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Determination of Demand Forecasting and Inventory Policies for Managing Raw Materials with Engineering to Order Characteristics in the Electricity Maintenance Industry

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Abstract - *Manufacturing industry with Engineering to Order (ETO) characteristics faces challenges in the production process in the form of the availability of raw materials needed. This research was conducted at a manufacturing unit owned by the electricity industry with the main task of producing spare parts for the generation, transmission, and distribution of electricity, this unit carries out the production process with regulations no inventory policy, these regulations make the raw material planning process more difficult and result in material shortages, production delays, and inability to meet delivery time targets, thus threatening customer satisfaction and operational efficiency of the unit. A critical raw material needs planning strategy will be developed using the demand forecasting method. The forecasting methods used include linear regression, double exponential smoothing, Winter's Model and Syntetos-Boylan Approximation. The results of this demand forecasting will be used as a basis for designing a more optimal inventory policy. Three inventory policy scenarios to be evaluated include existing review, continuous review (s,Q), and periodic review and order-up-to-level (R,S) and the method with the smallest stockout risk, the most optimal cost, and the method with the best raw material supply flexibility will be selected.*

Keywords - *Demand Forecasting, Inventory Policy, Engineering to Order, Reverse Engineering*

I. INTRODUCTION

Manufacturing industries with Engineering to Order (ETO) characteristics face inherent challenges in ensuring the timely availability of raw materials due to the absence of standardized products and the high variability of customer requirements. In such contexts, production delays are often directly linked to inefficiencies in demand forecasting and inventory management.

The electrical maintenance unit is one of the units of the company operating in the electrical power sector which producing Engineering to Order products. It receives assignments from other business units of the parent company to produce spare parts for the power generation, transmission, and distribution sectors. The assignments received are custom-made, with product types being specific in terms of shape and dimensions, tailored to the employer's needs, and produced through reverse engineering processes. The value of assignments received from 2021 to 2024 has seen a significant increase, from 239 billion rupiah in 2021 to 806 billion rupiah in 2023. For 2024, the target assignment value is set at 1.5 trillion rupiah by the end of December 2024. The determination of the 1.5 trillion rupiah assignment target for 2024 was based on the need for the electricity maintenance unit to cover its operational costs, but it did not comprehensively consider market opportunity evaluations. Figure 1 below shows the assignment values for the electricity maintenance unit from 2021 to 2024.

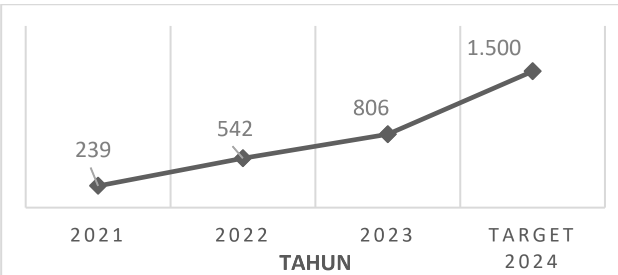

Figure 1 Assignment Values for Electricity Maintenance Units in 2021–2024

The average value of completed work with a delayed status and amendments made from 2022 to July 2024 is 18.13% of the value of assignments completed during that period. The delays or amendments were due to delays in the delivery of raw

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materials to be processed into products, with the longest delay duration in each period being ≤ 100 days. Additionally, there is an upward trend in delay duration from 2022 to July 2024, with 43.97% of the assignment value experiencing delays exceeding 300 days in 2024.To ensure that the production process is not hindered by the availability of raw materials, the electrical maintenance unit faces the challenge of regulations that prohibit holding inventory. Therefore, if raw materials are not properly planned, product delivery may not be made on time, and assignments may even be canceled.

In response to the no inventory regulation, the electrical maintenance unit implements a raw material supply strategy by entering into unit price contracts (KHS), whereby the contract becomes the master contract and subsequently, if there is a need for raw materials, the supplier will immediately deliver the products within the agreed lead time. The Unit Price Contract (KHS) in the electrical maintenance unit is not yet functioning ideally, as the unit does not immediately receive raw materials when needed.

Therefore, this study will focus on three critical raw materials in the production category that have the largest volume and value contributions in the KHS contract and are one of the main causes of delays in completing the work. Critical materials in this context are determined based on a combination of significant contract value, high actual usage volume, and their impact on the timeliness of delivering work results. This determination is made because delays in material procurement have been proven to directly contribute to delays in product delivery to the client, thereby affecting the overall performance of the unit. Thus, the analysis of planning and inventory management for these materials is crucial in supporting operational smoothness and the achievement of assignment targets.

