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A Comparison of the Application of the Exponential Smoothing, Arima, and Random Forest Regression Methods for Forecasting Main Distribution Unit (MDU) Material Requirements at PT XYZ

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Abstract

This study aimed to compare the performance of forecasting methods for MDU requirements at PT XYZ using weekly aggregated data. The materials analyzed included kWh meters and Miniature Circuit Breakers (MCBs). Three forecasting methods were compared: Exponential Smoothing as a deterministic approach, ARIMA as a stochastic time-series approach, and Random Forest Regression as a contemporary machine learning-based approach. ARIMA was selected because preliminary identification indicated that the weekly demand data did not exhibit strong seasonal patterns; therefore, a non-seasonal model was considered more appropriate. This research employed a quantitative approach using historical material usage data. The forecasting performance of each model was evaluated using forecasting error metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Furthermore, statistical comparisons of forecasting errors were conducted to determine whether performance differences among the methods were statistically significant. The best-performing forecasting model was then used as the basis for developing preliminary recommendations for inventory policy. This study is expected to contribute scientifically to the selection of appropriate forecasting methods based on the characteristics of MDU demand data. In addition, it provides practical contributions for PT XYZ by supporting more objective, measurable, and data-driven procurement planning and inventory management.

INTRODUCTION

Main Distribution Materials (Material Distribusi Utama/MDU) are strategic components in PT XYZ electricity distribution system operations. The availability of MDU in the appropriate quantity, type, and timing plays a crucial role in maintaining distribution system reliability, particularly in supporting network maintenance activities, disturbance handling, and new customer connections. Suboptimal MDU inventory management may create stockout risks that result in service delays and reduced network reliability, as well as overstock conditions that increase storage costs and reduce budget efficiency (Silver et al., 2016). In operations and supply chain management, material inventory serves a dual function as a buffer against demand uncertainty and as a cost element that requires effective control (Hamid, 2021; Khan et al., 2025; Silver et al., 2016). Errors in inventory planning may create an imbalance between service levels and inventory costs, particularly in maintenance environments where spare parts demand is uncertain and difficult to predict.

In practice, MDU consists of various material types with different functions and usage characteristics. Two material types that play important roles in the distribution system are kWh meters and Miniature Circuit Breakers (MCBs) (Ludwinek et al., 2017). kWh meters function as electricity consumption measurement devices for customers and are closely associated with customer connection activities, meter replacement programs, and improvements in energy measurement accuracy. Meanwhile, MCBs function as protective devices in customer installations and low-voltage distribution networks; therefore, their demand is related to new connections, power changes, equipment replacement, and operational customer service requirements. These functional differences result in distinct demand patterns between kWh meters and MCBs, requiring separate analysis in the material demand forecasting process (Hyndman & Athanasopoulos, 2021).

PT XYZ is responsible for managing material requirements across sixteen Customer Service Implementation Units (Unit Pelaksana Pelayanan Pelanggan/UP3). MDU requirements vary depending on customer growth, distribution network conditions and complexity, disturbance frequency, and the intensity of development and maintenance activities. The current planning process does not yet employ a standardized or consistently applied forecasting formula for determining MDU requirements at the Unit Induk level, whether for daily, weekly, or annual planning. Existing practices generally rely on simple historical approaches, using previous-year material usage realization as the primary basis for estimating current-year demand (Sirisha et al., 2022; Tyralis & Papacharalampous, 2017; Vagropoulos et al., 2016).

As distribution system complexity and customer demand dynamics continue to increase, assumptions of static demand patterns have become increasingly difficult to maintain. Previous studies have shown that operational demand data often contain trend patterns and fluctuations that require explicit modeling to ensure that requirement planning reflects actual field conditions (Banaś & Utnik-Banaś, 2021). This study compared three forecasting methods: Exponential Smoothing as a deterministic approach that is relatively simple and easy to implement; ARIMA as a stochastic time-series approach that models temporal dependencies through autoregressive, differencing, and moving average components; and Random Forest Regression as a machine learning-based approach capable of capturing nonlinear patterns without requiring specific distributional assumptions (Hyndman & Athanasopoulos, 2021; Dadang et al., 2022; Cavalcante et al., 2019).

