Vol. 7, No. 8, August 2026
E-ISSN:2723 – 6692 P-ISSN:2723– 6595
http://jiss.publikasiindonesia.id/

Design of a Cycle Counting Model Based on ABC-XYZ Classification in the Operational Materials Warehouse of PT X

Yudha Koessala Puja Andhika*, Iwan Vanany
Institut Teknologi Sepuluh Nopember, Indonesia
Email: yudhakoessala@gmail.com*, iwan.vanany@gmail.com

Keywords:
Warehouse;
Inventory Accuracy;
ABC-XYZ;
Cycle Counting;
Inventory Management.

Abstract

Inventory accuracy is essential for maintaining the reliability of power plant operations. PT X currently relies on annual physical stocktaking as its inventory control method; however, the average inventory accuracy during 2022–2024 was only 67.15%, below the company's target of at least 95%. This condition highlights the need for a more effective inventory control method capable of detecting discrepancies earlier and continuously. This study aims to develop an ABC-XYZ classification-based cycle counting model to improve inventory control in PT X's operational material warehouse. A quantitative approach was employed by analyzing Annual Consumption Value (ACV) and material demand patterns to determine inventory priorities and cycle counting frequencies. The results show that 253 items (10.4%) classified as Category A contributed 80% of the annual consumption value, while Category Z accounted for 66.3% of total items, indicating highly irregular demand patterns. Implementation of the proposed model during the first quarter of 2026 was completed largely according to schedule, with an overall completion rate of 83.0% and an average inventory discrepancy of 2%. The proposed model has the potential to help the company reach its inventory accuracy target, accelerate discrepancy detection without interrupting warehouse operations, and provide a more effective inventory control framework for PT X.

INTRODUCTION

PT X is a company unit engaged in the operation and maintenance of power generation plants, playing an important role in maintaining the reliability of electricity supply for the public and industrial sectors (Bornberg & Khaerunnisa, 2025; Gunarto, 2026; Hillenbrand, 2024; Ratten, 2022). The success of plant operations is determined not only by the performance of the main generation equipment but also by the effectiveness of supporting resource management, one of which is the management of materials and spare parts stored in the warehouse. The warehouse functions as a storage and management facility for consumable materials, as well as mechanical, electrical, and instrument spare parts that support preventive, corrective, and predictive maintenance activities. Failure to provide the required materials can lead to maintenance delays, decreased equipment reliability, and potential disruptions to plant operations (Al-Douri et al., 2022; Daya & Leonard, 2025; Peng et al., 2023; Vital-Soto & Olivares-Aguila, 2023; West et al., 2024).

Experts agree that the inventory accuracy target should be set at a level of ≥95% (Jeffrey C. Steinhoff, 2002). However, actual conditions show that PT X's inventory data accuracy has not yet reached this level, as demonstrated by the following historical annual stock opname (physical stocktaking) data.

Table 1. Historical Annual Stock Opname Data of PT X

Period	Duration (Days)	ERP Qty	Actual Physical Qty	Inventory Accuracy (%)
2022	29	50,826	33,893	66.68%
2023	27	41,956	24,119	57.49%
2024	30	49,666	38,389	77.29%

Source: PT X Warehouse Annual Stock Opname Report (2022–2024)

PT X's average inventory accuracy during 2022–2024 was only 67.15%, far below the company's target of ≥95%. This inaccuracy also contributed to high dead stock and potential dead stock values during the same period, reaching IDR 16.30 billion (2022), IDR 40.10 billion (2023), and IDR 23.13 billion (2024), respectively.

Previous studies have extensively examined inventory management techniques and their application in various industrial contexts. Frazelle (2016) established that world-class warehousing requires inventory accuracy levels of 98–99%, achievable through systematic cycle counting programs. Waters (2008) emphasized that inventory accuracy is fundamental to effective inventory management, as inaccurate records lead to stockouts, excess inventory, and increased operational costs. Dehoratius et al. (2023) demonstrated that inventory accuracy cannot be guaranteed through preventive improvements alone such as procedures, technology, or warehouse layout because inventory errors continue to arise from daily transaction activities, making continuous detection and correction processes essential.

