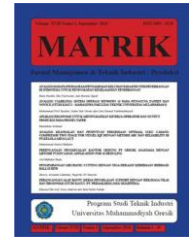




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Analytical Framework for Spare Parts Inventory Control Using K-Means and Adaptive Forecasting

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ABSTRACT

The increasing complexity of power plant operations has made spare parts inventory management increasingly critical. At PLTU XYZ, inventory value increased from IDR 11.85 billion in 2023 to IDR 20.79 billion in 2025, while inventory turnover decreased from 4.23 to 1.99 times per year and deadstock remained around IDR 3–4 billion. The existing system still relies on material classification and engineering evaluation, while demand forecasting has not been systematically applied. This study develops an analytical framework based on K-Means clustering and adaptive forecasting. Clustering of 1,215 items using criticality, availability, usage value, ADI, and CV² produced four clusters with a mean silhouette coefficient of 0.45. In the forecasting stage, nine sample items were evaluated using SES, Croston, SBA, TSB, mSBA, and mTSB through grid search. The results show that SBA performed best for four items, mSBA for three items, and Croston and TSB for one item each. Rolling-origin evaluation indicated that five items achieved method dominance of 85.7%–100%. This framework supports adaptive inventory control and the development of differentiated inventory policies.



1. Introduction

Spare parts inventory control is a crucial aspect of maintaining the operational reliability of power plants, as failure to provide critical spare parts may directly result in derating or even shutdown of generating units. At PLTU XYZ, inventory dashboard data show that the inventory value increased from approximately IDR 11.85 billion in 2023 to IDR 20.79 billion in 2025. During the same period, inventory turnover (ITO) decreased from 4.23 to 1.99 times per year, while deadstock value remained within the range of IDR 3–4 billion. This condition indicates that the current inventory control policy has not been fully adaptive to the heterogeneity of spare parts characteristics, particularly because the existing system still relies on material classification and engineering evaluation, while demand forecasting has not been systematically applied in requirement planning. This problem becomes more complex because spare parts demand is generally intermittent, characterized by numerous zero -

demand periods, long inter-demand intervals, and fluctuating demand sizes. Croston [1] developed a fundamental method for intermittent demand forecasting by separately estimating demand size and inter-demand interval. However, this method was later found to be biased in estimating demand. Syntetos and Boylan [2] developed the Syntetos-Boylan Approximation (SBA) to reduce this bias. Nevertheless, both Croston and SBA remain limited because they update estimates only when positive demand occurs. As a result, during long zero-demand periods, forecasts do not adjust to potential demand decline or obsolescence. Teunter et al [3] subsequently introduced the Teunter-Syntetos-Babai (TSB) method, which updates the demand probability in every period, making it more responsive to obsolescence risk. Babai et al [4] further developed the modified SBA (mSBA) to preserve the advantages of SBA while also responding to prolonged zero-demand periods.

Recent reviews and Bayesian studies confirm that intermittent spare parts demand requires method selection that accounts for

sparse demand occurrence, variable demand size, and inventory implications, because no single forecasting approach is consistently superior across all demand characteristics [5], [6].

On the other hand, machine learning-based studies indicate that intermittent demand characteristics can be addressed through more adaptive approaches. Mehringer et al. [7], for example, proposed a nested workflow combining K-Prototypes and K-Means clustering on spare parts master and consumption data to generate demand forecasts, showing that clustering items with similar characteristics improves forecasting accuracy for parts with scarce historical data. In the context of inventory control specifically, Balugani et al. [8] showed that K-Means produces faster and more stable item clusters than hierarchical methods, supporting its suitability for industrial decision-making involving large numbers of stock-keeping units. Zhuang et al. [9], for example, developed a combined forecasting approach by separating demand occurrence prediction from demand size prediction. Tian et al. [10] further demonstrated that intermittent-demand forecasting can be improved through a combined approach that selects the forecasting mechanism according to demand and inventory states. Using two large retail datasets, their proposed method outperformed SES, Croston, and SBA across multiple forecasting horizons. However, these study focused primarily on the automotive aftermarket context, whereas the integration of multicriteria segmentation and adaptive forecasting method selection in the context of power plant spare parts remains limited. In addition, most previous studies have emphasized the development of forecasting methods, but have not explicitly linked them with material segmentation based on criticality, availability, usage value, ADI, and CV² as a basis for inventory control.

