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An Implementation Analysis of AHP-TOPSIS and Music-3D for Optimizing Spare Part Inventory Control
(Case Study: PT. Bati)

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ABSTRACT

This study proposes an integrated spare part inventory control decision-making model using AHP-TOPSIS and MUSIC-3D. While previous studies applied these methods independently, this research combines them within a general trading context to address procurement prioritization and inventory segmentation. AHP was used to assign weights to three inventory criteria: annual consumption (ABC), turnover rate (FSN), and unit price (HML). These weights informed the TOPSIS ranking of 50 spare parts, identifying high-priority items such as MRCT 430 and WLOR XR96. MUSIC-3D further classified items into 16 multidimensional categories to support differentiated control strategies. A one-month implementation at PT. BATI demonstrated improvements in stock control and cost efficiency. The model provides a structured, scalable framework for companies facing high inventory complexity.

Keywords: *Inventory Management, AHP, TOPSIS, MUSIC-3D, Spare parts, Multi-Criteria Decision Making*

Introduction

Effective decision-making in inventory control poses a significant challenge for companies, especially when dealing with complex and dynamic systems. Companies risk imbalances between demand and stock availability without a systematic approach and proper methods, leading to waste or lost sales opportunities. Inventory represents a company's most significant asset, potentially accounting for up to 50% of total invested capital [1]. Thus, its optimal management is critical to sustaining business operations and enhancing profitability. In the Industry 4.0 era, advanced decision-making tools are essential to balance stock availability with cost efficiency, minimizing overstock and stockout risks [2].

PT. BATI, a general trading company specializing in procuring industrial mechanical and electrical spare parts, exemplifies such complexity. The company faces recurring issues, including overstock, stockouts, and difficulty determining procurement priorities due to the wide range of spare parts with different specifications, prices, and usage patterns. This aligns with the opinion of Bacchetti and Saccani in [3] that spare parts inventory management grows complex due to the large number of managed items and intermittent (lumpy) demand patterns.

Currently, inventory control at PT. BATI relies heavily on manual tracking via spreadsheets, which limits real-time monitoring and efficient decision-making. This situation results in excessive stock of non-essential parts, stock shortages of critical components, and increased procurement costs due to poor planning and reactive ordering practices.

To address this issue, this research proposes implementing the AHP (Analytical Hierarchy Process) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methods to determine spare part ordering priorities based on various criteria, such as annual consumption value, turnover rate, and unit price.[4], [5]. AHP is used to determine the weight of each criterion systematically [6][7]. TOPSIS ranks alternative spare parts based on their proximity to the ideal solution [8]–[11]. As complementary methods, the MUSIC-3D (Multi-Unit Spares Inventory Control – Three Dimensional) method is used to group spare parts based on three classification dimensions: annual consumption value (ABC), turnover rate (FSN), and unit value (HML), facilitating strategic segmentation and control policies of each spare part group. [12][13].

Grounded in MCDM theory, which supports structured decision-making in multi-criteria environments [14], and aligns with the Resource-Based View (RBV), where effective inventory management is seen as a strategic capability. This research contributes a hybrid method by integrating AHP, TOPSIS, and MUSIC-3D, which has rarely been implemented in general trading industries.

This study seeks to address the following key research questions:

1. What criteria influence spare parts inventory control at PT. BATI?
2. How do the AHP and TOPSIS methods help prioritize spare parts?
3. How does the MUSIC-3D method classify spare parts for strategic control?
4. Can the proposed integrated framework reduce overstock and stockout risks

Previous studies have widely applied AHP, TOPSIS, or MUSIC-3D independently within specific industrial sectors such as manufacturing and healthcare. [12][15][16]. However, limited research exists on integrating these methods in general trading environments characterized by highly diverse inventory portfolios. This study aims to fill that gap by developing and testing a hybrid model that prioritizes spare part procurement and segments items for policy differentiation based on multidimensional classification.

