

Application of Holt's Double Exponential Smoothing for Electrical Energy Demand Forecasting in an Assembly and Welding Manufacturing Facility

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ABSTRACT

This study aims to accurately forecast short-term electrical energy demand in a Jabodetabek industrial facility to support sustainable manufacturing and precise utility management. To address the highly dynamic and non-stationary nature of energy consumption, this research applied Holt's Double Exponential Smoothing method. A 24-month historical dataset, spanning from January 2024 to December 2025, was analyzed to generate a six-month operational projection. Model performance was rigorously evaluated using Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). The forecasting demonstrated outstanding predictive accuracy, yielding a MAPE of 1.26%, a MAD of 20,79, and an MSE of 690.40. The projection indicates a consistent linear escalation, with energy demand expected to reach 2.020,72 MWh by mid-2026. These findings confirm that Holt's algorithm effectively captures underlying linear trends without seasonal behaviors. Integrating this precise mathematical model into standard procedures provides crucial early warning signals for capacity planning, mitigates utility shortages, and strongly supports the strategic mandate of green operations.

INTRODUCTION

The industrial manufacturing sector acts as a primary engine for global economic development, yet it simultaneously stands as a major source of energy consumption and carbon emissions (Kusuma dan Saputra 2024). Consequently, transitioning towards sustainable green operations has become a critical strategic mandate for modern factories seeking to minimize their ecological footprint (Leon-medina et al. 2025; Mallala et al. 2025). A foundational element in achieving this environmental compliance is the rigorous implementation of precise energy efficiency planning directly on the production floor ((Farahani et al. 2025). Unfortunately, facility managers frequently struggle with highly dynamic electrical fluctuations, which ultimately lead to substantial resource waste and inflated operational budgets (Taleb, Guerard, dan Nguyen 2022; Timotius et al. 2023). Therefore, establishing proactive utility management

strategies is absolutely essential to maintain a continuous and cost-effective supply chain (Krajewski dan Malhotra 2022; Slack dan Brandon-jones 2019).

To navigate these operational uncertainties, predictive analytics and robust forecasting mechanisms have become indispensable tools for modern enterprise management (Heizer, Render, dan Munson 2020; Stevenson 2021). Accurate quantitative projections allow decision-makers to optimize inventory levels and precisely calculate long-term material planning requirements (Aulia et al. 2025; Chopra 2019). By evaluating historical data trends, manufacturers can effectively mitigate the bullwhip effect and ensure reliable raw material availability (Aulia et al. 2025; Kusuma dan Saputra 2024). Furthermore, systematic forecasting models empower production divisions, such as welding and assembly lines, to anticipate capacity bottlenecks before they disrupt daily operations (Kusuma et al. 2026). Ultimately, generating highly accurate demand predictions creates a stable operational rhythm that protects the company from both overproduction and stockout risks (Kusuma dan Saputra 2024).

The scientific foundation of these predictive capabilities relies heavily on time-series analysis methodologies to extrapolate future behaviors from past numerical observations (Box et al. 2016; Montgomery 2015). In heavy industries, the application of statistical forecasting has proven highly effective in modeling complex quantitative demands and utility requirements (Brahma et al. 2022; Dubey 2025). Specifically, empirical studies have successfully utilized various forecasting algorithms to predict short-term electrical loads across dense urban and industrial sectors (Fitria et al. 2023; Ilman 2024). Researchers continuously compare traditional mathematical approaches against emerging computational techniques to evaluate energy consumption patterns in smart factories (Huang et al. 2022). However, a persistent challenge remains in accurately modeling non-stationary time-series data that exhibits hidden linear trends without distinct seasonal behaviors (Hyndman 2014; Pangruruk et al. 2025).