The novelty of this research lies in several key aspects. First, this study provides a comprehensive comparison of three fundamentally different forecasting approaches—deterministic (Exponential Smoothing), stochastic (ARIMA), and machine learning-based (Random Forest Regression)—specifically applied to MDU demand forecasting at PT XYZ. Second, the study applies the Diebold–Mariano statistical test to determine whether observed differences in forecasting accuracy among the methods are statistically significant, providing rigorous validation beyond descriptive comparisons. Third, this study extends beyond forecasting accuracy evaluation by developing practical inventory policy recommendations based on the best-performing models, including safety stock and reorder point calculations that integrate forecasting outputs with operational parameters. Fourth, this research addresses a practical challenge in state-owned enterprise operations and contributes to the broader literature on public sector supply chain management in developing economies. This study contributes to forecasting literature by providing empirical evidence regarding method performance in the context of volatile and intermittent demand patterns commonly observed in electricity distribution materials. The findings provide practical guidance for PT XYZ in selecting appropriate forecasting methods for different material types, enabling more objective, measurable, and data-driven procurement planning and inventory management.

Based on this background, this study aimed to compare the application of three forecasting methods—Exponential Smoothing, ARIMA, and Random Forest Regression—in modeling and forecasting MDU requirements for two material types, kWh meters and MCBs, at PT XYZ (Athanasiadis et al., 2024). In addition to comparing forecasting performance based on MAE, MAPE, and RMSE metrics, this study also conducted statistical significance testing using the Diebold–Mariano test. Furthermore, forecasting results from the best-performing model were used as the basis for developing inventory policies, including safety stock determination, reorder point calculations, and identification of potential stockout and overstock conditions.

METHOD

Research Approach and Design

This study employed a quantitative approach with a comparative research design. This approach was selected because the research focused on processing and analyzing historical MDU usage data to develop forecasting models with objectively measurable accuracy. The historical data were processed as time-series data for each material category at PT XYZ, including kWh meters and MCBs.

Population and Sample

The population consists of historical MDU usage data from PT XYZ. The research analyzes two material types: kWh meters and MCB, selected because they are fast-moving materials with important roles in electricity distribution activities. Data was collected from the SAP system and aggregated into weekly time series for each material combination.

Data Collection

Data was collected from the SAP system of PT XYZ, covering the period from January 4, 2021 to December 29, 2025, totaling 261 weekly periods. The data includes transaction dates, working areas, implementing units, material groups, material codes, material names, quantity requirements, and material units. Pre-processing included missing value checks, outlier detection and handling, and transformation into weekly time series format. Weeks without transactions were retained in the data structure and assigned zero values to maintain consistent time intervals.

Forecasting Methods

Exponential Smoothing: Simple Exponential Smoothing (SES) was selected after identifying data characteristics (Barrow et al., 2020; Devon, 2016; Jiang et al., 2020). Parameter optimization was performed by minimizing Sum of Squared Errors (SSE) on training data, testing alpha values from 0.001 to 0.999 in 0.001 increments.

ARIMA: Modeling followed the Box-Jenkins methodology including stationarity checking using Augmented Dickey-Fuller (ADF) Test, order identification through ACF and PACF analysis, parameter estimation using Maximum Likelihood Estimation (MLE), residual diagnostics using Ljung-Box Test, and model selection based on AIC/BIC criteria (Elamin & Fukushige, 2018; Sirisha et al., 2022; Vagropoulos et al., 2016; Wahyuningsih et al., 2019).

Random Forest Regression: Time series data was transformed into supervised learning format through feature engineering. Nine features were constructed: four lag demand features (lag_1 to lag_4) and five calendar features (trend, year, month, quarter, week_iso). Grid search optimization was performed over 432 parameter combinations per material, evaluating estimators, max_depth, max_features, min_samples_split, and min_samples_leaf.

Evaluation Metrics

Forecasting accuracy was evaluated using three metrics:

MAE: Mean Absolute Error, measuring average absolute error in material units

MAPE: Mean Absolute Percentage Error, measuring error as percentage of actual values

RMSE: Root Mean Square Error, penalizing larger errors more heavily

Statistical Test

The Diebold-Mariano (DM) Test was applied to assess whether accuracy differences between method pairs were statistically significant at $\alpha = 0.05$. The test compares loss differential between two methods: $d_t = e_{1\_}t^2 - e_{2\_}t^2$. The Harvey et al. (1997) small-sample correction was applied with n=52, df=51, and t-critical ±2.008.

