

Integrated ABC-FSN Analysis of Inventory Classification and Demand Forecasting: A Case Study of Welding Industrial Engineering Program Warehouse

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Received
June 7, 2026

Revised
August 13, 2026

Accepted
September 24, 2026

ABSTRACT

This study employed a quantitative case-study approach to improve inventory management in the Welding Industrial Engineering Programme warehouse, Faculty of Industrial Education, Rajamangala University of Technology Isan. The study analyzed the complete inventory population of 17 stock-keeping units (SKUs). Purchasing records from 14 academic semesters (2019/1–2025/2) were used for ABC Analysis, while inventory withdrawal records from six semesters (2023/1–2025/2) were used for FSN Analysis. The integrated ABC-FSN classification identified 6 Class A, 4 Fast-moving, 9 Slow-moving, and 4 Non-moving items. The Grinding wheel 4"x6" mm was selected as an illustrative AF-class forecasting case. Moving Average, Single Exponential Smoothing, and Holt-Winters' Multiplicative Exponential Smoothing were evaluated using 14 semester-level demand observations. Holt-Winters achieved the lowest MAPE of 35.06%, compared with 47.53% for Moving Average and 51.41% for Single Exponential Smoothing, indicating comparatively better performance among the evaluated methods. The resulting safety stock and reorder point were 62 and 147 units, respectively. However, the forecasting results are subject to limitations arising from the single-item forecasting scope and the relatively short demand series.

Keywords: ABC Analysis, FSN Analysis, Demand forecasting, Inventory classification

Introduction

Inventory management is a critical driver of organizational efficiency across sectors, as poorly managed stock increases holding costs, disrupts operational continuity, and reduces service quality (The Economist Intelligence Unit, 2021). In educational institutions, however, inventory inefficiencies can be difficult to identify because materials are procured to support teaching and practical training rather than direct revenue generation. Consequently, excess or dormant inventory may remain embedded in procurement expenditure without immediate financial signals, while shortages of essential consumables can disrupt practical instruction. Effective inventory management in this context therefore requires not only control of inventory value but also systematic consideration of material movement and future demand.

The Welding Industrial Engineering Programme warehouse exemplifies this challenge. It stocks diverse materials and equipment, including welding consumables, personal protective equipment, hand and power tools, and precision instruments, whose consumption is episodic and closely linked to academic activities. The inventory profile demonstrates the problem: among 17 stock keeping units (SKUs), four were classified as Non-moving (N), with a combined annual consumption value of 4,995 Baht, representing 13.64% of the total value of 36,626.38 Baht. Notably, one Class A item, Welding wire LH2000 E7016 2.6 mm, had an annual consumption value of 2,955 Baht but zero recorded disbursement, indicating that high-value inventory may remain dormant when management relies solely on value-based classification.

ABC Analysis stratifies inventory items by annual consumption value, enabling differentiated management according to economic significance (Arree et al., 2020; Muenjitnoy and Aunyawong, 2025). FSN Analysis complements this approach by classifying items as Fast, Slow, or Non-moving based on transaction frequency and recency, capturing the movement dimension overlooked by value-based analysis (Prampree et al., 2024). Thus, ABC-FSN classification forms the first analytical layer by identifying both the economic importance and movement behaviour of each SKU. Demand forecasting provides the second layer by estimating future requirements for high-priority consumables and linking classification to replenishment decisions (Trapero et al., 2024). This is particularly relevant in educational warehouses, where demand follows academic semesters and procurement lead time is one semester. Accordingly, the framework sequentially identifies inventory priorities through ABC-FSN Analysis, selects a high-priority consumable for demand analysis, evaluates alternative forecasting methods, and translates the selected forecast into safety-stock and reorder-point parameters, as illustrated in Figure 1. In this framework, ABC-FSN determines which items require attention, forecasting estimates future requirements, and replenishment parameters determine when and at what inventory level action is required.

