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Integrating Demand Forecasting And Inventory Control Models To Enhance Operational Efficiency At An MRO Distributor: A Case Study Of PT XYZ

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ABSTRACT

Micro, Small, and Medium Enterprises (MSMEs) in the Maintenance, Repair, and Operations (MRO) sector often suffer from operational inefficiencies due to intuition-based inventory management. This study addresses such problems in PT XYZ, an MRO distributor that is experiencing significant overstocking and deadstock. Utilizing a quantitative case study methodology where 32 months of historical data have been used, this study classifies demand patterns based on the Syntetos-Boylan Categorization Matrix and tests the performance of different time-series forecasting models. The study determines the optimal inventory parameters (EOQ, ROP, Safety Stock) according to the most accurate forecasting models. Results indicate that the suggested data-driven system can release approximately Rp 604 million in frozen working capital and reduce annual inventory costs by 85.7% (Rp 113 million).

INTRODUCTION

The Maintenance, Repair, and Operation (MRO) supply market is a significant part of the international industrial market. The world market in MRO was projected to be $643.04 billion in 2023 and is projected to increase at CAGR of 2.2 between 2024 and 2030 (Grand View Research, 2024). In Indonesia, the market is growing at a high rate because infrastructure is being developed and industries are growing. However, Micro, Small, and Medium Enterprises (MSMEs) operating in this sector often face a significant operational complexity, particularly in inventory management.

Inventory is one of the costliest assets for companies, which often consume more than 50% of invested capital (Heizer, Render, & Munson, 2017). In the MRO sector, inventory may comprise 40% of total procurement cost (Driessen et al., 2015). The major reason of why MSMEs face a critical concern is the use of intuition-based replenishment instead of data-driven techniques. Research by Hu et al. (2018) indicates that firms relying on intuitive inventory decision incur cost 25-40% higher than those utilizing forecasting measurements. The result of this misalignment is frequently an overstocking in slow moving items and stock-outs in fast moving items.

PT XYZ, which is a technical equipment distributor in Surabaya, exemplifies these challenges. The company manages a huge portfolio of 6,866 Stock Keeping Units (SKUs). Initial findings indicate that the company is based on reactive decision-making, especially in the inventory replenishment process, which results in the overstocking of inventory and deadstock. As an example, products such as the "Rotary Hammer HM 2-24" are stocked with an 18.2 months of supply, which is considerably higher than the 3-4 months the industry requires. Besides, the company carries a huge deadstock of above Rp 84million.

The root cause of these inefficiencies are the absence of a systematic demand forecasting system and the lack of inventory control models (EOQ, Safety Stock, and ROP) utilized. MRO inventory is hard to manage, especially because of intermittent demand patterns which are characterized by random occurrence and fluctuating sizes of demand (Cavalieri et al., 2008. In this case, traditional forecasting frequently fails and more specific techniques are needed, such as the Croston method or the Syntetos-Boylan Approximation (SBA).

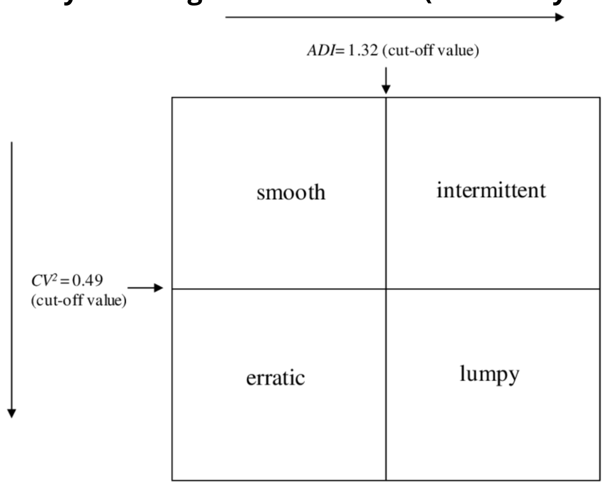
This study will address these issues by formulating an integrated inventory management framework. The aims are to: (1) evaluate the demand forecasting techniques in order to identify the best models to forecast high-value products; (2) identify the best inventory control parameters (EOQ, ROP, Safety Stock); and (3) measure the financial implication of the proposed system.