RESULTS AND DISCUSSION

Data Description and Preparation

Historical data analysis showed kWh meters had 16,550 transactions totaling 3,822,557 units, while MCB had 13,086 transactions totaling 1,215,130 units. Both materials covered the period from January 4, 2021 to December 31, 2025. Weekly aggregation resulted in 261 periods for each material.

Table 1. Data Description

No	Working Area	Material	Aggregation	Description
1	PT XYZ	kWh Meter	Weekly	Historical kWh meter demand data
2	PT XYZ	MCB	Weekly	Historical MCB demand data

Source: Processed Data, 2026

Table 2. Historical Data Summary

Area	Material	Start Period	End Period	Transactions	Total Demand
PT XYZ	kWh Meter	Jan 4, 2021	Dec 31, 2025	16,550	3,822,557
PT XYZ	MCB	Jan 4, 2021	Dec 31, 2025	13,086	1,215,130

Source: Processed Data, 2026

Weekly time series analysis revealed kWh meters averaged 14,645.81 units/week (max 43,635, std dev 8,062.52), while MCB averaged 4,655.67 units/week (max 28,594, std dev 2,819.95). Both materials showed zero values in certain weeks, indicating periods without transactions.

Table 3. Weekly Time Series Descriptive Statistics

Area	Material	Weekly Mean	Minimum	Maximum	Std Deviation
PT XYZ	kWh Meter	14,645.81	0	43,635	8,062.52
PT XYZ	MCB	4,655.67	0	28,594	2,819.95

Source: Processed Data, 2026

Model Development

Exponential Smoothing

Data was split into 80% training (209 weeks, Jan 2021–Dec 2024) and 20% testing (52 weeks, Jan–Dec 2025). Trend testing using linear regression showed R^2 of 2.74% for kWh meters and 5.00% for MCB, indicating trends were statistically significant but not practically meaningful. ACF analysis at lag-52 showed values of 0.047 for kWh meters and 0.062 for MCB, both below the ±0.135 significance threshold, confirming no significant annual seasonal patterns. Simple Exponential Smoothing (SES) was therefore selected (Rahmawati et al., 2021; Slawek, 2018; Smyl, 2020; Weiheng, 2019).

Alpha optimization through SSE minimization yielded $\alpha = 0.125$ for kWh meters and $\alpha = 0.039$ for MCB. Evaluation on testing data produced:

Table 4. SES, Holt, and Holt-Winters Accuracy Evaluation

No	Variant	Material	α	MAE	MAPE (%)	RMSE
1	**SES**	**kWh Meter**	**0.125**	**6,728.56**	**83.54**	**8,577.48**
2	Holt	kWh Meter	0.125	7,249.56	89.16	9,117.67
3	Holt-Winter	kWh Meter	0.125	6,957.10	71.91	8,915.23
4	**SES**	**MCB**	**0.039**	**2,613.49**	**162.21**	**4,225.45**
5	Holt	MCB	0.039	3,018.59	157.16	4,808.65
6	Holt-Winter	MCB	0.039	3,342.98	194.12	4,633.33

Source: Processed Data, 2026

ARIMA

ADF Test results showed both materials were stationary at d=0 and d=1, but d=1 was selected based on smaller AIC values. Grid search over p,q combinations with Ljung-Box Test for residual diagnostics selected ARIMA(2,1,2) for kWh meters (AIC=4,330.2, Ljung-Box p=0.37) and ARIMA(1,1,2) for MCB (AIC=3,828.7, Ljung-Box p=0.31).