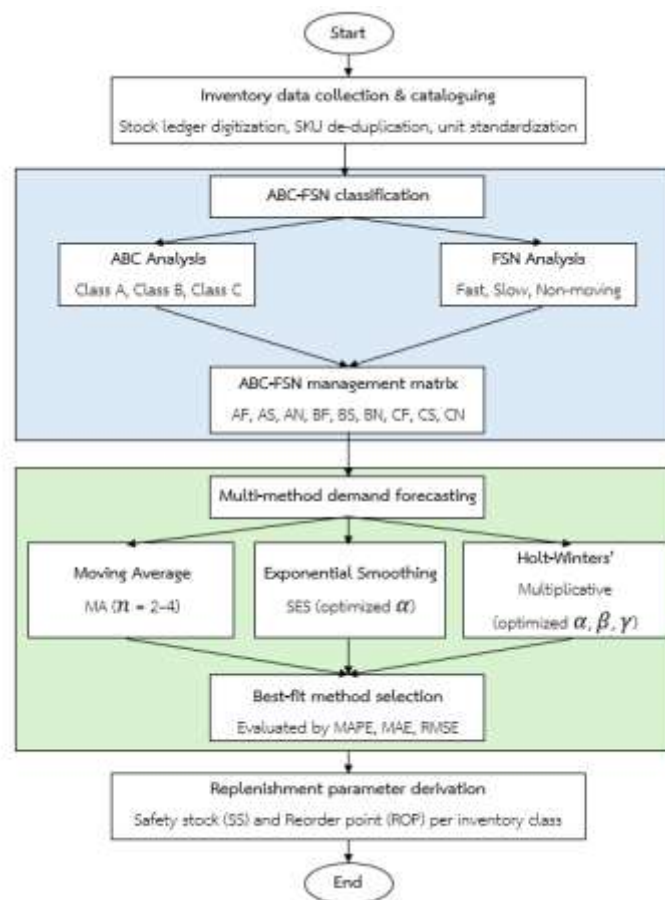


Figure 1. Integrated ABC-FSN and Demand Forecasting Methodology Flowchart

Although ABC, FSN, and forecasting techniques have been applied across commercial, manufacturing, healthcare, and community-enterprise settings, their integration remains fragmented. ABC-FSN studies mainly focus on classification and cost control, while forecasting studies generally evaluate prediction methods without linking item selection to multidimensional inventory classification (Insom and Kessomboon, 2025; Prampree et al., 2024; Kumar and Shukla, 2022). Moreover, existing evidence largely reflects continuous commercial demand, whereas educational warehouses experience semester-driven demand associated with academic schedules and practical training. Thus, whether an integrated classification, forecasting, and replenishment framework can provide actionable inventory-control information in a TVET warehouse remains unresolved. This gap limits evidence on integrating inventory value, movement, and time-dependent demand, potentially resulting in inefficient management of dormant high-value materials and inadequate replenishment planning. This study addresses the gap by integrating ABC-FSN classification, comparative demand forecasting, and replenishment-parameter derivation in a TVET educational warehouse. Four contributions are made: (1) extending ABC-FSN application to TVET by integrating inventory value

and movement velocity; (2) linking multidimensional classification with comparative forecasting for a high-priority consumable; (3) translating the selected forecasting model into quantitative safety-stock and reorder-point parameters; and (4) providing a practical decision-support framework without requiring dedicated enterprise resource planning infrastructure.

Objectives

1. To classify materials and equipment in the Welding Industrial Engineering Program warehouse using ABC-FSN Analysis and establish differentiated inventory management policies for each classification segment.
2. To evaluate and compare the accuracy of three demand forecasting methods: Moving Average, Single Exponential Smoothing, and Holt-Winters' Multiplicative Exponential Smoothing.
3. To calculate safety stock and reorder point parameters for the selected Grinding wheel 4"x6" mm, an AF-class consumable, using the most accurate forecasting method to support evidence-based replenishment planning.

Literature Review

1. ABC and FSN Analysis for Inventory Classification: ABC Analysis is grounded in the Pareto principle, whereby a small proportion of items accounts for most inventory value. Typically, Class A comprises 10–20% of Stock Keeping Units (SKUs) but 70–80% of annual consumption value; Class B comprises 30–40% of SKUs and 15–20% of value; and Class C comprises 50–60% of SKUs and only 5–10% of value, requiring progressively less management attention (Arree et al., 2020; Chonchiav et al., 2025) Empirical studies in Thai retail and manufacturing contexts support this pattern (Arree et al., 2020; Muenjitnoy and Aunyawong, 2025; Sansug et al., 2024) FSN Analysis complements ABC by capturing inventory movement. Fast-moving items have high and regular consumption, Slow-moving items are consumed intermittently, and Non-moving items have no recorded consumption within a defined period, typically 12 months (Insom and Kessomboon, 2025) This helps identify dormant inventory that value-based classification may overlook, particularly high-value items with zero consumption.