Based on this gap, this study develops an analytical framework that integrates multicriteria K-Means clustering and adaptive

intermittent demand forecasting. K-Means is used to segment spare parts based on material characteristics and demand patterns, while adaptive forecasting is used to select the best forecasting method at the item level through empirical evaluation. This approach is not intended to directly replace the company's existing policy, but rather to serve as decision support for developing differentiated inventory policies, inventory mapping, spare parts evaluation, and more adaptive inventory control directions at PLTU XYZ.

2. Research Method

This study is an applied quantitative case study conducted on spare parts inventory management at PLTU XYZ. The initial population consisted of 7,371 stock codes. A four-stage filtering process was applied:

1. Reconstruction of the Availability classification based on actual lead-time data, computed from Order Date and Onsite Receipt Date pairs within the same 34 month observation period (January 2023–October 2025) as the demand data, reducing the population to 2,482 items.
2. Exclusion of non moving (usage value D) items, resulting in 2,286 items.
3. Matching with historical issue/consumption data for the observation period, resulting in 2,233 items
4. Items with one or fewer demand occurrences were excluded because at least two non-zero demand occurrences are required to calculate ADI and CV² reliably following Chawla and Miceli [11]. This process resulted in a final sample of 1,215 inventory items used in this study. Five attributes were used as segmentation criteria, criticality which was derived from the company's expert judgment through its annual inventory policy forum; availability, which was reconstructed in this study using objective lead-time data rather than the company's original qualitative estimation, usage value, average demand interval (ADI), and squared coefficient of variation (CV²). Categorical attributes, including criticality, availability, and usage

value, were ordinally encoded ($A = 3$, $B = 2$, $C = 1$) to enable their processing using a Euclidean distance-based clustering algorithm. Since the five attributes have different value ranges, all attributes were normalized using Min-Max Normalization into the range $[0,1]$ prior to the clustering process. This step was conducted to prevent attributes with larger value ranges, particularly ADI and CV², from dominating the distance calculation.

The optimal number of clusters was determined using an Optimized K-Means approach based on the Silhouette Coefficient [12], with $k = 4$ selected as the best configuration based on the highest average Silhouette Coefficient value. The K-Means algorithm was then applied to the five normalized attributes to form the spare parts cluster profiles. In parallel, each item was also classified into four demand pattern quadrants, namely smooth, intermittent, erratic, and lumpy, based on ADI and CV² values following the categorization framework proposed by [13], [14]

The K-Means algorithm groups items into k clusters by minimizing the total squared Euclidean distance between each item and its corresponding cluster center, or centroid, as formulated below.

$$WCSS = \sum_{i=1}^k \sum_{x_j \in C_i} ||x_j - \mu_i||^2 \quad (1)$$

where C_i represents cluster i , x_j denotes data point j , and μ_i is the centroid of cluster C_i . The algorithm continues iteratively until the centroid values no longer change significantly, indicating that the data points have been effectively grouped into clusters [15]. In this study, the distance calculation was performed on five normalized attributes, namely criticality, availability, usage value, ADI, and CV². The centroids were iteratively updated until convergence, and the optimal number of clusters was selected based on the highest average Silhouette Coefficient.

In the forecasting stage, nine sample items were purposively selected from the priority

clusters to represent the four demand pattern quadrants. Six forecasting methods, namely SES, Croston, SBA, TSB, mSBA, and mTSB, were then applied adaptively at the item level based on accuracy evaluation.

The notation used in the forecasting methods is defined as follows: $\hat{Y}_t$ denotes the forecasted average demand per period at period t , Y_t denotes the actual demand, $\hat{Z}_t$ and Z_t represent the estimated and actual demand size, respectively, while $\hat{T}_t$ and T_t denote the estimated and actual inter-demand interval. For TSB-based methods, $\hat{p}_t$ represents the estimated probability of demand occurrence, and I_t is a binary demand occurrence indicator, where $I_t = 1$ if demand occurs and $I_t = 0$ otherwise. The parameters α and β denote the smoothing parameters, while t represents the time period index.