The ABC classification method has been widely applied to prioritize inventory management efforts based on economic value (Ayalew et al., 2025; Kaabi, 2022; Khanorkar & Kane, 2023; Nurprihatin et al., 2025; Paredes Rodríguez et al., 2023). Studies by Pandya and Thakkar (2016) and Stojanović and Regodić (2017) have shown that ABC analysis enables organizations to focus resources on high-value items that contribute most to consumption value. Meanwhile, XYZ classification groups materials based on demand pattern stability, with Kubasakova and Kubanova (2024) demonstrating its effectiveness in stock planning during periods of demand uncertainty. The integration of ABC and XYZ classification into a 9-quadrant matrix has been recognized as a powerful tool for inventory control, allowing organizations to determine appropriate counting frequencies and control intensities for different material categories (Turker et al., 2025).

Research on cycle counting implementation has also developed considerably. Rafael et al. (2023) examined the impacts of inventory record inaccuracy and cycle counting on distribution center performance, finding that cycle counting significantly improves accuracy and operational efficiency. Wijffels et al. (2016) developed an enhanced cycle counting approach utilizing historical inventory data, while Bagus et al. (2025) implemented an ABC-based cycle counting design in a poultry processing plant warehouse. Rossetti et al. (2001) provided a comprehensive review of inventory cycle counting methodologies, emphasizing the importance of prioritization in determining counting frequencies.

One of the main factors behind the low inventory accuracy is the control method, which still relies on annual stock opname a reactive approach that only provides a snapshot of inventory conditions at a single point in time. Dehoratius et al. (2023) emphasize that inventory accuracy cannot be guaranteed through preventive improvements alone, such as procedures, technology, or warehouse layout, because inventory errors continue to arise from daily transaction activities. Cycle counting is regarded as a more effective, continuous detection and correction process compared to periodic stock opname, as it can identify discrepancies early without halting warehouse operations.

PT X's warehouse has characteristics that differ from typical retail or manufacturing warehouses: a very large number of items (SKUs) with uneven usage levels, a small proportion of items that are highly critical to unit reliability while the majority are rarely used, unstable demand patterns particularly for corrective maintenance spare parts and highly varied item values. The effectiveness of cycle counting depends heavily on prioritizing which items to count given limited warehouse resources, making the application of ABC-XYZ classification relevant: ABC classification groups materials based on their economic importance, while XYZ classification groups materials based on the stability of their demand patterns. To date, no structured cycle counting model has been developed that matches the characteristics of PT X's operational materials warehouse, and this study therefore designs such a model as a guideline for sustainable inventory control.

Based on the above description, the research problems addressed in this study include: (1) the current condition of PT X's operational material inventory accuracy; (2) the characteristics of materials when classified using the ABC-XYZ method; (3) the design of a cycle counting model based on ABC-XYZ classification; and (4) the effect of implementing this model in PT X's warehouse. The corresponding research objectives are to analyze current inventory accuracy, classify materials using the ABC-XYZ method, design a cycle counting model, and evaluate conditions after model implementation. This study is limited to PT X's operational materials warehouse, focusing on the control aspect (cycle counting) rather than preventive aspects (layout improvement, technology, SOPs, or human resources), and does not consider external factors such as procurement policy, supplier performance, or regulatory changes.

METHOD

This study employed a quantitative approach through a case study of PT X's operational materials warehouse. The research stages include data collection, data processing (ABC-XYZ classification and cycle counting model design), implementation, and analysis of results and conclusions.

Data Collection

Secondary data were collected by extracting data from PT X's Enterprise Resource Planning (ERP) system, including stock opname results from previous years, material master data (item catalog, item name, item quantity, receipt and issuance transaction history, unit price, and frequency of use), as well as warehouse management procedure data, including PERDIR No. xxx.P.DIR.2024 on the Warehouse Governance System within PT X. Material usage data were collected for a nine-year period (2017–2025), covering 2,429 material items.

Data Processing: ABC-XYZ Classification

ABC classification was calculated using Equations (1)–(3), based on the average annual usage of each material over nine years multiplied by its unit price, then ranked and grouped according to cumulative ACV percentage. XYZ classification was calculated using Equations (4)–(6), based on the average and standard deviation of annual usage, then grouped according to the Coefficient of Variation value. The results of both classifications were then combined into a 9-quadrant matrix (AX, AY, AZ, BX, BY, BZ, CX, CY, CZ) following the framework described in Section 1.5.