Table 5. ARIMA Grid Search Results for kWh Meter

Model	AIC	BIC	MAE	MAPE (%)	RMSE	Ljung-Box	Status
ARIMA(2,1,2)	4,330.2	4,346.9	6,279	79.50	8,251	p=0.37	Pass
ARIMA(0,1,2)	4,331.4	4,341.3	6,700	82.70	8,514	p>0.05	Pass
ARIMA(2,1,1)	4,332.7	4,346.0	6,630	82.47	8,493	p>0.05	Pass
ARIMA(1,1,1)	4,348.9	4,358.9	6,474	80.01	8,262	p>0.05	Pass

Source: Processed Data, 2026

Table 6. ARIMA Grid Search Results for MCB

Model	AIC	BIC	MAE	MAPE (%)	RMSE	Ljung-Box	Status
ARIMA(1,1,2)	3,828.7	3,842.1	2,679	168.62	4,255	p=0.31	Pass
ARIMA(0,1,2)	3,839.0	3,849.0	2,573	157.09	4,210	p>0.05	Pass
ARIMA(1,1,1)	3,853.2	3,863.2	2,575	158.81	4,288	p>0.05	Pass

Source: Processed Data, 2026

Walk-forward forecasting on 52-week testing period produced:

Table 7. ARIMA Accuracy Evaluation

No	Material	MAE	MAPE (%)	RMSE	Model
1	kWh Meter	6,278.92	79.50	8,250.66	ARIMA(2,1,2)
2	MCB	2,679.03	168.62	4,254.99	ARIMA(1,1,2)

Source: Processed Data, 2026

Random Forest Regression

Feature engineering produced 9 features: 4 lag features (lag_1 to lag_4) and 5 calendar features (trend, year, month, quarter, week_iso). Grid search over 432 combinations per material selected optimal parameters: kWh Meter (n=100, depth=5, feat=7, split=4, leaf=5) and MCB (n=100, depth=3, feat=3, split=4, leaf=1). Feature importance analysis showed trend was the most important feature for both materials (kWh: 22.47%, MCB: 19.64%), followed by lag features.

Table 8. Grid Search Top 10 Combinations for kWh Meter

Rank	n_est	max_depth	max_feat	min_split	min_leaf	MAE	MAPE (%)	RMSE
1	100	5	7	4	5	6,127.81	78.44	8,123.08
2	100	5	7	10	5	6,127.81	78.44	8,123.08
3	100	5	7	2	5	6,127.81	78.44	8,123.08
4	200	5	7	2	5	6,176.51	78.01	8,138.35
5	200	5	7	4	5	6,176.51	78.01	8,138.35

Source: Processed Data, 2026

Table 9. Grid Search Top 10 Combinations for MCB

Rank	n_est	max_depth	max_feat	min_split	min_leaf	MAE	MAPE (%)	RMSE
1	100	3	3	4	1	2,870.63	178.88	4,301.18
2	100	3	3	2	1	2,860.04	180.17	4,313.26
3	100	3	3	10	1	2,886.48	180.94	4,311.26
4	100	3	3	10	2	2,894.97	181.18	4,340.08
5	300	3	3	4	2	2,899.09	181.13	4,344.24

Source: Processed Data, 2026

Table 10. Random Forest Accuracy Evaluation

No	Material & Parameters	MAE	MAPE (%)	RMSE
1	kWh Meter (n=100, depth=5, feat=7, split=4, leaf=5)	6,127.81	78.44	8,123.08
2	MCB (n=100, depth=3, feat=3, split=4, leaf=1)	2,870.63	178.88	4,301.18

Source: Processed Data, 2026

Model Comparison

The comparison of forecasting accuracy among the three methods—Exponential Smoothing (SES), ARIMA, and Random Forest Regression—revealed distinct performance patterns across the two material types. For the kWh Meter, Random Forest Regression demonstrated superior performance with the lowest MAE of 6,127.81, MAPE of 78.44%, and RMSE of 8,123.08, followed by ARIMA with MAE of 6,278.92, MAPE of 79.50%, and RMSE of 8,250.66, while ES (SES) produced the highest errors with MAE of 6,728.56, MAPE of

83.54%, and RMSE of 8,577.48. The Random Forest method achieved the smallest Rank Combined (RC) value of 3, indicating it ranked first across all three evaluation metrics, while ARIMA ranked second with RC of 6 and ES ranked third with RC of 9. In contrast, for the MCB material, Exponential Smoothing (SES) emerged as the best performing method with MAE of 2,613.49, MAPE of 162.21%, and RMSE of 4,225.45, outperforming ARIMA which produced MAE of 2,679.03, MAPE of 168.62%, and RMSE of 4,254.99, and Random Forest which yielded the highest errors with MAE of 2,870.63, MAPE of 178.88%, and RMSE of 4,301.18. The SES method achieved RC of 3 for MCB, while ARIMA ranked second with RC of 6 and Random Forest ranked third with RC of 9. This divergence in method performance between the two materials confirms that no single forecasting method universally outperforms others across all material types, and the selection of the most appropriate method must be based on the specific characteristics of each material's demand data.