Simple Exponential Smoothing (SES) updates the demand forecast in every period using the smoothing parameter α .

$$\hat{Y}_t = \hat{Y}_{t-1} + \alpha(Y_t - \hat{Y}_{t-1}) \quad (2)$$

Croston's method [16] separates the estimation of demand size and inter-demand interval, and updates both estimates only in periods with positive demand

$$\hat{Y}_t = \frac{\hat{Z}_t}{\hat{T}_t} \quad (3)$$

The estimated demand size $\hat{Z}_t$ and the estimated inter-demand interval $\hat{T}_t$ are updated only when positive demand occurs; during zero-demand periods, both estimates remain unchanged. If positive demand occurs ($Y_t > 0$):

$$\begin{aligned} \hat{Z}_t &= \hat{Z}_{t-1} + \alpha(Z_t - \hat{Z}_{t-1}) \text{ and} \\ \hat{T}_t &= \hat{T}_{t-1} + \beta(T_t - \hat{T}_{t-1}) \end{aligned} \quad (4)$$

If no demand occurs ($Y_t = 0$):

$$\hat{Z}_t = \hat{Z}_{t-1}, \hat{T}_t = \hat{T}_{t-1} \quad (5)$$

The Syntetos-Boylan Approximation (SBA) [2] corrects the positive bias of Croston's method by applying the correction factor $(1 - \beta/2)$.

$$\hat{Y}_t = \left(1 - \frac{\beta}{2}\right) \frac{\hat{Z}_t}{\hat{T}_t} \quad (6)$$

The updating mechanism of $\hat{Z}_t$ and $\hat{T}_t$ is identical to Croston's method, as shown in Equations (4) and (5)

The Teunter-Syntetos-Babai (TSB) method [3] replaces the inter-demand interval update with the demand occurrence probability, which is updated in every period, including periods with no demand.

$$\hat{Y}_t = \hat{p}_t \cdot \hat{Z}_t \quad (7)$$

Thus, unlike Croston and SBA, TSB continuously updates the probability of demand occurrence at each period. The TSB method applies the following updating mechanism. If positive demand occurs ($Y_t > 0$):

$$\begin{aligned} \hat{p}_t &= \hat{p}_{t-1} + \beta(1 - \hat{p}_{t-1}) \text{ and} \\ \hat{Z}_t &= \hat{Z}_{t-1} + \alpha(Z_t - \hat{Z}_{t-1}) \end{aligned} \quad (8)$$

If no demand occurs ($Y_t = 0$):

$$\hat{p}_t = \hat{p}_{t-1} + \beta(0 - \hat{p}_{t-1}) \text{ and } \hat{Z}_t = \hat{Z}_{t-1} \quad (9)$$

The Modified SBA (mSBA) method has the same estimator form as SBA. However, during zero-demand periods, the estimated inter-demand interval is conditionally updated when the actual interval exceeds the previous estimated interval [4]. This mechanism makes mSBA more responsive to an increasing risk of obsolescence.

$$\hat{Y}_t = \left(1 - \frac{\beta}{2}\right) \frac{\hat{Z}_t}{\hat{T}_t} \quad (10)$$

This estimator has the same form as SBA (equation 4). The main difference between mSBA and SBA lies in the interval-updating mechanism during zero-demand periods. If no demand occurs ($Y_t = 0$), then $\hat{Z}_t = \hat{Z}_{t-1}$, and the estimated inter-demand interval is conditionally updated as follows:

$$\hat{T}_t = \hat{T}_{t-1} + \beta(T_t - \hat{T}_{t-1}) \text{ if } T_t > \hat{T}_{t-1} \quad (11)$$

$$\hat{T}_t = \hat{T}_{t-1} \text{ if } T_t \leq \hat{T}_{t-1} \quad (12)$$

Yang et al. [17] proposed Modified TSB extends the TSB method by updating the probability of demand occurrence based on the comparison between the observed probability and the previous estimated probability. This mechanism enables the method to remain responsive even during prolonged zero-demand periods.

$$\hat{Y}_t = \hat{p}_t \cdot \hat{Z}_t \quad (13)$$

If positive demand occurs ($Y_t > 0$), the updating mechanism is the same as in TSB, as shown in Equation (8). If no demand occurs ($Y_t = 0$), then $\hat{Z}_t = \hat{Z}_{t-1}$, and the estimated probability is conditionally updated as follows:

$$\hat{p}_t = \hat{p}_{t-1} + \beta (0 - \hat{p}_{t-1}) \text{ if } p_t \leq \hat{p}_{t-1} \quad (14)$$

$$\hat{p}_t = \hat{p}_{t-1} + \beta (1 - \hat{p}_{t-1}) \text{ if } p_t > \hat{p}_{t-1} \quad (15)$$