The integrated application of AHP-TOPSIS and MUSIC-3D provides a structured approach to inventory control decision-making. This method has been proven to increase efficiency, reduce the risks of overstock and stockout, and improve overall procurement planning. [17][18]Consequently, this study hypothesizes that integrating AHP-TOPSIS for precise inventory prioritization with MUSIC-3D for strategic parts classification will lead to significant reductions in overstock levels, stockout occurrences, and associated ordering costs. The proposed framework contributes to the theoretical advancement of inventory management systems while offering a scalable solution with practical implications for organizations managing spare parts inventories.

Research Methods

This applied research adopts a mixed-methods approach, integrating qualitative and quantitative methodologies to optimize spare parts inventory control at PT. BATI through the implementation of AHP-TOPSIS and MUSIC-3D frameworks. The qualitative component captures organizational preferences and subjective assessments for criteria weighting in decision-making, while the quantitative analysis examines numerical inventory parameters, including demand patterns, lead times, pricing structures, and usage frequencies. The research steps can be seen in Figure 1.

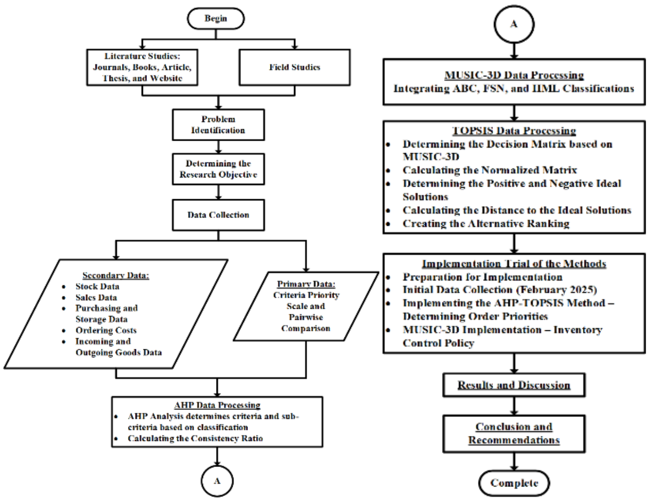

Figure 1. Research Flow Chart

Data Collection Technique

Data were collected from primary and secondary sources:

a. Primary Data: Obtained through interviews and questionnaires with key stakeholders (Director, Procurement Manager, and Warehouse Manager) to determine criteria and sub-criteria priorities for AHP.

b. Secondary Data: Historical company records from January 2023 to April 2025, including sales, stock levels, purchasing data, lead times, and pricing. Additional literature on AHP, TOPSIS, and MUSIC-3D was sourced from academic databases (e.g., Google Scholar, Elsevier).
c. Sample Selection: A sample of 50 spare parts was selected from PT. BATI's inventory of over 500 items using stratified sampling to ensure representation across ABC (consumption value), FSN (turnover rate), and HML (unit price) categories. This approach captured diverse mechanical and electrical components, varying in price and demand frequency, to reflect the company's inventory profile.

Data Processing and Analysis Technique

The study combines AHP, TOPSIS, and MUSIC-3D methods to address inventory issues, specifically overstock, stockout, and prioritization challenges. AHP is used to determine criteria weights, TOPSIS for ranking spare parts, and MUSIC-3D for classifying spare parts based on consumption value, turnover, and unit value [19]. The mixed-method approach involves qualitative data from interviews and questionnaires to establish criteria priorities and quantitative data for numerical analysis of inventory metrics.

Analytical Hierarchy Process (AHP)

AHP is a multi-criteria decision-making method developed by Thomas L. Saaty in 1980. The purpose of using AHP is to make decisions by considering both tangible and intangible criteria and sub-criteria [14]. This Method was utilized to determine the weighted criteria influencing sparepart inventory control. This involved:

a. Defining the problem and establishing a hierarchy of criteria and sub-criteria.
b. Developing pairwise comparison matrices used Saaty's 1–9 scale (1 = equal importance, 9 = extreme importance) [6][7] to evaluate the relative importance of each criterion, using input from key respondents (e.g., management personnel). Judgments from the three experts were synthesized using the geometric mean to create a consolidated matrix.
c. Synthesizing the comparisons to derive priority vectors, indicating the weight of each criterion.
d. Calculating the Consistency Ratio (CR) to ensure the consistency of judgments. A Consistency Ratio ($CR < 0.1$) was considered acceptable.