LITERATURE REVIEW

Demand Patterns and Classification

Identifying demand patterns is important for choosing suitable forecasting techniques. Demand is generally categorized into four types: smooth, intermittent, erratic, and lumpy (Syntetos, Boylan, & Croston, 2005). Smooth demand is defined by frequent occurrences with low variability whereas erratic demand is defined by frequent occurrences but high variability in quantity. Intermittent demand, which is common in the MRO industry, involves periods of zero demand mixed with non-zero demand, whereas lumpy demand combines intermittency with high variability. In order to collectively categorize these patterns, this paper makes use of the Syntetos-Boylan Categorization Matrix. In this model, the items are categorized by two statistical measures: the Average Demand Interval (ADI) and the squared Coefficient of Variation (CV^2) (Syntetos et al., 2005).

Figure 1 Syntetos-Boylan Categorization Matrix (Source: Syntetos et al., 2005)



Forecasting Models

The forecasting models have to be aligned with the determined demand patterns. In the case of smooth and erratic demand, the time-series models are commonly used. Simple Moving Average (SMA) is well suited in short-term predictions where demand is comparatively stable since it averages random variations. Simple Exponential Smoothing Simple Exponential Smoothing (SES) is appropriate when the data does not have a trend or seasonality and the weights attached to older data are exponentially decreasing. In cases where data show a linear trend, Double Exponential Smoothing (Holt Method) is applied; in this model, a second equation of smoothing is added to explain the trend part (Jacobs & Chase, 2020). In addition, Triple Exponential Smoothing (Holt-Winters) further expands the method by introducing a third parameter to represent the seasonality, which is applicable in the case of data that have both trend and seasonal changes.

In the case of items that are characterized as intermittent or lumpy, the traditional time-series models tend to fail because of the occurrence of zero-demand period (Petropoulos et al., 2016). Croston's Method addresses this by forecasting the amount of demand and the gap between demands individually. However, Croston's method is known to contain a positive bias. To correct this, the Syntetos-Boylan Approximation (SBA) adds a deflating factor to the forecast which often leads to improved accuracy for intermittent items (Syntetos & Boylan, 2005).

Inventory Control Models

Inventory management involves striking a balance between cost and service level. The Economic Order Quantity (EOQ) model reduces the total inventory costs by finding the optimum level of order that considers a balance between ordering and holding costs (Eid Bait Bin Saleem & Ullah, 2023). The Reorder Point (ROP) calculation is used to determine the particular level of inventory that will lead to a replenishment order to avoid stockouts during lead times (Nobil et al., 2020). This is often paired by Safety Stock (SS), which is a buffer stock that is calculated using demand variability to counter demand and supply uncertainties (Esmail Mohamed, 2024; Heizer et al., 2017).

METHODS

Sampling

The target population of this study is the inventory portfolio of PT XYZ, an MRO distributor based in Surabaya, Indonesia. Since the research had limited resources and the operational fact that a small proportion of inventory usually represents a large portion of value, the study adopted the purposive sampling methodology that relies on ABC-XYZ analysis. First, a stratification of the population was done with the help of the ABC analysis (stratification based on an inventory value) and the XYZ analysis (stratification based on variability of demand). The sampling frame is concentrated on the items that are included in the category A since they produce the greatest revenue and they impact the most on the company financially. From this high-priority category, six representative SKUs were chosen as the units of analysis. The reason behind selecting these items was to have a variety of demand behaviors, namely, smooth, erratic, and intermittent demand behaviors. This stratification will make the findings and suggested models strong across various categories of inventory characteristics that exist in the MRO industry.

Data Collection

Data Collection was conducted using archival research methods. The secondary data was obtained through the internal database of inventory management of PT XYZ. The dataset covers a 32-month observation period from January 2023 to August 2025. Two primary datasets were extracted:

1. Sales Data: Monthly sales quantities for all SKUs to reconstruct demand history.
2. Operational Cost Data: Procurement records including supplier lead times, unit costs, ordering costs (administrative and shipping), and holding costs (storage and opportunity costs).

To maintain validity, the data was cleaned up to eliminate errors in entries. Time-series data was then separated into two different sets to be used in the model validation: the initial 26 months (January 2023 - February 2025) represents the model training set, and the remaining 6 months (March 2025 - August 2025) corresponds to the testing set used to compare the performance of the model predictions and the real demand.

Measures

The study employed three categories of measurement to evaluate demand patterns, forecast accuracy, and inventory efficiency:

1. Demand Pattern Classification: To categorize the demand pattern of each SKU, two statistical metric were calculated:

- ADI (Average Demand Interval): Measures the average time gap between two consecutive demand occurrences. The formula to calculate Average Demand Interval is shown in the equation below.

$$ADI = \frac{Total\ Periods}{Total\ Non-zero\ Demand\ Occasions}$$

- CV^2 (Squared Coefficient of Variation): Measures the variability of demand sizes. The formula to calculate Squared Coefficient of Variation is shown in the equation below.

$$CV^2 = (\frac{Standard\ Deviation\ of\ Non-zero\ Demand}{Average\ of\ Non-zero\ Demand})^2$$

These metrics were mapped onto the Syntetos-Boylan Categorization Matrix to classify items as smooth, erratic, intermittent, or lumpy.