The six forecasting methods were implemented adaptively at the item level, with the optimal smoothing parameter combination (α, β) for each item selected through grid search based on the lowest MASE value. RMSE were used as supporting metrics.

$$q_t = \frac{|Y_t - \hat{Y}_t|}{\frac{1}{n-1} \sum_{i=2}^n |Y_i - Y_{i-1}|}$$

$$MASE = \frac{1}{n} \sum_{t=1}^n q_t \quad (16)$$

In Equation (16), MASE is calculated as the average scaled absolute error, where the scaling factor is the in-sample one-step naive forecast error. Thus, $MASE < 1$ indicates that the evaluated method outperforms the naive benchmark, whereas $MASE > 1$ indicates otherwise.

3. Results and Discussion

The clustering process resulted in four optimal clusters with a mean Silhouette Coefficient of 0.45, indicating a moderate cluster structure with partially overlapping boundaries. This result is reasonable because the clustering attributes combine variables with different origins and measurement scales: criticality is an ordinal (expert judgment based classification), availability is an ordinal

classification derived from objective lead-time calculations, usage value is an ordinal classification based on Pareto analysis, while ADI and CV² are continuous variables derived from demand data. The heterogeneity in variable types and sources may naturally result in some degree of overlap between clusters, as the resulting profiles reflect multiple dimensions of spare parts characteristics rather than a single homogeneous measurement scale.

The clustering results were then summarized based on item distribution and centroid values to highlight the main characteristics and relative composition of each cluster, as presented in Table 1.

Table 1. Cluster Centroids and Item Distribution

Cluster	Total Item	Usage	Criticality	Availability	ADI	CV ²
C 1	206	2,34	1,17	1,13	4,71	0,65
C 2	175	2,32	1,20	1,35	15,06	0,14
C 3	377	1,00	1,07	1,18	15,41	0,16
C 4	457	1,00	1,02	1,04	5,08	0,59

As shown in Table 1, the K-Means algorithm grouped 1,215 spare parts into four clusters. Cluster 4 represents the largest group, consisting of 457 items or 37.6% of the dataset, followed by Cluster 3 with 377 items or 31.0%. Cluster 1 consists of 206 items or 17.0%, while Cluster 2 contains 175 items or 14.4%. The centroid values indicate distinct characteristics across clusters. Clusters 1 and 2 have relatively high usage values, while Cluster 1 is characterized by the highest demand variability, as indicated by CV² = 0.651. Cluster 2 shows very rare demand occurrences, reflected by its high ADI value of 15.06, combined with relatively high usage and criticality values. Cluster 3 also has a high ADI value but low usage, indicating rarely used low-value items. Meanwhile, Cluster 4 has low usage value and relatively more regular demand compared with Clusters 2 and 3. These centroid characteristics provide the basis for interpreting the managerial

profile and assigning the label of each cluster. To further examine the demand behavior within each cluster, the distribution of demand pattern quadrants was analyzed, as presented in Table 2.

Table 2. Distribution of Demand Pattern Quadrants Across Clusters

Cluster	Intermittent	Lumpy	Erratic	Smooth	Total
C1	99	91	9	7	206
C2	162	13	0	0	175
C3	338	39	0	0	377
C4	259	185	11	2	457
Total	858	328	20	9	1,215

Table 2 shows that intermittent demand dominates the dataset, representing 858 out of 1,215 items. Cluster 2 has the strongest intermittent demand concentration, with 162 of 175 items classified as intermittent and no erratic or smooth items. This supports its interpretation as Strategic Spare Part, characterized by rare demand occurrences, relatively high usage value, and higher criticality. Cluster 3 is also dominated by intermittent demand but has lower usage value, indicating rarely used low-value items. Cluster 4 contains a substantial number of lumpy items, while Cluster 1 has the most diverse demand pattern composition, which is consistent with its high CV² value.