Calculations were performed using Microsoft Excel

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a multi-criteria decision-making (MCDM) technique introduced by Yoon and Hwang in 1981. This technique assists in selecting the best solution from several available options by identifying the solution that is closest to the ideal condition and furthest from the worst condition [20] And was employed to rank spare parts based on their closeness to the ideal solution. The steps included:

a. Making a decision matrix based on MUSIC-3D classification
b. Normalizing the decision matrix to ensure comparability of criteria.
c. Weighting the normalized matrix using the criteria weights obtained from AHP.
d. Determining the positive and negative ideal solutions.
e. Calculating the Euclidean distances of each alternative from the ideal solutions.
f. Computing the relative closeness to the ideal solution to rank the spare parts.

Multi-Unit Spares Inventory Control – Three Dimensional (MUSIC-3D)

MUSIC-3D is an approach in inventory management that classifies spare parts based on three dimensions to optimize inventory control. This approach is helpful for units or systems with many components or spare parts, where inventory management is crucial. According to [21] There are several group approach models, such as consumption value (ABC analysis), turnover rate (FSN analysis), and unit value (HML analysis) .

ABC analysis according to [22] Classified spare parts into three categories by annual consumption value:

a. A Class: High-value consumption, requiring tight control (70-80% of value, 15% of items).
b. B Class: Medium-value consumption (15-25% of value, 30% of items).
c. C Class: Low-value consumption, looser control (5% of value, 55% of items).

FSN analysis categorizes spare parts based on their movement rate, utilizing the Turn Over Ratio (TOR) to quantify how quickly inventory is sold or used within a specific period.:

a. Fast-moving (F): High TOR ($TOR > 3$), frequent usage.
b. Slow-moving (S): Low TOR ($1 \le TOR \le 3$), infrequent usage.
c. Non-moving (N): Very low/no TOR ($TOR < 1$), obsolete/dormant.

HML analysis classified spare parts by unit price:

a. High (H): High-value units.
b. Medium (M): Mid-value units.
c. Low (L): Low-value units.

Implementation Trial

A one-month trial (March–April 2025) evaluated the methods' effectiveness by comparing baseline data (February 2025) with trial outcomes. The focus was on reductions in stockout, overstock, and ordering costs. Trial data were analyzed to quantify improvements in inventory performance metrics.

Results and Discussion

This section presents the findings from applying AHP-TOPSIS and MUSIC-3D to optimize spare part inventory control at PT. BATI addresses the research questions and hypothesis.

AHP Results: Determining Criteria Weights

Criteria Selection

This study's selection of criteria and sub-criteria is rooted in the MUSIC-3D inventory classification framework, which has been widely applied in inventory optimization to categorize spare parts based on multiple dimensions. PT. BATI deals with a large and diverse range of spare parts, including mechanical and electrical components, each varying in price, consumption frequency, and criticality. To handle this complexity, a structured classification method is required to support strategic inventory control. In this research, these three dimensions serve as the main criteria. Each criterion has three sub-categories, forming a hierarchical structure suitable for AHP analysis. The hierarchy model is illustrated in Figure 2.