Integrating ABC and FSN into a 3x3 matrix provides greater management discrimination than either method alone. Insom and Kessomboon (2025) identified high-value, Non-moving items in a hospital warehouse that were not sufficiently distinguished by ABC alone, while Prampree et al. (2024) reported a significant reduction in inventory holding costs after ABC-FSN-guided reclassification in a community enterprise warehouse. Kumar and Shukla (2022) further validated the approach in the retail sector, supporting its generalizability. However, to the authors' knowledge, published

research has not applied formal ABC-FSN classification together with multi-method demand forecasting to educational program warehouses. This context-specific integration represents the primary scholarly gap addressed by the present study.

2. Demand Forecasting Methods: Three forecasting methods are commonly applied in institutional inventory contexts. Moving Average (MA) assigns equal weight to historical periods, making it less responsive to recent demand changes (Taengphukieo and Issarapong, 2019) Single Exponential Smoothing (SES) improves responsiveness by assigning geometrically declining weights to older observations (Vanitkun et al., 2023) When demand exhibits trend and seasonality, as expected in semester-driven educational warehouses, Holt-Winters' multiplicative method is appropriate because it separately models level, trend, and seasonal components (Phuchittrasin et al., 2024; Kumar et al., 2024) Evidence from Thai institutional and related contexts generally supports Holt-Winters' when genuine seasonal patterns exist. Vanitkun et al. (2023) reported MAPE reductions of 6–9 percentage points over moving average baselines in hospital demand forecasting, while Sarika et al. (2024) and Sumranhun et al. (2023) found comparable advantages in retail and industrial contexts, providing empirical support for its evaluation in the present study.

Research Methodology

1. Population and Data Structure

This study employed a quantitative case-study approach to improve inventory management in the Welding Industrial Engineering Program warehouse, Faculty of Industrial Education, Rajamangala University of Technology Isan. The study population comprised all 17 stock-keeping units (SKUs) in the warehouse, which were analyzed using a census approach. Purchasing records from 14 academic semesters (2019/1–2025/2) were used for ABC Analysis, while inventory withdrawal records from six semesters (2023/1–2025/2), maintained by warehouse personnel and material requesters, were used for FSN Analysis. For demand forecasting, 14 semester-level demand observations (2019/1–2025/2) of the selected Grinding wheel 4"x6" mm were used. A structured data-recording form was used to extract the required information from inventory, purchasing, and withdrawal records. Data quality was verified by cross-checking item identification, quantities, unit prices, and academic-semester records against the original documents. The datasets were also checked for missing, duplicate, inconsistent, or implausible records, with questionable entries verified against the original sources before analysis.

2. ABC-FSN classification

2.1 ABC Analysis: ABC Analysis was performed for all 17 inventory items using purchasing records covering 14 academic semesters from 2019/1 to 2025/2. For each SKU, the purchasing quantities recorded over the 14 semesters were averaged to obtain the average purchasing quantity per semester ($\bar{D}_i$). The semester-level average was then annualized by multiplying it by two, corresponding to the two academic semesters in one academic year. The resulting annual average purchasing quantity was multiplied by the unit price (C_i) to obtain the Annual Consumption Value (ACV_i), expressed in Baht per year as shown in Equation (1):

$$ACV_i = 2\bar{D}_i C_i \quad (1)$$

The ABC analysis follows the Pareto-based approach in which items are stratified by Annual Consumption Value (ACV) and cumulative value percentages are computed. Classification thresholds follow widely adopted conventions: Class A encompasses items representing approximately 70–80% of cumulative ACV; Class B covers the next 15–20%; and Class C covers the remainder 5–10% (Chonchiav et al., 2025; Anansuwanchai and Khokhajaikiat, 2023; Sriyom et al., 2021; Arree et al., 2020)

2.2 FSN Analysis: For each SKU i , the average quarterly disbursement rate CR_i is computed across the four study quarters as shown in Equation (2):

$$CR_i = d_{iq}/4 \quad (2)$$

Where d_{iq} is the disbursement quantity of item i in quarter q . Items are classified as Fast-moving (F) if $CR_i \geq \text{threshold}_F$, Slow-moving (S) if $\text{threshold}_S \leq CR_i < \text{threshold}_F$, and Non-moving (N) if $CR_i < \text{threshold}_S$. Following Insom and Kessomboon (2025), classification thresholds are derived empirically from the quartile distribution of CR_i across the SKU population, using the standard $(n+1)$ interpolation formula. With $n = 17$ items, the first quartile (Q1) yields $\text{threshold}_S = 0.50$ units/quarter and the third quartile (Q3) yields $\text{threshold}_F = 2.63$ units/quarter.