Inaccurate demand forecasting for raw materials conducted by the electrical maintenance unit has caused delays in the delivery of products to the client, thereby affecting the overall performance of the unit. An inappropriate inventory policy can also exacerbate the negative impact of inaccurate demand forecasting, whether in the form of shortages or surpluses of raw materials, thereby disrupting the production process of the power maintenance unit. With a no inventory policy, the unit cannot store raw materials on site, making it highly dependent on accurate material requirements planning. Therefore, the relationship between demand forecasting and inventory policy is crucial to ensuring the continuity of production. The use of appropriate forecasting methods also provides certainty regarding material requirements to suppliers, enabling inventory policies to be implemented optimally to minimize the risk of material shortages (stockouts) and optimize operational costs. Thus, the development of accurate demand forecasting strategies for raw materials directly contributes to improving inventory policy performance.

Previous studies on demand forecasting for spare parts (e.g., Bacchetti & Saccani, 2012; Rinaldi et al., 2023) have demonstrated various statistical and heuristic methods tailored for intermittent demand. However, limited research has addressed the integration of these forecasting methods with inventory policy design under no-stock regulations. Moreover, the intersection between forecasting accuracy and service-level-oriented inventory control in ETO environments remains underexplored, especially in contexts with extended procurement lead times and varying supplier reliability.

This study addresses these gaps by:

1. Identifying critical raw materials that significantly influence operational performance,
2. Evaluating multiple demand forecasting methods suited for intermittent demand, and
3. Designing optimal inventory policies that minimize stockout risk while maintaining cost efficiency.

By bridging operational challenges with academic models, this research provides both practical solutions for improving operational efficiency and theoretical insights for spare parts management in ETO settings.

II. LITERATURE REVIEW

Engineering to Order (ETO)

Engineering to Order (ETO) is a business model that produces products with specific and unique specifications. Products are designed, developed, and manufactured according to customer requirements, so there are no standards for each product. In the production process, products are created through specialized design and engineering processes, differing from the Make to Stock (MTS) or Make to Order (MTO) business models, where products are produced without considering specific customer requests.

Demand Forecasting

Bacchetti & Saccani (2012) emphasize the importance of demand classification in improving forecast accuracy for spare parts. Syntetos et al. (2005) propose the Syntetos–Boylan Approximation (SBA) for intermittent and lumpy demand, outperforming traditional smoothing methods. However, these studies often assume flexibility in inventory holding, which may not apply in *no-inventory*. While neural network and hybrid methods (Guiterrez et al., 2008; Affonso et al., 2024) demonstrate potential for improved accuracy, their computational complexity may limit applicability in operational environments with limited analytics infrastructure.

Inventory Policy

An inventory system is a set of policies and controls that monitor inventory levels and determine safety stock, reorder points, and order quantities. Raw material inventory management is a supply policy set at a certain level to support stable production processes when demand changes due to various factors. The material inventory set by the company is needed to prevent production processes from stopping due to material shortages.

Traditional inventory control models, Continuous Review (s, Q) and Periodic Review (R, S) balance cost and service level (Nahmias & Olsen, 2015). This review highlights a research gap: there is a lack of empirical studies that simultaneously evaluate forecasting method suitability and inventory control strategies under regulatory restrictions prohibiting physical stockholding, particularly in ETO contexts.

III. METHODOLOGY

This research began with a background analysis of the unit and the collection of historical data on raw material demand and usage. It was followed by an analysis of critical material classification, selection of the most accurate forecasting method, and calculation of inventory policy simulations.

Materials are grouped using two methods:

- ABC analysis to identify materials with the highest value contribution (category A).
- ADI-CV classification to determine demand patterns: smooth, intermittent, lumpy, or irregular.

Materials with a cumulative value contribution of ≥ 80% are categorized as critical materials.

Demand Forecasting Methods. Four forecasting methods were tested and compared based on error values:

1. Regression Linear
2. Double Exponential Smoothing (Holt's)
3. Winter's Model
4. Syntetos–Boylan Approximation (SBA)

The selection of the best method is based on the minimum error results using the Mean Absolute Percentage Error (MAPE).

Table I Scenario Design

Scenario	Inventory System	Object
Existing	Existing Inventory with No Inventory system in the unit electrical maintenance, using Contracts Unit Price (Inventory at the material supplier)	Sample from selected classification results
1	Continuous Review (s, Q System)	
2	Periodic Review and Order Up to Level (R, S system)	

IV. FINDINGS AND DISCUSSION

This section presents the results of the analysis and interpretation of data carried out to identify critical raw material requirements and formulate optimal inventory policies for the Electrical Maintenance Unit.

Classification of Raw Materials with ABC Analysis. Of the 35 material groups, 8 groups are classified as Category A (critical materials), contributing 81.76% of the total contract realization value. This study focuses on 3 critical materials from the generation category: Material 1, Material 4, and Material 7.