Cycle Counting Model Design

The design of the cycle counting model is based on the principle that more important and critical materials should be counted more frequently than less critical materials. Counting frequency was determined based on the ABC-XYZ matrix as follows.

Table 2. Cycle Counting Frequency Based on ABC-XYZ Classification

ABC-XYZ Class	Cycle Count Frequency	CC Priority
AX	Weekly	1 – Very High
AY	Weekly	2 – Very High
AZ	Monthly	3 – High
BX	Monthly	4 – High
BY	Quarterly	5 – Medium
BZ	Quarterly	6 – Medium
CX	Semi-annual	7 – Low
CY	Semi-annual	8 – Low
CZ	Annual	9 – Very Low

Source: Authors' cycle counting model design based on ABC-XYZ classification framework (2026)

Based on these frequencies, a cycle counting schedule was developed in the form of a 52-week calendar, along with staff assignments (a rotation of five officers, with two officers on duty each week, following the blind count principle in which the ERP balance is not displayed during the physical count to maintain objectivity), and a standard procedure comprising five stages: (1) preparation (data mapping, printing blind count worksheets, staff briefing); (2) physical count execution (counting, recording, checking for hanging tag and barcode availability); (3) verification and reconciliation (comparing count results with ERP balances, recounting to confirm discrepancies, root cause analysis); (4) ERP balance correction (inputting corrections, document archiving, notification of relevant departments); and (5) reporting and follow-up (accuracy calculation, monthly dashboard updates, improvement recommendations). The research flow diagram and model implementation stages are shown in Figures 2 and 3.

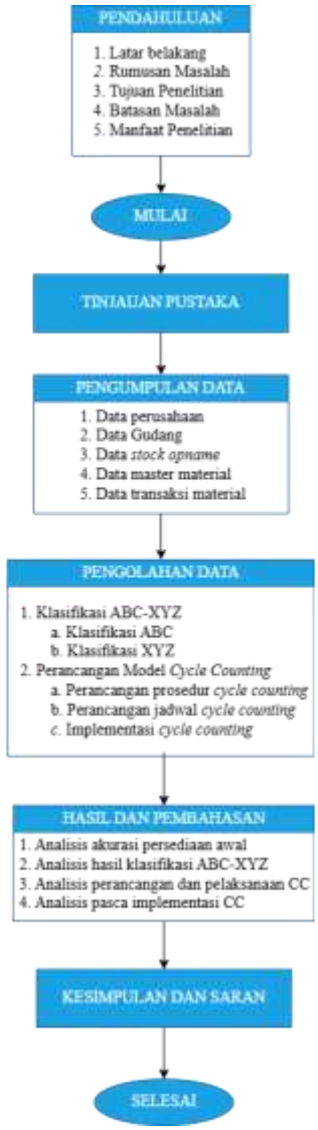

Figure 1. Research Flow Diagram
Source: Authors' research design and methodology (2026)

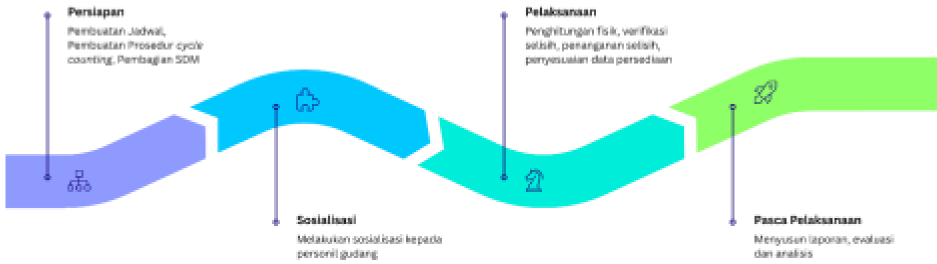

Figure 2. Cycle Counting Implementation Stages
Source: Authors' cycle counting model design (2026)

Model implementation was carried out at PT X during January–March 2026, consisting of a preparation stage (week 1), socialization to warehouse staff and users (week 2), weekly physical counting (weeks 3 through 12), and a post-implementation stage involving analysis, Material Discrepancy Report preparation, and reconciliation through weekly Supply Chain Management meetings.