Based on the centroid values and the distribution of demand pattern quadrants, each cluster was further interpreted and assigned a managerial label. The cluster naming was not based on a single attribute, but on the combined interpretation of usage value, criticality, availability, ADI, CV², and the dominant demand pattern. The resulting cluster profiles and labels are presented in Table 3

A key finding from the clustering results is the identification of Cluster 2 as Strategic Spare Part, a segment that is not fully captured by the company's conventional rule-based classification system. While the existing classification relies mainly on criticality, availability, and annual usage or usage value,

the proposed clustering approach also incorporates demand behavior through ADI and CV².

Table 3. Cluster Profiles and Inventory Control Implications

Cluster	Main Characteristics	Control Implications
C1 - High Value Operational and Maintenance Part	High usage value ; relatively frequent usage with mean ADI of 4.71 ; and fluctuating demand size with CV ² of 0.651.	Requires a combination of adaptive forecasting and risk-based control due to high value and high demand variability.
C 2 - Strategic Spare Part	High usage value ; very rare demand occurrence with ADI ≥ 8.5 ; the highest concentration of critical items A/B; and the highest supply risk.	Requires control based on criticality and technical considerations; statistical forecasting has limited applicability.
C 3 - General-Slow Moving Spare Part	Low usage value ; very rare demand frequency ; and dominated by non-critical items, particularly criticality C.	Can be managed conservatively with relatively low control priority.
C 4 - Low Value-Routine and Consumable Part	The largest cluster ; low usage value ; relatively more regular demand frequency ; and dominated by non-critical items	Relatively suitable for adaptive forecasting support because the demand pattern is more regular.

Although not all items in Cluster 2 are administratively classified under the highest

criticality category, this cluster reflects a strategic profile because it combines high usage value, very rare demand occurrence, relatively stable demand size, and the highest concentration of supply-risk and critical items. This suggests that multicriteria clustering can capture the strategic characteristics of spare parts more comprehensively than single-attribute or bivariate classification rules.

The strategic profile identified in Cluster 2 is also consistent with recent multicriteria studies showing that spare parts priorities should be derived from the joint interpretation of criticality, value, maintainability, and operational context rather than from a single administrative category [18], [19], [20]

Before discussing the forecasting results, Table 4 presents the descriptive statistics of the nine selected sample items over the 34-month observation period. The samples were purposively selected from the priority clusters to represent the four demand pattern quadrants, namely smooth, intermittent, erratic, and lumpy. This provides the basis for evaluating adaptive forecasting methods in the following section.

Table 4. Descriptive Statistics of the 34-Month Demand Series for Nine Sample Items

Stock Code	Quadrant	% Zero Periods	Demand Size: Mean	Demand Size: Std.	Interval: Mean
135738	Intermittent	65%	1,9	0,9	2,4
203961	Intermittent	76%	28,0	15,8	3,4
200707	Smooth	15%	175,4	118,1	1,1
201225	Smooth	21%	5,7	4,0	1,2
200711	Smooth	6%	23,8	15,4	1,0
200504	Erratic	18%	63,6	69,2	1,2
202026	Erratic	23%	7,1	5,1	1,2

200672	Lumpy	91%	8,0	5,7	5,0
200751	Lumpy	62%	20,1	30,7	2,2

Table 4 presents the descriptive statistics of the 34-month demand series for the nine selected sample items. Stock code 200672 and 203961 show the highest zero-demand proportions, indicating a high degree of intermittency, while stock code 200504 and 200707 exhibit the highest demand size variability. These characteristics confirm that the selected samples represent diverse demand behaviors across the four demand pattern quadrants. Accordingly, the forecasting stage was conducted adaptively at the item level rather than by applying a uniform method to all items.

Based on these demand characteristics, the six forecasting methods were then evaluated for each sample item. The forecasting performance results are presented in Table 5.

Table 5. Optimal Forecasting Parameters and Accuracy Metrics for Each Sample Item

Stock Code	Best Method	α	β	MASE	RMSE
135738	SBA	0,5	0,70	1,197	0,944
203961	mSBA	0,9	0,90	0,504	11,602
200707	SBA	0,5	0,30	0,661	91,994
201225	Croston	0,1	0,90	0,628	3,396
200711	TSB	0,3	0,10	0,431	9,761
200504	SBA	0,1	0,70	0,380	50,165
135738	SBA	0,7	0,70	0,755	5,077
203961	mSBA	0,1	0,30	2,236	4,708
200707	mSBA	0,1	0,90	1,936	38,293

The evaluation of six forecasting methods across nine sample items shows that the best-performing method differs by item and cannot be generalized only from the ADI-CV² demand pattern quadrant. This suggests that forecasting performance is more strongly affected by item-level characteristics, such as zero-demand proportion and demand size variability. SBA

was selected as the best method for four items across the smooth, intermittent, and erratic quadrants, while mSBA was selected for three items, including both lumpy items. Croston and TSB were each selected for one item, whereas SES and mTSB were not selected as the best method for any sample item.