2. Forecasting Accuracy Measures: To evaluate the accuracy of the forecasting models, the study measured the deviation between forecasted values and actual data in the testing sets.

- MAD (Mean Absolute Deviation): Measures the average absolute difference between actual and forecasted values in units The formula to calculate MAD is shown in the equation below.

$$\text{MAD} = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n}$$

Where A_t = Actual value in period t, F_t = Forecasting value in period t, n = number of data.

- MAPE (Mean Absolute Percentage Error): Used for non-intermittent demand to measure the average percentage deviation. The formula to calculate MAPE is shown in the equation below.

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

Where A_t = Actual value in period t, F_t = Forecasting value in period t, n = number of data.

- wMAPE (Weighted Mean Absolute Percentage Error): Used where zero-demand periods occur in the data test, as standard MAPE calculation would result in division by zero errors. The formula to calculate wMAPE is shown in the equation below.

$$wMAPE = \left(\frac{\sum_{t=1}^{n}|A_t - F_t|}{\sum_{t=1}^{n} A_t}\right) x(100\%)$$

Where A_t = Actual value in period t, F_t = Forecasting value in period t, n = number of data.

3. Inventory Control Measures: Operational efficiency was measured using standard inventory formulas:

- EOQ (Economic Order Quantity): Calculated using Annual Demand (*D*), Ordering Cost (*S*), and Holding Cost (*H*) to determine the optimal batch size. The formula to calculate Economic Order Quantity is shown in the equation below.

$$EOQ = \sqrt{\frac{2\ x\ D\ x\ S}{H}}$$

  Where D= Annual demand quantity, S = Ordering cost per order, H = Annual holding cost per unit.

- ROP (Reorder Point): Measured as the sum of Lead Time Demand (*L x D)* and Safety Stock (*SS*) to determine the trigger point for replenishment. The formula to calculate the Reorder Point is shown in the equation below.

$$ROP = (d\ x\ L) + ss$$

  Where d = Average demand per day, L = Lead time for a new order in days, ss = Safety stock

- SS (Safety Stock): Calculated based on the standard deviation of demand during lead time and a target Service Level of 95% (*Z = 1.645*) to measure the necessary buffer against uncertainty. The formula to calculate the safety stock is shown in the equation below.

$$SS = ZsdLT$$

  Where Z= Number of standard deviations necessary to obtain acceptable service level, sdLT = Standard deviation of demand during lead time.

RESULTS

Demand Pattern Classifcation

The first stage of the analysis was the classification of the demand patterns of the six high-value SKUs (Category A) based on the monthly sales data of each SKU. The descriptive statistics comprised of the enclosed Demand Interval (ADI) and Squared Coefficient of Variation (CV^2) were determined to plot each item in the Syntetos-Boylan Categorization Matrix.

The analysis revealed three different types of demand in the sample as indicated in Table1. Four items were characterized by Smooth demand (ADI < 1.32, CV^2 < 0.49), one item was characterized by Erratic demand (ADI < 1.32, $CV^2 \geq 0.49$) and one item was characterized by Intermittent demand (ADI ≥ 1.32, CV^2 < 0.49). None of the items in the sample fell under the Lumpy category.

Table 1. Demand Classification

Item Name	ADI	CV^2	Demand Category
Blander Potong Yamato M LPG	1.103	0.43	Smooth
Demolition HBM 650-HL Bitech	1.032	0.28	Smooth
High Pressure QL- 12000 H&L	1	0.58	Erratic
Level Block 1,6 T x 1,5 M Vios	1.103	0.477	Smooth
Chain Hoist 2 T x 5 M Vios	1.14	0.32	Smooth
Rotary Hammer HM 2-24 DRE-HB	1.33	0.24	Intermittent

Forecasting Model Performance

The 6 forecasting models were tested on the testing set (6 months). Mean Absolute Deviation (MAD) was used to measure the magnitude of errors in units, whereas Mean Absolute Percentage Error (MAPE) or Weighted MAPE (wMAPE) was used to measure relative accuracy.