Diebold-Mariano Test Results

The Diebold-Mariano Test was conducted to determine whether the observed accuracy differences among the three forecasting methods were statistically significant. The test was applied to six pairwise comparisons: ES versus ARIMA for kWh Meter (DM Statistic = 1.5666, p-value = 0.1234), ES versus ARIMA for MCB (DM Statistic = -0.7624, p-value = 0.4494), ES versus Random Forest for kWh Meter (DM Statistic = 1.5867, p-value = 0.1188), ES versus Random Forest for MCB (DM Statistic = -0.6183, p-value = 0.5391), ARIMA versus Random Forest for kWh Meter (DM Statistic = 0.3498, p-value = 0.7279), and ARIMA versus Random Forest for MCB (DM Statistic = -0.4341, p-value = 0.6660). All six pairwise comparisons yielded p-values greater than the significance level of 0.05, with the DM statistics falling within the acceptance region between -2.008 and +2.008 (t-critical value for df=51 at α=0.05). Consequently, the null hypothesis (H_0) that there is no statistically significant difference in forecasting accuracy between the two methods being compared was failed to be rejected for all six pairs. These findings indicate that although empirical accuracy differences exist as reflected in the MAE, MAPE, and RMSE values, these differences are not statistically significant at the 95% confidence level. The lack of statistical significance can be attributed to the high volatility characteristics inherent in MDU demand data, where extreme weekly fluctuations cause the loss differential between methods to vary substantially across different periods—some weeks favoring one method while other weeks favoring another. This high variability in loss differential increases the variance of the DM estimator, resulting in smaller DM statistics and larger p-values. Nevertheless, from a practical standpoint, the empirical accuracy differences remain meaningful for operational decision-making, and the selection of the best method should continue to be based on the smallest MAE, MAPE, and RMSE values, which for this study are Random Forest for kWh Meter and SES for MCB, while also considering implementation simplicity and interpretability as relevant factors in method selection.

Inventory Policy Development

Based on the best performing models identified from the accuracy comparison—Random Forest Regression for kWh Meter and Exponential Smoothing (SES) for MCB—inventory policy parameters were calculated to support MDU planning at PT XYZ. The calculations assumed a 95% service level with corresponding Z-score of 1.645 and a 2-week lead time based on operational procurement conditions. For the kWh Meter, the safety stock was calculated as $1.645 \times 1{,}918.25 \times \sqrt{2} = 4{,}462.58$ units, rounded to 4,463 units, with average demand forecast of 15,916.50 units per week and standard deviation of forecast of 1,918.25 units. The Reorder Point (ROP) was determined as (15,917 × 2) + 4,463 = 36,296 units, with maximum stock of 68,129 units and order quantity of 32,000 units (approximately twice the average weekly demand). For the MCB, the safety stock was calculated as 1.645 × 444.52 × √2 = 1,034.12 units, rounded to 1,034 units, with average demand forecast of 5,086.63 units per week and standard deviation of forecast of 444.52 units. The ROP was determined as (5,087 × 2) + 1,034 = 11,207 units, with maximum stock of 21,381 units and order quantity of 10,000 units. The larger safety stock for kWh Meter reflects the higher forecast standard deviation compared to MCB, indicating greater demand uncertainty for this material. Simulation of the inventory policy over 52 weeks from January to December 2025 using the Min-Max inventory system demonstrated that both materials achieved 100% service level with zero stockout weeks, as the inventory position remained consistently above the ROP threshold. For kWh Meter, inventory position ranged between 27,658 and 54,167 units with 25 orders placed throughout the period, while MCB inventory position ranged between 7,074 and 15,596 units with 26 orders placed. No overstock conditions were observed as inventory levels did not exceed the established maximum limits. These simulation results confirm that the integration of forecasting results with inventory parameters provides measurable and effective inventory control foundations for MDU planning, balancing material availability with inventory cost efficiency.