To examine the robustness of the item-level model selection, the forecasting methods were re-evaluated using a rolling-origin procedure comprising seven chronological train-test configurations, from T18 to T30, with the available training history progressively increasing from 18 to 30 months. Unlike a single holdout split, this repeated out-of-sample design preserves the temporal order of the observations and evaluates model performance across multiple forecast origins, thereby reducing dependence on a particular data partition [21]. The analysis therefore assesses whether the initially selected method remains dominant as the training window changes and additional observations become available. Table 6 reports the winning method under each configuration and the percentage of schemes in which the reference method retained its dominance for each sample item.

Table 6. Robustness Method Accros Seven Rolling-Origin Evaluation Schemes

Stock Code	Reference Method	Dominance (7 Schemes)
135738	SBA	71,4%
203961	mSBA	100%
200707	SBA	100%
201225	Croston	100%
200711	TSB	57,1%
200504	SBA	100%
135738	SBA	71,4%
203961	mSBA	71,4%
200707	mSBA	85,7%

Table 6 shows that the robustness of the selected forecasting methods varies across sample items. Stock Code 203961, 200707, 201225, and 200504 achieved 100% dominance, indicating that the best-performing method remained stable across all rolling-origin

schemes. In contrast, 200711 showed the lowest dominance level at 57.1%, suggesting that its best method was more sensitive to changes in the training-testing split. This occurred because the MASE values of TSB and SES were very close, resulting in only a narrow performance margin. These findings confirm that the best forecasting method cannot be generalized solely based on the ADI-CV² demand quadrant. Instead, method performance is more strongly influenced by item-level demand characteristics, such as zero-demand proportion and demand size variability. This result is consistent with previous study who reported that the accuracy of intermittent demand forecasting methods varies depending on the characteristics of the demand data [17], [22]

The item-specific variation observed in this study is consistent with recent findings that forecasting performance depends on demand features and obsolescence conditions, and that hybrid or machine-learning models may dominate only for particular item groups rather than universally [23], [24], [25].

The absence of SES as the best-performing method reflects its limitation in handling intermittent demand, as it does not separately estimate demand size and inter-demand interval. Meanwhile, the superior performance of mSBA on several items, including both lumpy items, supports the relevance of methods that can respond to prolonged zero-demand periods. However, mTSB was not selected as the best method in this sample, indicating that its performance advantage may not be directly generalized to power plant spare part demand.

Overall, the results suggest that ADI-CV² quadrants are useful for initial demand classification, but they should not be used as the sole basis for selecting forecasting methods. Therefore, an adaptive item-level forecasting approach is more appropriate for spare part inventory control. The synthesis of clustering and forecasting results provides an analytical basis for differentiated inventory control priorities, while the formulation of specific procurement strategies remains beyond the scope of this study.

4. Conclusions and Recommendations

This study developed an analytical framework that integrates multicriteria K-Means clustering and adaptive intermittent demand forecasting as decision support for

spare parts inventory control at PLTU XYZ. The results show that K-Means clustering generated four spare part profiles with distinct managerial characteristics and identified strategic items that were not fully captured by the company's conventional classification system. The forecasting results indicate that the best-performing method is item-specific and cannot be generalized solely based on ADI-CV² demand quadrants or cluster profiles. Therefore, adaptive item-level forecasting is more appropriate than applying a uniform method across categories. The ADI-CV² classification remains useful as an initial demand segmentation framework, but it should not be treated as the sole determinant of forecasting method selection. Overall, the proposed framework provides analytical support for the development of differentiated inventory policies, inventory mapping, material evaluation, and more adaptive spare parts inventory control in power plant operations. Future studies may also incorporate similarity-based transfer learning for items with extremely limited demand histories by borrowing demand information from structurally similar spare parts. The extended framework should be evaluated not only in terms of forecasting accuracy but also through inventory-performance measures, including stockout risk, inventory levels, and replenishment costs [13].

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