RESULTS AND DISCUSSION

Initial Inventory Accuracy Condition

PT X's historical annual stock opname data show inventory accuracy of 66.68% (2022), 57.49% (2023), and 77.29% (2024), with an average of 67.15% over the past three years. Compared with the Frazelle (2016) benchmark in Table 2, this condition consistently falls into the Poor category (<95%), indicating that inventory control has not been well managed, with the potential for high dead stock and unreliable material planning. The fluctuating pattern from 66.68% down to 57.49% before rising again to 77.29% indicates that accuracy improvements achieved in one stock opname period could not be sustained in the following period, consistent with the view of Dehoratius et al. (2023) that inventory accuracy cannot be guaranteed through periodic annual checks alone.

ABC Classification Results

PT X's inventory data as of December 31, 2025, recorded a total of 2,429 material items with a total stock quantity of 38,316 units and a total inventory value of IDR 22.43 billion, distributed across eight user categories: Mechanical (720 items, 41.7% of value), Primary Energy (367 items, 19.1% of value), Instruments (487 items, 18.4% of value), Bearings (174 items, 7.6% of value), Electrical (416 items, 6.2% of value), General Materials (228 items, 3.6% of value), Outage (35 items, 2.5% of value), and Operations (2 items, 0.9% of value). The Mechanical group dominates both in terms of item count and value, consistent with the large volume of mechanical components required in coal-fired power plant operations.

ACV calculations for all 2,429 items produced a total ACV of IDR 4,576,867,616.24. Based on cumulative ACV percentage, ABC classification resulted in Category A comprising 253 items (10.4% of total items) that contributed 80% of annual usage value, Category B comprising 391 items (16.1%), and Category C comprising 1,785 items (73.5%).

Table 3. Summary of ABC Classification Results

Category	Number of Items	% Items	% Value Contribution (ACV)
A	253	10.4%	80%
B	391	16.1%	15%
C	1,785	73.5%	5%

Source: Primary Data, Processed (2026)

The proportion of Category A items at PT X (10.4%) is relatively lower than the ideal 20% proportion in classical Pareto theory; however, this is still reasonable given the characteristics of a power plant warehouse, which has a very large number of SKUs concentrated in a relatively small number of high-value components.

XYZ Classification Results

XYZ classification of nine-year usage patterns (2017–2025) produced Category X comprising 754 items (31.0%), Category Y comprising 65 items (2.7%), and Category Z comprising 1,610 items (66.3%). The dominance of Category Z validates the characteristics of PT X's operational materials warehouse, which exhibits highly unstable and difficult-to-predict demand patterns, particularly for corrective maintenance spare part needs.

Table 4. Summary of XYZ Classification Results

Category	Number of Items	% Items	Characteristics
X	754	31.0%	Very stable usage ($CV < 0.50$)
Y	65	2.7%	Moderate usage ($0.50 \leq CV \leq 1.00$)
Z	1,610	66.3%	Highly fluctuating usage ($CV > 1.0$)

Source: Primary Data, Processed (2026)

ABC-XYZ Matrix

Integration of the ABC and XYZ classifications produced a 9-quadrant matrix. Quadrants AX (7 items) and AY (17 items) represent the most ideal condition high-value materials with relatively stable and predictable usage patterns covering routine operational needs such as coal feeder belts, liquid gaskets, penetrants, and dozer filters. Quadrant AZ contains 229 items with high consumption value but highly irregular usage patterns, dominated by mechanical, instrument, and primary energy materials, making it a top control priority despite its lower monthly cycle counting frequency compared to AX/AY. The most significant finding comes from quadrant CX, where 346 items are classified as dead stock (ACV close to zero) yet hold a physical stock value of IDR 7.12 billion, indicating working capital inefficiency in the form of non-moving materials and forming the basis for further evaluation recommendations beyond the scope of this study.

Based on this integration, the distribution of cycle counting frequency by classification is as follows: weekly frequency for AX/AY (24 items, 1.0%, 52 times/year); monthly for AZ/BX (237 items, 9.8%, 12 times/year); quarterly for BY/BZ (383 items, 15.8%, 4 times/year); semi-annual for CX/CY (762 items, 31.4%, 2 times/year); and annual for CZ (1,023 items, 42.1%, 1 time/year).

Further analysis of the ratio of inventory value to item count for each user group reveals differing levels of value concentration among groups, as shown in Table 6.