3. Demand Forecasting Methods

3.1 Moving Average (MA): The n -period Moving Average forecast for period $t+1$ as shown in Equation (3):

$$F_{t+1} = \frac{\sum_{i=1}^n D_{(t-i+1)}}{n} \quad (3)$$

where D_t denotes actual demand in period t . The optimal order n was selected via grid search over $n \in \{2, 3, 4\}$ by minimizing MAPE on a hold-out validation set (Taengphukieo and Issarapong, 2019; Moonphala and Kawtummachai, 2014)

3.2 Single Exponential Smoothing (SES): SES adapts the forecast by applying exponentially declining weights to historical observations as shown in Equation (4):

$$F_{t+1} = \alpha D_t + (1 - \alpha)F_t \quad (4)$$

Where $\alpha \in (0,1)$ is the smoothing parameter optimized by minimizing the sum of squared forecast errors on the training set (Moonphala and Kawtummachai, 2014)

3.3 Holt-Winters' Multiplicative Exponential Smoothing: For items exhibiting biannual semester-cycle seasonality, the Holt-Winters' multiplicative method is employed as shown in Equation (5):

$$F_{t+h} = (L_t + hT_t)S_{(t-m+h)} \quad (5)$$

$$\text{where } L_t = \alpha \frac{D_t}{S_{(t-m)}} + (1 - \alpha)(L_{(t-1)} + T_{(t-1)})$$

$$T_t = \beta(L_t - L_{(t-1)}) + (1 - \beta)T_{(t-1)}$$

$$S_t = \gamma \frac{D_t}{L_t} + (1 - \gamma)S_{(t-m)}$$

and $m = 2$ for biannual seasonality, h is the forecast horizon, and α, β, γ are smoothing parameters jointly optimised via Nelder–Mead simplex minimization of MAPE on the training set (Phuchittrasin et al., 2024)

Forecast accuracy is evaluated using Mean Absolute Percentage Error (**MAPE**) as the primary metric, with Mean Absolute Error (**MAE**) and Root Mean Squared Error (**RMSE**) as supplementary measures as shown in Equation (6)-(8):

$$MAPE = \left(\frac{\sum_{t=1}^n |D_t - F_t|}{n D_t} \right) \times 100\% \quad (6)$$

$$MAE = \left(\frac{\sum_{t=1}^n |D_t - F_t|}{n} \right) \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (D_t - F_t)^2}{n}} \quad (8)$$

Where **MAPE** is the primary reporting metric for comparability with the extant Thai and international forecasting literature (Sarika et al., 2024; Sumranhun et al., 2023)

4. Safety Stock and Reorder Point

Safety stock (**SS**) and reorder point (**ROP**) are calculated for Class A and B fast-moving items using Equation (9)-(10):

$$SS = Z \sigma_D \sqrt{L} \quad (9)$$

$$ROP = D_{avg} L + SS \quad (10)$$

Where Z is the service-level z-score ($Z = 1.645$ for 95% service level), σ_D is the standard deviation of periodic demand, L is procurement lead time in periods, and D_{avg} is average demand per period (Moonphala and Kawtummachai, 2014).

Result

This section presents the findings in five sequential stages: (1) ABC-FSN classification of all 17 materials and equipment items; (2) demand pattern analysis for the selected AF-class item;

(3) forecasting results from three competing methods; (4) forecast accuracy comparison; and (5) safety stock and reorder point calculation. The classification results serve as the analytical foundation from which the target item for demand forecasting is identified and justified.

1. ABC-FSN Classification Result

The complete ABC-FSN classification results for all 17 materials and equipment items stocked in the Welding Industrial Engineering Program warehouse. The dual-axis classification integrates the ABC dimension, which is based on annual consumption value (ACV) ranked by cumulative percentage, with the FSN dimension, which is based on the average quarterly disbursement rate (CR) is presented in Table 1.

Table 1. ABC-FSN Classification Results for All Materials and Equipment.