Five items that categorized as smooth and erratic demand (ADI <1.32) were tested using four standard models, which are Simple Moving Average (SMA), Simple Exponential Smoothing (Holt), and Triple Exponential Smoothing (Holt-Winters). Table 2 presents the comprehensive error of each model.

Table 2. Comparative Error Metrics for Smooth and Erratic Items

Item Name	Demand Pattern	Error Metric	SMA	SES	Holt	Holt-Winters
Blander Potong Yamato M LPG	Smooth	MAD	5.5	4.46	8.64	6.95
		MAPE	36.30%	28.16%	52.32%	41.85%
Demolition HBM 650-HL Bitech	Smooth	MAD	5.50	4.31	3.48	3.34
		wMAPE	62.26%	48.78%	39.42%	37.78%
High Pressure QL- 12000 H&L	Erratic	MAD	9.17	11.80	9.56	4.12
		MAPE	196.96%	390.69%	248.93%	37.07%
Level Block 1,6 T x 1,5 M Vios	Smooth	MAD	3.44	4.44	5.29	6.97
		MAPE	44.04%	44.72%	50.63%	69.44%
Chain Hoist 2 T x 5 M Vios	Smooth	MAD	1.44	1.33	1.79	1.42
		MAPE	51.11%	43.00%	61.01%	37.30%

The table underscores the need to test various models. Simple Exponential Smoothing (SES) was better fit in case of “Blander Potong Yamato” (MAPE 28.16%). Even more complicated models such as the Holt method failed (MAPE 52.32%) due to it assuming a linear trend which was non-existent resulting in high over-forecasting.

Holt-Winters was crucial in products which are seasonal or volatile. In the case of the High “Pressure QL-1200”, more basic models (SMA, SES) were disastrous, producing errors in excess of 190%. It was only Holt-Winters who could follow the unpredictable spikes and lowered the error was lowered to an acceptable MAPE of 37.07%. Similarly, it captured the seasonal demand of the “Chain Hoist 2 T x 5 M Vios”, achieving the lowest MAPE (37.30%). On contrary, Simple Moving Average (SMA) was unexpectedly the most accurate forecasting model for the Level Block 1.6T. This product showed no trend or seasonality, only random noise that was of the zigzag type. Complex models attempted to fit this noise, producing greater error (e.g. Holt-Winters MAPE 69.44%), but SMA was able to smooth the volatility (MAPE 44.04%).

For the “Rotary Hammer HM 2-24 DRE-HB”, which exhibits a intermittent demand (ADI ≥ 1.32), standard models are not applicable to this type of demand. Therefore, Croston’s method was compared against the Syntetos-Boylan Approximation (SBA).

Table 3. Comparative Error Metrics for Intermittent Items

Item Name	Demand Pattern	Error Metric	Croston	SBA
Rotary Hammer HM 2-24 DRE-HB	Intermittent	MAD	2.25	2.26
		MAPE	47.01%	47.1%

While the literature often suggests SBA is superior for bias correction, the results in Table 3 show that Croston's Method performed slightly better for this specific dataset, achieving a lower MAD of 2.25 units. Operationally, this means the forecast misses the actual demand by an average of only 2 units per month, which is highly precise compared to the company's current practice of holding 78 units of stock.

Based on the lowest error metric from each model, the final models selected for inventory parameter calculation are provided in Table 4.

Table 4. Selected Forecasting Models and Error Metrics

Item Name	Selected Model	Reason of Selection
Blander Potong Yamato M LPG	Simple Exponential Smoothing	Lowest MAPE (28.16%)
Demolition HBM 650-HL Bitech	Holt-Winters Method	Lowest wMAPE (37.78%)
High Pressure QL- 12000 H&L	Holt-Winters Method	Lowest MAPE (37.07%)
Level Block 1,6 T x 1,5 M Vios	Simple Moving Average	Lowest MAPE (44.04%)
Chain Hoist 2 T x 5 M Vios	Holt-Winters Method	Lowest MAPE (37.3%)
Rotary Hammer HM 2-24 DRE-HB	Croston’s Method	Lowest MAPE (47.0075%)

Inventory Parameter

Based on the forecasted demand (D) by the chosen models, the optimal inventory parameters (EOQ, ROP, Safety Stock) have been calculated and compared to the existing intuitively based inventory at the company. The results in Table 5 show a significant difference between the current inventory levels and the optimum levels calculated. As an example, the existing inventory of the item, “Rotary Hammer HM 2-24 DRE-HB”, stands at 78 units, whereas the Reorder Point (ROP) is 3 units with Economic order quantity (EOQ) of 3 units.