While artificial intelligence and hybrid machine learning models offer sophisticated predictive capabilities, their high computational complexity often restricts practical implementation on the shop floor (Farahani et al. 2025; Taleb, Guerard, dan Nguyen 2022). Conversely, fundamental forecasting models require specific adaptations, such as utilizing dual smoothing parameters, to effectively capture underlying data trends (Hyndman 2014; Makridakis, Wheelwright, dan Hyndman 1998). The exponential smoothing family has consistently demonstrated high efficacy in smoothing out volatile industrial datasets, including commodity pricing and fuel consumption (Oil et al. 2023; Saphira, Ula, dan Retno 2024). Among these variations, advanced smoothing techniques are specifically tailored to handle time-series forecasting that involves both level and trend components simultaneously (Andriani, Wahyuningsih, dan Siringoringo 2022; Imron et al. 2023). Consequently, Holt's Double Exponential Smoothing provides mathematical superiority for industrial practitioners seeking a balance between computational simplicity and high predictive accuracy (Omer, Blbas, dan Kadir 2021; Purwanto dan Hakim 2025).

Responding to the urgent need for practical energy planning tools, this research specifically proposes the application of Holt's method to forecast industrial utility fluctuations (Anjali dan Tirkaamiana 2026). The study investigates a 24-month historical dataset of electrical consumption from an active manufacturing facility located in the Jabodetabek industrial region. To validate the model's reliability, this research strictly targets a Mean Absolute Percentage Error (MAPE) threshold of under ten percent (Tarigan dan Sitompul 2023). The predictive performance of Holt's algorithm is meticulously benchmarked against conventional baseline methods to ensure the absolute minimization of numerical forecasting errors (Hilal et al. 2024; Rangkuti et al. 2024). Ultimately, integrating these precise mathematical forecasts into the facility's standard operating procedures will significantly strengthen utility management policies and drive long-term sustainable manufacturing goals (Faris et al. 2024; Leon-medina et al. 2025).

Therefore, the primary objective of this study is to accurately forecast short-term electrical energy demand utilizing Holt's Double Exponential Smoothing method. To validate the model's reliability, this research strictly targets a Mean Absolute Percentage Error (MAPE)

threshold of under ten percent (Tarigan dan Sitompul 2023). The predictive performance of Holt's algorithm is meticulously benchmarked against conventional baseline methods to ensure the absolute minimization of numerical forecasting errors (Hilal et al. 2024; Rangkuti et al. 2024). Ultimately, integrating these precise mathematical forecasts into the facility's standard operating procedures aims to significantly strengthen utility management policies and drive long-term sustainable manufacturing goals (Faris et al. 2024; Leon-medina et al. 2025)

RESEARCH METHODS

This study employs a quantitative descriptive research design tailored for applied industrial engineering to address the critical need for precise energy planning in sustainable manufacturing. The population observed in this study encompasses the total electrical energy consumption within a selected manufacturing facility situated in the Jabodetabek industrial area. To conduct the analysis, the research sample utilizes monthly historical energy demand data collected over a 24-month period, specifically spanning from January 2024 to December 2025. This purposive sampling approach was deliberately chosen to capture a timeframe that reflects steady production growth and operational stabilization, ensuring that the data exhibits a clear linear trend without extreme seasonal disruptions.

The research workflow was systematically structured to ensure the highest analytical rigor and practical relevance for shop-floor implementation. Initially, raw operational data was retrieved from the facility's energy management database. This data underwent pre-processing to verify the presence of an upward trend, which is a critical prerequisite for selecting the appropriate forecasting model. Subsequently, the data was processed using Holt's Double Exponential Smoothing method. This specific analytical technique was prioritized because of its inherent capacity to dynamically update both the base level and the trend slope of non-stationary data. This step is essential for preventing the lagging forecasts typical of simpler moving average methods. Finally, the generated forecast values were rigorously evaluated against actual consumption data to measure the model's accuracy and reliability for future utility procurement.