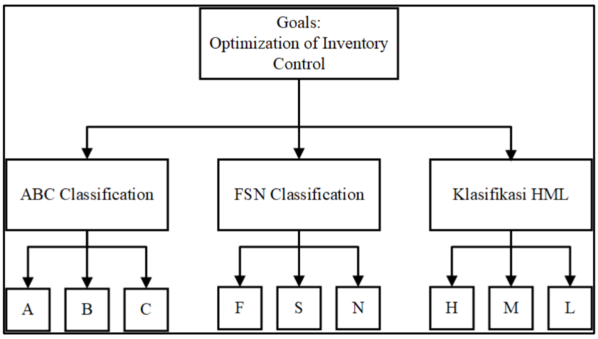

Figure 2. AHP Hierarchy Structure

The AHP method is applied to determine the relative importance (weights) of these criteria and sub-criteria. The process involved gathering expert judgments from three decision-makers in PT. BATI: the warehouse manager, procurement officer, and operations supervisor. These judgments were synthesized using the Geometric Mean method to build a consolidated pairwise comparison matrix, suitable for group decision-making.

Calculation of Criteria Weights

The first step in AHP was constructing a pairwise comparison matrix between the three main criteria: ABC, FSN, and HML. Each pair was compared based on its perceived importance in determining inventory prioritization. For example, ABC (value of consumption) was considered more influential than FSN (frequency of usage) and HML (unit price), as it directly reflects the financial risk of overstocking or stockout.

The geometric mean was calculated for each pair to obtain a representative judgment across respondents:

$$G_m = (Y_1 \times Y_2 \times \ldots \times Y_N)^{\frac{1}{N}} \qquad (1)$$

The resulting matrix is shown in Table 1:

Table 1. Pairwise Comparison Matrix of Criteria

Criteria	ABC	FSN	HML
ABC	1	4,932	4,762

Criteria	ABC	FSN	HML
FSN	0,203	1	2,268
HML	0,210	0,441	1
Total	**1,413**	**6,373**	**8,030**

Each element in the matrix represents the relative importance of one criterion compared to another. For example, a score of 4.932 indicates that the ABC criterion is nearly five times more important than FSN in spare part prioritization at PT. BATI.
To derive the weights, the matrix was normalized by dividing each element by the sum of its column:
The normalized matrix and calculated weights are shown in Table 2:

Table 2. Normalized Matrix and Resulting Weights

Criteria	ABC	FSN	HML	Weights
ABC	0,708	0,774	0,593	0,692
FSN	0,144	0,157	0,282	0,194
HML	0,149	0,069	0,125	0,114

These weights suggest that ABC (annual consumption value) is the most critical criterion in managing spare parts inventory, followed by FSN (turnover rate), and finally HML (unit price). To validate the reliability of the comparison matrix, consistency was assessed using the Consistency Index (CI) and Consistency Ratio (CR). The result was CR = 0,072. Since CR < 0.1, the consistency of judgments is acceptable.

Calculation of Sub-Criteria Weights

AHP was also used to analyze each main criterion's sub-categories for local weights. For instance, in the ABC category, class A was judged significantly more critical than B and C due to its impact on finance and procurement urgency. Similar pairwise comparisons were done for FSN and HML. All matrices passed the consistency ratio (CR) threshold.

Table 3. Local Weights of Sub-Criteria

Sub-Criteria	Weights
Class A	0,614
Class B	0,311
Class C	0,075
Fast	0,756
Slow	0,177
Non-Moving	0,067
High	0,213
Medium	0,365
Low	0,422

Calculation of Global Weights

To determine the overall influence of each sub-criterion in the decision-making process, global weights were computed by multiplying the local weight of each sub-category by its respective criterion weight. These global weights were the basis for evaluating spare part alternatives in the following TOPSIS ranking, ensuring inventory decisions considered value, movement, and cost.

Table 4. Global Weights of Sub-Criteria

Criteria	Weights	Sub-Criteria	Weights	Global Weight
		Class A	0,614	$0{,}692 \times 0{,}614 = 0{,}425$
ABC	0,692	Class B	0,311	$0{,}692 \times 0{,}311 = 0{,}215$
		Class C	0,075	$0{,}692 \times 0{,}075 = 0{,}052$
		Fast	0,756	$0{,}194 \times 0{,}756 = 0{,}147$
FSN	0,194	Slow	0,177	$0{,}194 \times 0{,}177 = 0{,}034$
		Non-Moving	0,067	$0{,}194 \times 0{,}067 = 0{,}013$
HML	0,114	High	0,213	$0{,}114 \times 0{,}213 = 0{,}024$