No.	List of materials and equipment	Total value or ACV (Baht/year)	%Value (%)	%Accumulated value (%)	Class of ABC Analysis	Consumption Rate (unit)	Class of FSN Analysis	ABC-FSN Analysis
1	Welding wire, RB26 E6013 2.6 mm	7,465.00	20.38	20.38	A	1.17	S	AS
2	Welding wire, LB52 E7016 2.6 mm	4,154.00	11.34	31.72	A	1.42	S	AS
3	Welding wire, RB26 E6013 3.2 mm	3,535.00	9.65	41.37	A	0.58	S	AS
4	Welding Jacket	3,342.84	9.13	50.50	A	2.67	F	AF
*5	Grinding wheel 4"x6" mm	3,032.60	8.28	58.78	A	5.33	F	AF
6	Welding wire, LH2000 E7016 2.6 mm	2,955.00	8.07	66.85	A	0.00	N	AN
7	Leather Arm Sleeves	2,640.00	7.21	74.06	B	2.42	S	BS
8	Welding wire, LH2000 E7016 3.2 mm	1,840.00	5.02	79.08	B	1.50	S	BS
9	Long, smooth leather gloves	1,806.74	4.93	84.01	B	2.67	F	BF
10	Grinding wheel 4"x3" mm	1,501.92	4.10	88.11	B	4.42	F	BF
11	Welding Head	1,200.00	3.28	91.39	C	0.33	N	CN
12	Welding Mask	1,100.00	3.00	94.39	C	2.58	S	CS
13	Ground Clamp	700.00	1.91	96.31	C	0.42	N	CN
14	Welding glass #10	612.00	1.67	97.98	C	0.75	S	CS
15	Grinding wheel 7"x6" mm	392.00	1.07	99.05	C	1.08	S	CS
16	Welding glass (clear)	209.28	0.57	99.62	C	1.25	S	CS
17	Grinding wheel 6"x6" mm	140.00	0.38	100.00	C	0.25	N	CN
Total		36,626.38	100.00					

From table 1 shows that two items are classified as AF, indicating high annual consumption value and disbursement velocity: the Welding Jacket and the Grinding wheel 4"x6" mm. Both warrant rigorous replenishment control. However, this study selects the Grinding wheel 4"x6" mm for demand forecasting and replenishment parameter derivation because it is a consumable requiring regular replenishment, whereas the Welding Jacket is reusable personal protective equipment that does not require consumption-based replenishment planning. Focusing on a consumable item is methodologically appropriate and practically meaningful, as its replenishment directly affects procurement frequency and safety-stock requirements (Sansug et al., 2024)

To examine the demand pattern of the selected item prior to forecasting, Figure 2 presents the historical demand for the Grinding wheel 4"x6" mm across 14 consecutive semesters spanning the academic years 2019 through 2025.

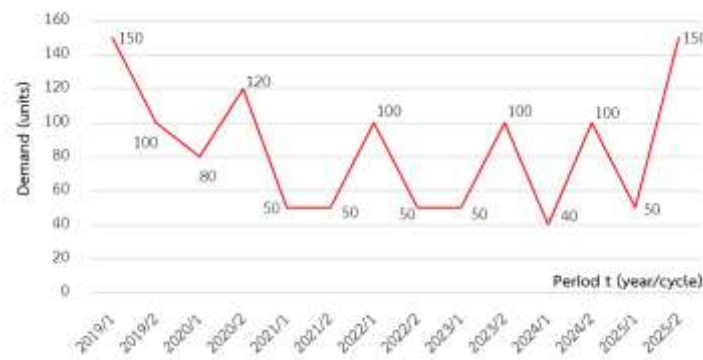


Figure 2. Demand of Grinding wheel 4"x6" mm

From Figure 2, the demand for the Grinding wheel 4"x6" mm exhibits an irregular fluctuating pattern throughout the study period, with values ranging from a minimum of 40 units to a maximum of 150 units, yielding an overall mean of 85 units per semester and a coefficient of variation of 44.7%, indicating moderate-to-high demand variability. The series does not follow a stable seasonal cycle; while Semester 2 periods tend to record higher demand on average (mean = 95.71 units) compared to Semester 1 (mean = 74.29 units), this pattern is inconsistent across years collectively indicate that a forecasting method capable of adapting to both trend and seasonal components, such as Holt-Winters' multiplicative exponential smoothing, is more appropriate than simpler non-adaptive methods.

