the replenishment quantity equal to the shortage amount. Stockout events within the simulation were evaluated using the fill rate metric. The remaining performance measures were consistent with those applied in the previous analysis, including holding costs, procurement costs, and transportation costs. The detailed simulation results are provided in the Appendix, while a summary of the results is presented in Table 8 below.

Table 8. Summary of Warehouse Operation Simulation Results Under No Risk Pooling and Risk Pooling Schemes

Indikator	CT		
	No Risk Pooling	Full Risk Pooling	Partial Risk Pooling
Material Procurement Cost	56.871.991.680	56.364.206.040	56.364.206.040
Holding Cost (HC)	41.443.229.680	26.946.626.706	33.470.098.044
Inter-Warehouse Transportation Cost	-	2.519.551.072	2.100.362.560
Total Cost	**98.315.221.360**	**85.830.383.818**	**91.934.666.644**
Fill Rate (%)	57%	20%	50%
Disruption Response	Fast	Slow	Moderately Fast

Source: Authors' simulation results, 2024

The holding cost analysis indicates that the full risk pooling scheme achieves the lowest holding cost, which is 34% lower than the no risk pooling scheme and 19% lower than the partial risk pooling scheme. Conversely, the no risk pooling scheme demonstrates a significant advantage in terms of equipment replacement responsiveness compared with both the partial and full risk pooling schemes. As long as sufficient spare parts inventory is maintained at each branch warehouse to satisfy user demand, a higher service level can be sustained. Under the no risk pooling scheme, the primary operational focus is on demand responsiveness, transportation distance, and service level performance (Milewski, 2020).

The partial risk pooling scheme exhibits performance characteristics that lie between those of the no risk pooling and full risk pooling schemes. In terms of total cost, the partial risk pooling scheme reduces total inventory costs by IDR 6.38 billion compared with the no risk pooling scheme, while experiencing only a 7% reduction in fill rate. In contrast, compared with the full risk pooling scheme, the partial risk pooling scheme incurs an additional cost of IDR

6.10 billion but achieves a 30% improvement in fill rate.

Considering the overall performance in terms of total cost, fill rate, and disruption response capability, the partial risk pooling scheme is recommended as the preferred spare parts inventory management strategy. This scheme provides a balanced trade-off between cost efficiency and service performance, thereby supporting both operational responsiveness and inventory optimization objectives.

CONCLUSION

Based on spare parts requirement estimation, the Poisson-based approach applied to Current Transformer (CT) spare parts, using installed equipment population data, historical equipment failure records from the previous seven years, and procurement lead times, resulted in lower inventory requirements compared with the company's existing spare parts planning policy. Across Warehouses A–F, the Poisson-based approach reduced projected spare parts requirements by an average of 36% compared with the existing policy. This reduction was expected to contribute directly to lower procurement and inventory holding costs.

The simulation results indicated that the full risk pooling scheme provided the highest holding cost efficiency; however, it exhibited limitations in service level performance and disruption responsiveness. Conversely, the no risk pooling scheme achieved superior fill rate performance and faster equipment replacement response but resulted in higher inventory costs. Among the evaluated alternatives, the partial risk pooling scheme demonstrated the most balanced performance. Compared with the no risk pooling scheme, it generated cost savings of approximately IDR 6.38 billion while resulting in only a modest 7% reduction in fill rate. Furthermore, compared with the full risk pooling scheme, the partial risk pooling scheme improved the fill rate by 30% with an additional cost of approximately IDR 6.10 billion. Therefore, considering total cost, service level (fill rate), and disruption response capability, the partial risk pooling scheme was recommended as the optimal spare parts inventory management strategy. This approach provided the most appropriate balance between cost efficiency and service performance, thereby supporting inventory optimization and the operational reliability of the transmission system.

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