Criteria	Weights	Sub-Criteria	Weights	Global Weight
		Medium	0,365	$0{,}114 \times 0{,}365 = 0{,}042$
		Low	0,422	$0{,}114 \times 0{,}422 = 0{,}048$

TOPSIS Results: Ranking of Spare Part Alternatives

After determining the global weights through AHP, the TOPSIS method was applied to rank 50 spare part alternatives based on their relative closeness to the ideal solution. The criteria used were derived from the MUSIC-3D classification (ABC, FSN, HML), and each spare part was scored accordingly.

The TOPSIS analysis involved several key steps, including matrix normalization, weighted value computation, and determination of the ideal and negative-ideal solutions. These calculations obtained the distance of each alternative to the ideal solution (S^+) and the negative-ideal solution (S^-). These distances were then used to calculate the closeness coefficient (C*), which indicates the proximity of each spare part to the optimal decision point.

Table 5. TOPSIS Closeness Coefficients and Rankings

Item Name	C* Score	Ranking	Item Name	C* Score	Ranking
MRCT 430	0,70169	1	CG D35	0,28828	25
WLOR XR96	0,70169	1	CLCD SO965 60A	0,28828	25
DLTA B2-0721	0,70169	1	CG EC3016	0,28828	25
EBM R3G3	0,69914	4	BNNR SM312	0,18244	29
MRCT 435	0,69914	4	WLOR WM03	0,18244	29
MRCT 230	0,69892	6	SICK NT6	0,18244	29
CLCD S09424 25A	0,69892	6	CLCD SO965 50A	0,17663	32
DLTA AFB03	0,69892	6	NOT FSP51	0,17663	32
PLZ S4 750	0,69594	9	BAUMR IFRM08P3	0,17663	32
PLZ S3 750	0,67840	10	CG HSX	0,17663	32
MRCT 830	0,67610	11	CG PL	0,17663	32
PRFCE PFGXP450	0,31279	12	SICK 08BPSZCOS	0,17663	32
EMRSN ZR125KC	0,31279	12	WAGO 280-901	0,17663	32
IKO NATA 5902	0,31259	14	OMR 220B 220V	0,17663	32
MRCT 205	0,31259	14	SM Z73	0,17663	32
MINDM MVSC 24V	0,31259	14	SICK 0B8PS-ZW1	0,17663	32
MTIK RB924	0,31259	14	BNNR QELVCQ	0,11629	42
ETEK EH-44	0,31259	14	EBM W2D2	0,11629	42
IFM IY5036	0,31259	14	EBM R3G175	0,10594	44
CG OR5	0,31259	14	ACO SI18-C5	0,10500	45
PLZ S4 751	0,29117	21	OMR 220B 24V	0,10500	45
PLZ S3 751	0,29117	21	IFM II53	0,09877	47
PLZ X2.8P 77301	0,29117	21	CG EC3025	0,09877	47
WENTK FHDX-820	0,28850	24	OMR D2FC	0,09877	47
MINDM MAFR	0,28828	25	NB NiAn 6 x M5	0,09877	47

The top-ranked spare parts, including MRCT 430 and WLOR XR96, achieved high scores due to a combination of characteristics: high consumption value (ABC Class A), frequent usage (FSN Fast-moving), and medium-to-high unit value (HML). These factors indicate that these items are financially significant and operationally critical. Their prioritization reflects the need for tight inventory control to prevent stockouts and ensure service continuity.

Conversely, lower-ranked items such as **CG EC3025** and **OMR D2FC** were classified with low consumption and minimal usage rates, making them suitable for looser control strategies or reorder on demand. This ranking enables PT. BATI to apply differentiated procurement strategies, allocating resources more efficiently and minimizing overstock and stockout risks.