Table 5. Comparison of Inventory Parameters (Current vs Proposed)

Item Name	Current Stock (Unit)	Proposed EOQ	Proposed Safety Stock	Proposed ROP
Blander Potong Yamato M LPG	229	228	34	6
Demolition HBM 650-HL Bitech	77	110	10	2
High Pressure QL- 12000 H&L	132	135	19	3
Level Block 1,6 T x 1,5 M Vios	31	140	13	2
Chain Hoist 2 T x 5 M Vios	22	72	10	1
Rotary Hammer HM 2-24 DRE-HB	78	55	3	2

Financial Impact Analysis

Table 6 presents the aggregate financial impact of switching to these proposed parameters. The "Frozen Capital" represents the value of inventory held above the optimal level, while "Total Annual Cost" is the total cost of holding and storing each item in the inventory annually.

Table 6. Financial Comparison (Current vs Proposed System)

Metric	Current System (Actual)	Proposed System (Simulated)	Difference (Savings)
Total Inventory Value	Rp 662.218.425	Rp 57.890.275	Rp 604.328.150
Total Inventory Annual Cost	Rp 132.443.685	Rp 18.888.489	Rp 113.555.196

The results show that the current system holds approximately 11 times more inventory value than necessary, resulting in an 85.7% inefficiency in annual inventory costs.

DISCUSSION

The main purpose of conducting this study was to resolve the operational inefficiencies at PT XYZ due to the use of intuition-based inventory management. The current study helps the literature on MSME operations management by introducing an integrated framework of demand forecasting and inventory control, which can be effectively scaled down to smaller business in the MRO industry by applying data-driven techniques.

The outcome of this classification is the support of the complexity of MRO inventory showing that a one-size-fits-all forecasting method cannot be used. These findings align with Syntetos et al. (2016), who claim that accuracy in a forecast is a precondition of demand classification.

The study revealed that even within the smooth demand category, model selection varies Although the simplest forecasting model (Simple Moving Average) fitted the "Level Block 1.6T" with no trend or seasonality, other smooth items needed the Exponential Smoothing or Holt-Winters to capture small trends or data weighting preferences. This nuances the general assumption that all smooth items should be treated identically, highlighting the importance of individual SKU testing. Moreover, intermittent and erratic items needed more advanced methods (Holt-Winters and Croston Method, respectively).

The quantification of the cost of intuition is the most significant findings to the management. The findings show that PT XYZ is already maintaining a stock worth more than Rp 604 million of only six items. This finding supports the assertion by Silver et al. (2016) that scientific inventory control significantly frees up working capital. In practice, the research proposes that the company should:

1. Stop using a fixed interval ordering and adopt a Reorder Point (ROP) system.
2. Use different forecasting models on different product lines.
3. Utilize the released capital to expand the product range or improve marketing efforts, rather than letting it sit as deadstock.

CONCLUSION

The PT XYZ inventory management, which is based on intuition, has resulted in serious financial inefficiencies. This paper has shown that a combination of demand forecasting and inventory control model could be a viable solution.

First, demand classification is an obligatory requirement to forecast accuracy. The analysis has verified that a one-size-fits-all strategy does not apply to distributors of MRO.

Second, scientific inventory control is far superior to intuitive ordering. The Economic order quantity (EOQ) and Reorder Points (ROP) calculation revealed extreme overstocking in the existing system. Indicatively, the company has 18 months' supply of some of the products when the required weeks are only a few. The proposed system moves the paradigm of stocking as much as possible to stocking precisely what is required. The financial impact of the proposed system is substantial. The simulation demonstrates that the conversion into this proposed framework will free Rp 604.328.150 of frozen working capital with only six items. Moreover, annual inventory cost of holding these 6 items in the inventory is estimated to decrease by Rp 113.555.196, or 85.7 percent efficiency improvement.

In conclusion, PT XYZ should move away from subjective estimation and fully adopt this integrated forecasting and inventory control framework. Immediate priority should be given to Category A items, as optimizing these high-value SKUs offers the most significant immediate return on investment and operational stability.

LIMITATION

Although the outcomes are encouraging, there exist limitations that affect validity. First, the study analyzed only six "Category A" items out of 6,866 SKUs. Although these items are of high value, the demand of C items (slow movers) might vary widely and thus may need some different models that have not been tested here. Second, suppliers assume fixed lead times in the study. The fact is that global supply chain disruptions may lead to fluctuations in lead time, which was not accounted in the safety stock calculations.

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