Table 5. Inventory Value Ratio Compared to Item Count per User Group

User Type	% Item Count	% Inventory Value	Value/Item Ratio
Mechanical	29.6%	41.7%	1.41
Primary Energy	15.1%	19.1%	1.26
Instruments	20.0%	18.4%	0.92
Bearing	7.2%	7.6%	1.06
Electrical	17.1%	6.2%	0.36
General Materials	9.4%	3.6%	0.38
Outage	1.4%	2.5%	1.79
Operations	0.1%	0.9%	9.00

Source: Primary Data, Processed (2026)

The Electrical and General Materials groups have ratios below 1 (0.36 and 0.38), indicating a large number of low-value items that are generally consumable in nature with insignificant criticality but that still require control due to their large volume. Conversely, the Operations and Outage groups have ratios well above 1, indicating few items but very high value per unit, meaning recording errors in these groups have a greater financial impact despite their low frequency.

Cycle Counting Implementation and Results

Implementation of cycle counting in the first quarter of 2026 (January–March) achieved an overall completion rate of 83.0% (1,453 of 1,750 scheduled tasks), with an average inventory discrepancy of 2.0%. Weekly realization is shown in Table 7.

Table 6. Cycle Counting Results, January–March 2026

Week	Period	Total Scheduled Items	Items Checked	% Progress	Discrepancy Count	% Discrepancy
W1	Jan 2–11	148	0	0.0%	0	0.0%
W2	Jan 12–18	149	0	0.0%	0	0.0%
W3	Jan 19–25	148	148	100.0%	7	4.7%

W4	Jan 26–Feb 1	137	137	100.0%	0	0.0%
W5	Feb 2–8	150	150	100.0%	6	4.0%
W6	Feb 9–15	147	147	100.0%	2	1.4%
W7	Feb 16–22	149	149	100.0%	1	0.7%
W8	Feb 23–Mar 1	140	140	100.0%	2	1.4%
W9	Mar 2–8	147	147	100.0%	2	1.4%
W10	Mar 9–15	146	146	100.0%	1	0.7%
W11	Mar 16–22	148	148	100.0%	6	4.1%
W12	Mar 23–29	141	141	100.0%	2	1.4%
TOTAL	–	1,750	1,453	83.0%	29	2.0%

Source: PT X Cycle Counting Implementation Report, Q1 2026 (Primary Data)

The 0% achievement in Weeks 1 and 2 does not represent implementation failure but rather reflects the preparation stage (determining ABC-XYZ classification, developing procedures) and socialization to warehouse staff and users before physical counting effectively began in Week 3. Accordingly, the more relevant schedule-compliance performance to evaluate is that from Week 3 through Week 12, all of which was realized 100% as scheduled indicating that the designed cycle counting model can be implemented consistently once the preparation stage is complete. Weekly workload ranged from 137–150 items, with no indication of significant workload imbalance across weeks or among staff under the five-officer rotation scheme. With checks conducted by two officers per week over an average of five working days, each officer checked approximately 15 items per day a relatively light workload that did not disrupt daily warehouse operations.

A recap of 57 findings during the implementation period shows that the largest causes of discrepancy were the categories 'zero stock requiring reorder' (27 findings) and 'material required before contract issuance' (15 findings), followed by 'material issuance liability due to financial transaction closing' (9 findings), '2025 SO discrepancy' (2 findings), 'emergency requirements' (2 findings), 'installation at external workshop' (1 finding), and 'unreadable barcode' (1 finding). In aggregate, 82.7% of all quantity discrepancies identified during cycle counting stemmed from administrative factors delayed recording of goods receipt and issuance rather than physical loss or damage to materials.

The accuracy pattern based on the ABC-XYZ matrix classification further reinforces the justification for this model's success. Quadrants AX and AY, checked weekly, recorded relatively lower conformity ratios of 90.0% and 94.7% compared to less frequently checked quadrants such as BY and CX at 98.7% and 99.4%. This pattern confirms that the early-detection mechanism for high-value AX/AY items successfully identified recording gaps within a matter of weeks, compared to the annual stock opname mechanism, which only detects accumulated discrepancies once a year, with potentially much larger discrepancy values that are more difficult to trace back to their root causes.