Calculation of Coefficient of Variance (CV) and Average Demand Interval (ADI). The demand pattern of sample materials is analyzed using CV and ADI.

Table II CV – Adi Classification And Recommended Forecast Methods

No	Name Material	CV	CV2	ADI	CV – ADI Classification	Recommended Methods Forecast (Syntetos, et al., 2005)
1	Material 1	0,896	0,802	2,476	Lumpy	Syntetos – Boylan Approximation
2	Material 4	2,275	5,175	1,857	Lumpy	Syntetos – Boylan Approximation
3	Material 7	1,529	2,339	1,238	Erratic	Syntetos – Boylan Approximation

Based on this classification, the Syntetos-Boylan Approximation (SBA) method is recommended for forecasting all three materials due to their lumpy and erratic demand characteristics.

The analysis identified eight critical material groups, with three Materials 1, 4, and 7 selected for detailed evaluation due to their high contract value contribution and role in production delays. The *Coefficient of Variation* (CV) and *Average Demand Interval* (ADI) classified all three as lumpy or erratic demand, confirming the suitability of the SBA method for forecasting.

Raw Material Demand Forecast. Forecasting is performed using Linear Regression, Double Exponential Smoothing, Winter's Model, and SBA. MAPE, MAD, and MSE measure accuracy.

Table III Results of Material Forecasting Accuracy Test 1

Error	Regression Linear	Double Exponential Smoothing	Winter's Method	Syntetos–Boylan Approximation
MAPE	91	191	158	78,75
MAD	5.446	6.533	6.205	4.933,24
MSE	42.527.508	72.153.520	53.496.155	44.195.089,92

Forecasting method for Material 1 that produced the best forecasting accuracy test used the Syntetos–Boylan Approximation method and the total costs that must be incurred to meet the needs of Material 1 for 12 periods, with the amount of material following the forecast results, are 5,801,760,000 Rupiah.

Table IV Results of Material Forecasting Accuracy Test 4

Error	Regression Linear	Double Exponential Smoothing	Winter's Method	Syntetos–Boylan Approximation
MAPE	397	1.782	1.126	206,59
MAD	9.816	12.409	15.060	8.367,52
MSE	531.686.164	860.259.967	634.958.759	547.083.897,31

Forecast method for Material 4 that produces the best forecast accuracy test uses the Syntetos–Boylan Approximation method. The results of the demand forecast for Material 4 using the Syntetos–Boylan Approximation method are as follows and the total cost that must be incurred to meet the needs of Material 4 for 12 periods, with the amount of material following the forecast results, is 3,049,518,000 Rupiah.

Table V Results of Material Forecasting Accuracy Test 7

Error	Regression Linear	Double Exponential Smoothing	Winter's Method	Syntetos–Boylan Approximation
MAPE	656	852	836	369,22
MAD	9.617	12.317	10.281	8.381,4
MSE	230.441.356	436.638.765	226.234.601	260.430.722,05

Forecasting method for Material 7 that yielded the best forecasting accuracy was the Syntetos–Boylan Approximation method. The demand forecast results for Material 7 using the Syntetos–Boylan Approximation method are as follows and the total cost that must be incurred to meet the needs of Material 7 for 12 periods, with the amount of material following the forecast results, is 2,783,526,600 Rupiah.

Across all three materials, SBA consistently achieved lower MAPE, MAD, and MSE compared to regression-based or smoothing methods, confirming its robustness for irregular demand patterns. This implies that reliance on traditional smoothing methods in such contexts could lead to systematic under- or over-estimation, increasing the risk of material shortages or excess procurement costs.

For the inventory policy calculation, the recapitulation of Total Cost and Service Level Inventory Policy. Each method used aims to identify the most efficient inventory management policy, taking into account cost, lead time, and desired service level. In this context, the targeted service level is 95%, but still reflects the most optimal cost level.

Table VI Result Inventory Policy Calculation

	Existing		Continuous Review (s, Q System)		Periodic Review dan Order Up to Level (R, S)	
	Total cost	Service Level	Total cost	Service Level	Total cost	Service Level
Material 1	293.576.888	49,62%	144.246.536	77,14%	157.439.898	95%
Material 4	282.613.523	7,75%,	103.569.883	92,03%	79.479.688	95%
Material 7	40.753.481	85,83%	20.811.645	95,30%	76.766.102	95%

Inventory Policy and Service Level Analysis per Material

Material 1.