MUSIC-3D Classification Results: Spare Part Segmentation

The MUSIC-3D (Multi-Unit Spares Inventory Control – Three Dimensional) approach was applied to further categorize spare part items into strategic control groups based on three dimensions: consumption value (ABC), turnover (FSN), and unit price (HML). This classification enables PT. BATI will adopt differentiated inventory policies for various spare parts categories, optimizing both service level and inventory cost.

ABC Classification: Annual Consumption Value

The ABC classification was used to rank spare parts based on their total annual consumption in monetary terms[23]–[25]. Items were then sorted from highest to lowest total value, and cumulative percentages were calculated to classify the items into three categories[26]–[28]:

a. Class A: Top - 10-20% of items contributing ~70–80% of total consumption value.
b. Class B: Middle - 20-30% of items contributing ~15–25% of total consumption value.
c. Class C: Remaining - 50-70% of items contributing ~5–10% of total consumption value.

Table 6. ABC Classification Summary

Category	Number of Items	% of Items	Value Contribution	% of Value Contribution
A	11	22%	Rp 3.877.880.000	69,75%
B	16	32%	Rp 1.144.932.000	20,59%
C	23	46%	Rp 536.490.000	9,65%
Total	**50**	**100%**	**Rp 5.559.302.000**	**100%**

FSN Classification: Turnover Ratio

FSN classification was applied based on each item's Turnover Ratio (TOR), representing how frequently an item was issued from inventory. Based on the TOR values, the following categories were assigned:

a. Fast-Moving (F): TOR > 3
b. Slow-Moving (S): $1 \leq$ TOR ≤ 3
c. Non-Moving (N): TOR < 1

Table 7. FSN Classification Summary

Category	Number of Items	% of Items
Fast	32	64%
Slow	14	28%
Non-Moving	4	8%
Total	**50**	**100%**

HML Classification: Unit Price Value

The HML classification was performed using the unit price of each spare part. Items were sorted in descending order of unit cost and categorized as:

a. High (H): Top 10–15% of items by price.
b. Medium (M): Middle 20–25% of items.
c. Low (L): Bottom 60–70%.

Table 8. HML Classification Summary

Category	Number of Items	% of Items
High	7	14%
Medium	13	26%
Low	30	60%
Total	**50**	**100%**

Integrated MUSIC-3D Matrix and Strategic Grouping

By integrating the three dimensions (ABC, FSN, and HML), a 3D classification matrix with 3×3×3=27 possible combinations were constructed. Each combination theoretically represents a distinct inventory group with tailored control strategies. However, based on the actual analysis of 50 spare part items at PT. BATI, only 16 of the 27 possible categories were populated. This indicates that not all theoretical combinations are present in the company’s inventory profile, allowing for more focused inventory management. The most common categories were CFL (20%) and BFL (16%), while high-priority groups such as AFM and AFL, though smaller in number, require stricter control due to their financial importance and fast movement. This classification supports the implementation of differentiated inventory strategies tailored to each group's characteristics.

The absence of 11 theoretical combinations highlights an opportunity to rationalize inventory structure. It may reflect redundancy or underutilized stock clusters, which could be optimized or reconsidered in procurement planning. By understanding the distribution of spare parts across multiple dimensions, PT. BATI can better align inventory policies with each item's operational criticality and financial impact.

Table 9. MUSIC-3D Classification Matrix

ABC	FSN	HML	Category Combination		
A	F	H, M, L	AFH	AFM	AFL
A	S	H, M, L	ASH	ASM	ASL
A	N	H, M, L	ANH	ANM	ANL
B	F	H, M, L	BFH	BFM	BFL
B	S	H, M, L	BSH	BSM	BSL
B	N	H, M, L	BNH	BNM	BNL
C	F	H, M, L	CFH	CFM	CFL
C	S	H, M, L	CSH	CSM	CSL
C	N	H, M, L	CNH	CNM	CNL

Each combination represents a unique inventory group with its own recommended policy. Such as:

Table 10. Integrated MUSIC-3D Matrix

Category	Characteristics	Control Strategy Implications
AFH	High consumption value, fast movement, high price	1. Highest priority 2. Maintain high safety stock 3. Daily/weekly monitoring 4. Automated reorder system
AFM	High consumption value, fast movement, medium price	1. High priority 2. Weekly monitoring 3. Economic Order Quantity (EOQ) purchasing
AFL	High consumption value, fast movement, low price	1. High priority 2. Loose inventory control with EOQ consideration
ASH	High consumption value, slow movement, high price	1. Strict cost control 2. Small quantity, low-frequency orders 3. Tight monitoring due to high unit value
ASM	High consumption value, slow movement, medium price	1. Routine monitoring 2. Procurement based on usage history with low order frequency
BFH	Medium consumption value, fast movement, high price	1. EOQ + safety stock calculation 2. Regular ordering schedule
BFL	Medium consumption value, fast movement, low price	1. Moderate control 2. Medium batch ordering
BSH	Medium consumption value, slow movement, high price	1. Cost and volume monitoring 2. Small quantity orders adjusted to demand
BSM	Medium consumption value, slow movement, medium price	1. Monthly monitoring (stock level, demand emergence, ROP proximity) 2. Historical pattern-based procurement
BSL	Medium consumption value, slow movement, low price	1. Loose control 2. Customer demand-based ordering
CFM	Low consumption value, fast movement, medium price	1. Occasional but rapid ordering 2. Minimal safety stock
CFL	Low consumption value, fast movement, low price	1. Demand-based ordering 2. No need for large stock (calculated)

Category	Characteristics	Control Strategy Implications
CSH	Low consumption value, slow movement, high price	1. Carefully calculated procurement/ROP (avoid excess) 2. Prevent deadstock
CSM	Low consumption value, slow movement, medium price	1. Periodic monitoring 2. Customer demand-based ordering
CSL	Low consumption value, slow movement, low price	1. No need to stock 2. Actual demand-based procurement
CNL	Low consumption value, no movement / very slow, low price	1. Consider for removal 2. Avoid new orders 3. Actual demand-only procurement

Comparative Analysis Before and After Implementation

To evaluate the effectiveness of the proposed AHP-TOPSIS and MUSIC-3D methods, a comparative analysis was conducted using inventory performance data before and after implementation. The evaluation focused on three key indicators: overstock frequency, stockout incidents, and inventory ordering cost. Data was collected one month before implementation (baseline) and one month after implementation.

Table 11. Inventory Performance Comparison

Indicator	Before Implementation	After Implementation	Change
Overstock Incidents	16	7	↓ 56,25%
Stockout Incidents	9	7	↓ 22,22%
Ordering Cost	Rp 10.096.750	Rp 9.554.525	↓ 29,36%

The integrated method's application significantly reduced overstock and stockout cases while also reducing ordering costs. These improvements reflect better demand anticipation, more accurate procurement prioritization, and a more efficient allocation of inventory resources.

This outcome demonstrates the practical value of integrating multi-criteria decision-making with classification-based inventory control, offering measurable performance benefits for companies with diverse and high-volume inventory systems such as PT. BATI.

Conclusion

Integrating AHP-TOPSIS and MUSIC-3D in this study has proven effective in enhancing inventory control strategies at PT. BATI. By combining multi-criteria prioritization and multidimensional classification, the framework supports data-driven decisions that reduce inefficiencies in stock management. The approach prioritized spare parts based on value, turnover, and cost dimensions and provided actionable segmentation for tailored inventory policies.

The improvement observed during the one-month trial reinforces the model’s practical benefits, especially in reducing overstock and stockouts. Moreover, the study contributes methodologically by demonstrating how MCDM techniques can be adapted for general trading environments with complex inventory structures.

This hybrid model can serve as a reference for similar organizations seeking to improve their procurement planning and inventory governance. Future research could explore real-time integration with ERP systems or extend the classification to include risk or criticality dimensions for more nuanced inventory decisions. The integrated method is not only applicable to PT. BATI, but also adaptable for other companies facing similar challenges in spare parts management.

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