Comparison of Conditions Before and After Implementation

Table 7. Comparison of Conditions Before and After Cycle Counting

Indicator	Before (Annual Stock Opname 2022–2024)	After (Cycle Counting Q1 2026)
Control method	Annual stock opname (1x/year)	ABC-XYZ classification-based cycle counting
Discrepancy detection frequency/year	1x/year for all items	52x (AX/AY), 12x (AZ/BX), 4x (BY/BZ), 2x (CX/CY)
Average inventory accuracy	67.15%	Potential of up to 100%
Benchmark category (Frazelle, 2016)	Poor (<95%)	Excellent (98–99%)
Gap detection time range	Up to 12 months	1 week to 6 months
Operational downtime	At least 1 month	No downtime required

Source: Authors' comparison of pre- and post-implementation conditions (2026)

Applying the ABC-XYZ classification-based cycle counting model resulted in a potential inventory accuracy improvement of 33.85 percentage points, from an average of 67.15% to a potential of up to 100%, as inventory gaps can be identified and detected earlier, allowing corrective follow-up to be carried out promptly. This improvement also has the potential to exceed PT X's Supply Chain Management Pillar Asset Management Maturity Level KPI target of ≥95%, which had not been achieved through the annual stock opname mechanism over the past three years.

CONCLUSION

PT X's inventory accuracy during 2022–2024 fell into the Poor category, with an average of 67.15%, indicating that the inventory control system had not been effective. Implementation of cycle counting during January–March 2026 showed an average inventory discrepancy of 2%, indicating that stock data discrepancies still occur even with periodic checks, underscoring the need for cycle counting to be applied consistently and sustainably. ABC-XYZ integration successfully identified inventory control priorities, with quadrant AZ representing a high-risk group due to its high consumption value combined with uncertain demand. The presence of 346 items in quadrant CX, holding an inventory value of IDR 7.12 billion, shows that non-moving materials continue to tie up company capital and require further evaluation. The designed cycle counting model can be implemented effectively and consistently. Once the preparation stage was complete, the entire inspection schedule was realized as planned with an evenly distributed workload (137–150 items per week, or an average of 15 items per person per day), making implementation operational, balanced, and non-disruptive to routine warehouse activities. The application of ABC-XYZ classification-based cycle counting proved more effective than annual stock opname, with the potential to improve inventory accuracy from 67.15% to as high as 100% and to accelerate discrepancy detection from a maximum of 12 months to between 1 week and 6 months, without halting warehouse operations. The finding that 82.7% of discrepancies stemmed from delayed administrative recording, together with the higher number of findings in quadrants

AX/AY, confirms that cycle counting is able to detect and correct deviations earlier on a sustainable basis. Based on these findings, the ABC-XYZ classification-based cycle counting model is recommended for full implementation by PT X and other units as a routine inventory control method to replace or support the annual stock opname, supported by schedule compliance, refined SOPs, and improved transaction recording discipline. Future research is encouraged to further develop the model by integrating VED (Vital, Essential, Desirable) classification or other multi-criteria methods, so that cycle counting priorities also consider the criticality of materials to plant operational reliability, rather than consumption value and demand patterns alone. Further evaluation is also needed regarding the effectiveness of slow-moving or non-moving inventory in relation to the needs of plant operation and maintenance activities.

REFERENCES

Al-Douri, A., El-Halwagi, M. M., & Groth, K. M. (2022). Emergency shutdowns of propylene production plants: Root cause analysis and availability modeling. *Journal of Loss Prevention in the Process Industries, 80*, 104921.

Ayalew, A. B., Alemu, A. G., & Worku, A. M. (2025). The application of ABC-VED with multi-criteria analysis for drug inventory management. *Scientific Reports, 16*(1), 2328.

Bagus, F., Hari, A., & Waluyo, M. (2025). Implementasi rancangan cycle counting menggunakan metode analisis ABC di gudang teknis rumah potong ayam XYZ. *Jurnal Teknik Industri, 8*(1).

Bornberg, R., & Khaerunnisa. (2025). The social and spatial layers of Borobudur Temple compounds, Java, Indonesia. In *Sacred heritage and pilgrimages in cities* (pp. 123–143). Springer.

Daya, A., & Leonard, J. (2025). Maintenance plan improvement using failure mode effect and criticality analysis: A case study on mining equipment. *Engineering Science and Technology Journal, 6*(3), 86–103.