Recommended Forecasting Methods

Based on the comprehensive evaluation of accuracy metrics and practical implementation considerations, the recommended forecasting methods for MDU of PT XYZ are as follows. For the kWh Meter, Random Forest Regression with parameters n=100, max_depth=5, max_features=7, min_samples_split=4, and min_samples_leaf=5 is recommended, as it achieved the smallest MAE, MAPE, and RMSE values (RC=3) and demonstrated capability to capture short-term autocorrelation patterns through lag_1 to lag_4 demand features. For the MCB, Exponential Smoothing with Simple Exponential Smoothing (SES) variant and alpha parameter of 0.039143 is recommended, as it produced the smallest MAE, MAPE, and RMSE values (RC=3) with the very small alpha generating stable smooth predictions suitable for the highly volatile MCB demand data. These recommendations confirm that MDU requirement planning at PT XYZ should not employ a single uniform forecasting method for all materials, but rather should consider each material's specific demand characteristics. The kWh Meter, with its more structured short-term autocorrelation patterns, benefits from the machine learning approach, while the MCB, with its extreme volatility and irregular demand spikes, is better served by the simple smoothing approach. This differentiated approach aligns with the "no free lunch" principle in forecasting, acknowledging that method selection must adapt to data characteristics. The recommended methods can serve as the initial basis for MDU requirement estimation and inventory policy implementation, with the understanding that final operational decisions should incorporate actual field conditions, including customer connection plans, meter replacement programs, maintenance activities, actual stock levels, procurement lead times, and budget policies.

CONCLUSION

Based on the data processing, forecasting modeling, accuracy evaluation, Diebold–Mariano testing, and inventory policy development conducted in this study, several conclusions can be drawn. The analysis of historical data characteristics revealed that MDU requirements at PT XYZ, particularly kWh meters and MCBs, exhibited fluctuating weekly usage patterns. kWh meters had higher average weekly requirements compared with MCBs, whereas MCBs showed patterns that were more sensitive to demand spikes during certain periods. These findings indicate that MDU requirement planning cannot be conducted using a uniform approach and must consider the specific characteristics of each material type.

The comparison of three forecasting methods—Exponential Smoothing, ARIMA, and Random Forest Regression—showed that the best-performing method differed depending on the material type. For kWh meters, Random Forest Regression achieved the best performance with an MAE of 6,127.81, a MAPE of 78.44%, and an RMSE of 8,123.08. For MCBs, Exponential Smoothing using the Simple Exponential Smoothing (SES) variant produced the best performance, with an MAE of 2,613.49, a MAPE of 162.21%, and an RMSE of 4,225.45. These results indicate that more complex forecasting methods are not necessarily optimal for all material types; therefore, forecasting method selection should be adjusted according to the characteristics of each dataset.

The Diebold–Mariano test results showed that differences in forecasting accuracy among the methods were not statistically significant at the 5% significance level. This indicates that although empirical MAE, MAPE, and RMSE values suggested differences in performance among the methods, these differences were not statistically significant.

The forecasting results from the best-performing models were used as the basis for developing MDU inventory policies at PT XYZ. For kWh meters, Random Forest Regression forecasts were used to calculate a safety stock level of 4,463 units and a reorder point of 36,296 units. For MCBs, Exponential Smoothing forecasts were used to determine a safety stock level of 1,034 units and a reorder point of 11,207 units. These values can serve as initial references for determining minimum inventory levels and appropriate reorder timing.

Based on inventory policy simulations conducted over 52 weeks from January to December 2025, the implementation of forecasting-based inventory policies helped identify potential stockout and overstock risks. The findings demonstrate that integrating forecasting results with safety stock and reorder point parameters can provide an initial foundation for maintaining material availability while controlling excessive inventory risks. Future research should incorporate additional variables, such as macroeconomic factors, seasonal patterns, and material price fluctuations, to improve forecasting accuracy. Furthermore, integrating these findings into an automated decision-support system could enhance procurement planning efficiency at PT XYZ.

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