- Existing Policy: Costs Rp 293,576,888 with a service level of only 49.62%. It indicates very poor performance and a high risk of stockouts, which can lead to project delays and penalties.
- Continuous Review (s, Q): Offers the most optimal solution with a cost of Rp 144,246,536 and a service level of 77.14%. While not yet reaching 90%, this is a significant improvement over the existing condition with a much lower cost. Sensitivity to the (s, Q) parameter needs to be considered.
- Periodic Review (R, S): Achieves a service level of 95% at a cost of Rp 157,439,898. It costs more than the optimal continuous review, but provides higher service reliability, suitable for highly critical materials.
- For Material 1, Continuous Review *(s, Q)* provides the best cost efficiency, but Periodic Review *(R, S)* ensures higher service reliability, suitable when delay penalties are severe.

Material 4.

- Existing Policy: Cost of Rp 282,613,523 with a very low service level of only 7.75%. It demonstrates the inability of the existing system to meet the demand for this material.
- Continuous Review (s, Q): Achieved a service level of 92.03% at a cost of Rp 103,569,883. It represents a significant improvement in service and cost efficiency compared to the existing policy.
- Periodic Review (R, S): The most efficient option with a cost of Rp 79,479,688 and a service level of 95%. It demonstrates that for Material 4, the periodic review approach can provide the best balance between cost and high service levels.

- For Material 4, the Periodic Review approach achieves both the lowest cost and highest service level, suggesting that review-based ordering cycles may be more effective for high-criticality, high-variability items.

Material 7.

- Existing Policy: Costs Rp 40,753,481 with a service level of 85.83%. While better than Materials 1 and 4, there is still room for improvement towards the ideal target.
- Continuous Review (s, Q): Offers the most optimal solution at a cost of Rp 20,811,645 and a service level of 95.30%. It is a significant improvement in service with a drastic reduction in costs.
- Periodic Review (R, S): Achieves a service level of 95% at a cost of Rp 76,766,102. While effective in achieving high service, the cost is higher than the optimal continuous review for this material.
- For Material 7, Continuous Review offers optimal results in both cost and service level, making it the preferred policy

Inventory Policy Analysis Conclusion. There is a clear trade-off between total inventory cost and service level. The existing policy is inadequate for critical materials. Continuous Review (s, Q) offers high cost efficiency with good service potential if parameters are properly calibrated. Periodic Review (R, S) provides higher service stability, suitable for materials with intolerable critical risk, although at a potentially higher cost. The optimal policy selection must consider the specific characteristics of the material and stockout risk tolerance.

Managerial and Theoretical Contributions

From a managerial perspective, combining SBA forecasting with tailored inventory policies per material type can significantly enhance service levels while controlling costs, even within a no-stock constraint. From a theoretical standpoint, this study extends spare parts forecasting literature by testing and validating forecasting-policy integration in a real-world ETO environment with regulatory limitations, an area rarely examined in prior research.

V. CONCLUSION

1. The critical raw material requirements were analyzed using the ABC Analysis approach for 35 material groups. The results showed that 8 material groups were included in Category A with a cumulative contribution of 81.76% of the total contract value. This confirms that these material groups are strategic and need to be prioritized in procurement. Four Category A materials also showed actual usage volumes exceeding contract quotas, necessitating adjustments to planning and regular contract evaluations. Furthermore, analysis of demand patterns using Average Demand Interval (ADI) and Coefficient of Variance (CV) revealed that most materials exhibit lumpy and erratic demand characteristics, meaning they are irregular and intermittent. These characteristics indicate that needs arise randomly and discontinuously, necessitating responsive and data-driven demand planning. To support more accurate demand planning, demand forecasting was conducted using four methods: Linear Regression, Double Exponential Smoothing, Winter's Method, and Syntetos–Boylan Approximation (SBA). The evaluation results show that the SBA method provides the best performance for the three sample materials, with the lowest error values (MAPE, MAD, and MSE) compared to other methods. This proves that the SBA method is most suitable for estimating material demand with intermittent patterns and high uncertainty, making it the primary reference for planning critical material needs in the future.
2. Simulations of various inventory control policies show that each approach has its advantages and limitations. In the existing scenario, where the company does not keep stock and relies solely on contract-based ordering (KHS), inventory costs are relatively moderate, but the resulting service level is low (<50% for Materials 1 and 4), posing a risk of disrupting operational smoothness. The Continuous Review approach (s, Q) shows high cost efficiency potential and service level achievement of ≥95%, provided that parameters such as reorder point, order quantity, and safety stock are set appropriately. However, this method is sensitive to parameter estimation errors, which can lead to supply imbalances. Meanwhile, the Periodic Review approach (R, S) provides more stable results with high and consistent service levels, although accompanied by higher inventory costs. This method is more suitable for materials with high critical risk and non-postponable service requirements. Considering these results, an adaptive inventory control strategy is recommended, combining the most accurate forecasting method (Syntetos–Boylan Approximation/SBA) with inventory policy selection based on material classification and risk level. This approach is believed to enhance supply reliability, reduce the risk of stockouts, and support operational efficiency and continuity of the Electrical Maintenance Unit.

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