2. Demand Forecasting Results

Three demand forecasting methods were applied to the historical demand data of the Grinding wheel 4"x6" mm across 14 periods (2019/1–2025/2): Moving Average (MA), Single Exponential Smoothing (SES), and Holt-Winters' Multiplicative Exponential Smoothing. For the MA

method, three window sizes ($n = 2, 3, 4$) were evaluated and the best-performing order selected. For SES, nine smoothing parameter values ($\alpha = 0.1, 0.2, \dots, 0.9$) were systematically tested and the optimal α identified. For Holt-Winters' method, the three smoothing parameters (α, β, γ) were optimised through a grid search across all combinations within $\{0.1, 0.2, \dots, 0.9\}$. Each method was evaluated using Mean Absolute Error (*MAE*), Root Mean Squared Error (*RMSE*) and Mean Absolute Percentage Error (*MAPE*) as accuracy metrics, with *MAPE* serving as the primary criterion for method ranking due to its scale-independence (Sarika et al., 2024; Vanitkun et al., 2023). It should be noted that the number of periods evaluated differs across methods because each method requires a different number of initialisation periods before forecasting begins; therefore, *MAE* and *RMSE* values are not directly comparable across methods and *MAPE* is used as the definitive ranking criterion. The accuracy results for all three methods are summarised in Table 2.

Table 2. Forecast Accuracy Comparison for the Grinding wheel 4"x6" mm.

Method	Best parameter	<i>MAE</i>	<i>RMSE</i>	<i>MAPE</i> (%)	Period 15 forecast	Rank
Moving Average	$n=3$	33.33	38.80	47.53	100.00	2
Single Exponential Smoothing	$\alpha=0.5$	38.64	42.38	51.41	107.44	3
Holt-Winters' Multiplicative	$\alpha=0.1, \beta=0.9, \gamma=0.5$	31.76	38.30	35.06	54.13	1

From Table 2, Holt-Winters' Multiplicative Exponential Smoothing achieved the highest forecasting accuracy, yielding the lowest *MAPE* value of 35.06%, followed by the Moving Average method (47.53%) and Single Exponential Smoothing (51.41%). Based on the *MAPE* ranking criterion, Holt-Winters' method was selected as the most suitable forecasting model for the Grinding wheel 4"x6" mm inventory item. In addition to producing the lowest forecasting error, the method also generated the lowest *MAE* and *RMSE* values among the evaluated models. The results suggest that the historical demand pattern contains trend and seasonal variations that can be effectively captured by the Holt-Winters model. Using the optimal parameter combination ($\alpha = 0.1, \beta = 0.9, \gamma = 0.5$), the forecasted demand for Period 15 was estimated at 54.13 units in Figure 3.

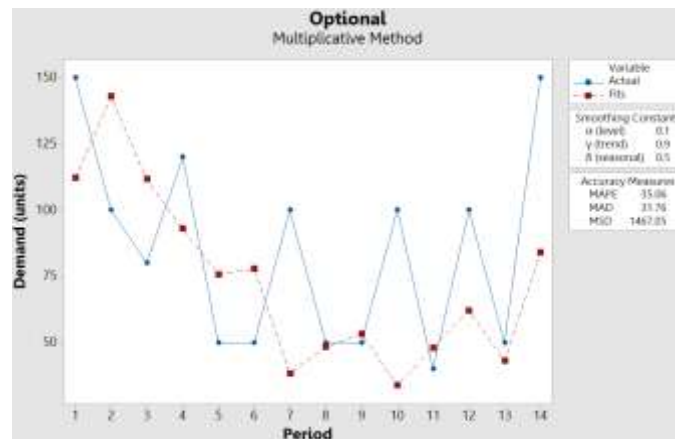


Figure 3. Fitted demand values using Holt-Winters' Multiplicative Exponential Smoothing for the Grinding wheel 4"x6" mm inventory item from Minitab 18.0 program.

3. Safety Stock and Reorder Point Results

Based on the Holt-Winters' Multiplicative Exponential Smoothing forecast, safety stock (SS) and reorder point (ROP) were calculated for the Grinding wheel 4"x6" mm as a representative AF-class consumable item. The parameters used in the calculation are presented in Table 3.

Table 3. Input parameters for Safety Stock and Reorder Point calculation.