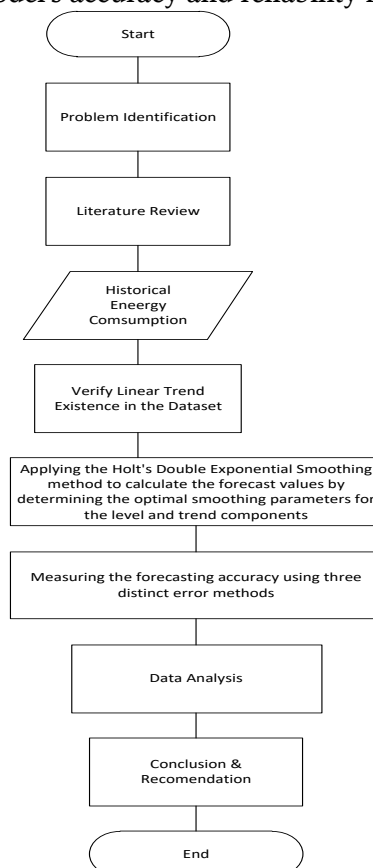


Figure 1. Research Flowchart

The technical analysis relies primarily on Holt's dual-smoothing mathematical formulation during the data processing stage. This method was selected for its capability to dynamically update both the base level and the trend slope of the data, which is essential for preventing the lagging forecasts typically produced by simple moving averages. The equations are placed in the left alignment and numbered sequentially in brackets to the right of the margin: (Aulia et al. 2025; Kusuma et al. 2026; Kusuma dan Saputra 2024)

$$S_t = \alpha * X_t + (1 - \alpha) * (S_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \gamma * (S_t - S_{t-1}) + (1 - \gamma) * (b_{t-1}) \quad (2)$$

$$F_{t+m} = S_t + b_{t+m} \quad (3)$$

Where S_t represents the forecast for period t , X_t is the actual time series value, b_t is the trend at period t , α is the first smoothing parameter for the observation value, γ is the second smoothing parameter for the trend, and F_{t+m} is the forecast result for m periods ahead. To ensure the research is replicable, the determination of the smoothing parameters was conducted through a systematic trial-and-error approach. By iteratively testing various combinations of α and γ , the technical analysis identifies the optimal smoothing parameters that yield the lowest MAPE, specifically targeting an error rate below 10% to meet stringent industrial reliability standards.

To validate the precision of the forecasting model in the error evaluation stage, three parameters of forecasting accuracy were observed and calculated. Measuring these errors is vital to ensure that the generated projections do not misguide the facility's strategic capacity planning. The accuracy measurement formulations are as follows: (Aulia et al. 2025; Kusuma et al. 2026; Kusuma dan Saputra 2024)

Mean Absolute Deviation (MAD):

$$MAD = \frac{\sum_{i=1}^n x_i - f_i}{n} \quad (4)$$

Mean Square Error (MSE):

$$MSE = \frac{\sum (x_i - f_i)^2}{n} \quad (5)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{\frac{\sum x_i - f_i}{x_i} * 100\%}{n} \quad (6)$$

By iteratively testing various combinations of α and γ , the technical analysis identifies the optimal smoothing parameters that yield the lowest MAPE, specifically targeting an error rate below 10% to meet stringent industrial reliability standards. A decrease in the MAPE value indicates good forecasting results. The criteria for the MAPE value are as follows: (Aulia et al. 2025; Kusuma et al. 2026; Kusuma & Saputra 2024).

Table 1. MAPE Value Criteria

No	MAPE Value	Criteria
1	$X \leq 10\%$	Excellent Forecasting Ability-
2	$10\% \leq X \leq 20\%$	Good Forecasting Ability
3	$20\% \leq X \leq 50\%$	Fairly Good Forecasting Ability
4	$X \geq 50\%$	Poor Forecasting Ability

RESULTS AND DISCUSSION

The historical data utilized in this observation covers a consecutive 24-month period, from January 2024 to December 2025. Overall, the electrical energy demand data (measured in MWh) at the manufacturing facility exhibits a consistently increasing linear trend, accompanied by minor operational fluctuations during specific periods.