Dehoratius, N., Holzapfel, A., Kuhn, H., Mersereau, A. J., & Sternbeck, M. (2023). Mengevaluasi prosedur prioritas penghitungan untuk meningkatkan akurasi inventaris di toko ritel. *Manufacturing & Service Operations Management*.

Frazelle, E. H. (2016). *World-class warehousing and material handling* (2nd ed.). McGraw-Hill Professional.

Gunarto, H. (2026). *Magnificent Prambanan and Borobudur temples: UNESCO cultural heritage sites and symbol of Indonesian peace and religious harmony*. Arigato Publishing.

Hillenbrand, R. (2024). The Islamic art of Southeast Asia. In *Southeast Asian Islam* (pp. 234–262). Routledge India.

Kaabi, H. (2022). Comparative analysis of multicriteria inventory classification models for ABC analysis. *International Journal of Information Technology & Decision Making, 21*(5), 1617–1646.

Khanorkar, Y., & Kane, P. V. (2023). Selective inventory classification using ABC classification, multi-criteria decision making techniques, and machine learning techniques. *Materials Today: Proceedings, 72*, 1270–1274.

Kubasakova, I., & Kubanova, J. (2024). Pemanfaatan irisan analisis ABC dan XYZ dalam perencanaan stok di gudang pada masa Covid. *Acta Logistica, 11*(3), 461–472. https://doi.org/10.22306/al.v11i3.532

Nurprihatin, F., Prasetyo, Y. T., Chandra, R., Widiwati, I. T. B., Lestari, T. E., & Islam, S. S.

(2025). Strategic inventory control using economic order quantity and ABC classification to enhance operational excellence. In *2025 4th International Conference on Computational Modelling, Simulation and Optimization (ICCMSO)* (pp. 40–46).

Paredes Rodríguez, A. M., Bravo Bastidas, J. J., Osorio Gómez, J. C., Peña Orozco, D. L., & González Feliu, J. (2023). Fuzzy AHP TOPSIS methodology for multicriteria ABC inventory classification. *Journal of Engineering, 2023*(1), 7661628.

Peng, H., Li, S., Shangguan, L., Fan, Y., & Zhang, H. (2023). Analysis of wind turbine equipment failure and intelligent operation and maintenance research. *Sustainability, 15*(10), 8333.

Rafael, I., Hedler, F., Somensi, K., & Taboada, C. (2023). The impacts of inventory record inaccuracy and cycle counting on distribution center performance. *Production, 33*, e20220077. https://doi.org/10.1590/0103-6513.20220077

Ratten, V. (2022). Cultural conditions and heritage tourism in Southeast Asia. In *Driving entrepreneurship in Southeast Asia* (pp. 31–43).

Rossetti, M. D., Collins, T., & Kurgund, R. (2001). Inventory cycle counting: A review. In *Proceedings of the 2001 Industrial Engineering Research Conference* (pp. 457–463).

Steinhoff, J. C. (2002). *Best practices in achieving consistent, accurate physical counts of inventory and related property* (p. 79).

Stojanović, M., & Regodić, D. (2017). The significance of the integrated multicriteria ABC-XYZ method for the inventory management process. *International Journal, 14*(5), 29–48.

Turker, A. K., et al. (2025). A systematic literature review on spare parts classification, inventory and warehouse management from a maintenance-repair perspective. https://doi.org/10.35378/gujs.1484883

Vital-Soto, A., & Olivares-Aguila, J. (2023). Manufacturing systems for unexpected events: An exploratory review for operational and disruption risks. *IEEE Access, 11*, 96297–96316.

Waters, D. (2008). *Inventory control and management* (2nd ed.). John Wiley & Sons.

West, J., Siddhpura, M., Evangelista, A., & Haddad, A. (2024). Improving equipment maintenance—Switching from corrective to preventative maintenance strategies. *Buildings, 14*(11), 3581.

Wijffels, L., Giannikas, V., Woodall, P., McFarlane, D., & Lu, W. (2016). Pendekatan penghitungan siklus yang disempurnakan dengan memanfaatkan data inventaris historis. *IFAC-PapersOnLine, 49*(12), 1347–1352. https://doi.org/10.1016/j.ifacol.2016.07.748