Parameter	Value	Unit	Source
Average demand per semester: D_{avg}	85.00	units/semester	Historical data (2019/1–2025/2)
Standard deviation of demand: σ_D	37.98	units	Historical data (2019/1–2025/2)
Service level z-score (95%): Z	1.645	-	Standard statistical table
Procurement lead time: L	1	semester	Assumed: institutional procurement
Period 15 forecast (2026/1): F_{15}	55	units	Holt-Winters' (Minitab 18.0)

The safety stock and reorder points are calculated using Equations (9) and (10) respectively: 62 units and 147 units. From Table 3, the safety stock for the Grinding wheel 4"x6" mm is 62 units, which serves as a buffer to absorb demand variability during the procurement lead time and maintain a 95% service level. The reorder point of 147 units indicates that a new purchase order should be placed when the on-hand inventory falls to or below 147 units, ensuring that stock will not be depleted before the replenishment order arrives. The high safety stock relative to the period 15 forecast (55 units) reflects the large historical demand variability of this item ($\sigma_D = 37.98$; $CV = 44.7\%$), confirming that maintaining a conservative buffer is warranted for this AF-class consumable (Moonphala and Kawtummachai, 2014; Sriyom et al., 2021)

Summary and Discussion

This study applied an integrated ABC-FSN classification and demand forecasting framework to the materials warehouse of a Welding Industrial Engineering Programme, addressing a methodological gap in TVET educational warehouse management. The ABC-FSN classification of 17 SKUs identified 6 Class A items (35.3% of SKUs), accounting for 66.85% of total annual consumption value, while FSN analysis identified 4 Fast-moving, 9 Slow-moving, and 4 Non-moving items. The AN-class Welding wire KOBE LH2000 E7016 2.6 mm, with a CR of 0.00, was identified as a potential dormant-capital item that ABC analysis alone would not identify as a priority for inventory disposition (Insom and Kessomboon, 2025; Prampree et al., 2024). This finding suggests that combining consumption value with movement characteristics provides a more comprehensive basis for inventory prioritization than relying on a single classification dimension, consistent with the inventory-segmentation principle underlying ABC-FSN analysis.

Among the two AF-class items, the Grinding wheel 4 "x6 " mm was selected as the forecasting target based on its consumable nature. Holt-Winters' Multiplicative Exponential Smoothing achieved the lowest MAPE of 35.06%, compared with Moving Average (47.53%) and Single Exponential Smoothing (56.42%). The comparatively lower error of Holt-Winters may reflect its greater flexibility in representing systematic variation in semester-level demand than the less complex Moving Average and Single Exponential Smoothing approaches, as also examined in comparative inventory-forecasting research (Kumar et al., 2024). This finding is consistent with previous studies reporting improved forecasting performance from methods that account for demand patterns in institutional or educational settings (Phuchittrasin et al., 2024; Sarika et al., 2024; Vanitkun et al., 2023). The resulting safety stock of 62 units and reorder point of 147 units provide practical parameters for replenishment planning in the educational warehouse context (Sansug et al., 2024; Muenjitnoy and Aunyawong, 2025). However, the 35.06% MAPE also indicates that substantial forecasting uncertainty remains; therefore, Holt-Winters should be regarded as the best-performing method among those evaluated in this case rather than as a universally superior forecasting approach.

Recommendation

1. Practical Implications: The ABC-FSN framework provides a systematic basis for prioritizing inventory according to consumption value and movement characteristics. Class A and AF items should receive greater attention in monitoring and replenishment, while AN items should be considered for inventory reduction or disposition. In addition, the 35.06% MAPE also might affect the actual application of safety stock and reorder point values.

2. Future Research: Future studies should address the limitations of this single-warehouse case study, including the use of 17 SKUs, one AF-class forecasting item, and 14 semester-level observations. Longer demand series, multiple representative items, and genuine out-of-sample or rolling-origin validation should be considered to improve forecasting reliability and generalizability. External demand factors, such as student enrollment and course offerings, could also be incorporated to explain demand variation and improve the forecasting framework.

Ethical Considerations

The study was approved by the Institutional Review Board (IRB) of Rajamangala University of Technology Isan Khon Kaen Campus under the project title “Classification of Materials and Equipment Using ABC-FSN Analysis and Demand Forecasting: A Case Study of the Department of Industrial Welding Education Materials Warehouse.”, no. HEC-02-69-018.

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