Table 2. Data Collection

No	Periode	Data Collection
1	Jan-24	1520
2	Feb-24	1545
3	Mar-24	1530
4	Apr-24	1560
5	Mei-24	1585
6	Jun-24	1570
7	Jul-24	1610
8	Agu-24	1635
9	Sep-24	1620
10	Okt-24	1650
11	Nov-24	1680
12	Des-24	1675
13	Jan-25	1710
14	Feb-25	1735
15	Mar-25	1720
16	Apr-25	1760
17	Mei-25	1790
18	Jun-25	1785
19	Jul-25	1820
20	Agu-25	1845
21	Sep-25	1830
22	Okt-25	1870
23	Nov-25	1895
24	Des-25	1910

At the beginning of the observation period (January 2024), the energy demand was recorded at 1.520 units. This figure gradually increased throughout the first and second quarters, with minor corrections (temporary declines) typical of shop-floor dynamics, such as in March (dropping to 1.530) and June (dropping to 1.570). Entering the second half of 2024, the surge in demand stabilized and strengthened, moving from 1.610 in July to reach its annual peak in November with a total of 1.680 units. The year 2024 concluded with a slight adjustment in December at 1.675.

The upward trend, indicative of production expansion, became increasingly evident entering 2025. Demand in January 2025 opened at 1.710, which was significantly higher than the previous year's average. The fluctuation pattern in 2025 shared similar characteristics with 2024, experiencing slight declines at the end of the first quarter (March at 1.720) and towards the

end of the second quarter (June at 1.785). Nevertheless, the positive trend momentum continued to dominate into the second semester. Demand surpassed the 1.800 mark starting in July and persistently climbed to achieve the highest consumption record over the two-year observation period, reaching 1.910 units by December 2025.

Based on the descriptive review above, this energy demand dataset possesses two primary characteristics:

1. **Significant Upward Trend:** There is a clear total volume increase from the beginning to the end of the period (from 1,520 to 1,910). This indicates a continuous expansion in machinery capacity or manufacturing production volume.
2. **Absence of Extreme Seasonality:** Despite minor cyclical fluctuations in certain months (e.g., March, June, and September), the data does not exhibit drastic seasonal spikes that deviate from its primary linear trajectory.

These characteristics stationary growth accompanied by a linear trend—provide the strongest mathematical justification for why Holt's Double Exponential Smoothing method is highly ideal for this study. Holt's method utilizes the α (alpha) parameter to smooth out random monthly fluctuations (such as the minor drops in March or September) while simultaneously employing the γ (gamma) parameter to continuously update and track the steep upward slope towards the end of 2025.

Double Exponential Smoothing by Holt

Table 2. Forecasting Result With Double Exponential Smoothing by Holt

No	Periode	Forecasting Result
25	Jan-26	1927
26	Feb-26	1945
27	Mar-26	1964
28	Apr-26	1983
29	Mei-26	2002
30	Jun-26	2021

The projection of electrical energy demand for the next six months (January to June 2026) exhibits a consistent linear increase. The forecasting results indicate an estimated demand of 1.926,60 MWh in January 2026, which sequentially rises to 1.945,43 MWh (February), 1.964,25 MWh (March), 1.983,07 MWh (April), and crosses the 2.000 MWh threshold in May with a value of 2.001,90 MWh. This upward trend peaks in the June 2026 projection with an estimated demand of 2.020,72 MWh.

Analytically, this sequence of forecasted figures confirms the reliability of Holt's Double Exponential Smoothing method in handling non-stationary data. The constant monthly increment ranging from 18,82 to 18,83 MWh is a direct representation of the trend component successfully isolated by Holt's equations. This finding strongly aligns with the fundamental principles of time-series analysis, where double smoothing techniques are specifically designed to accommodate datasets with a trend slope but no seasonal pattern, ensuring the forecasting results do not lag behind the actual historical data growth (Box et al. 2016; Hyndman 2014; Makridakis, Wheelwright, dan Hyndman 1998). If the facility relied solely on traditional moving average methods, the forecasting model would certainly fail to anticipate the demand surge approaching 2.020 MWh by mid 2026.

From an operations and supply chain management perspective, this projected increase in energy demand serves as a highly essential early warning signal for facility managers. The ability

to identify that power requirements will surge from the 1,900 MWh range to over 2,000 MWh within a five-month period allows the company to execute precise capacity planning, thereby preventing bottlenecks in primary production lines such as the assembly and welding divisions (Chopra 2019; Kusuma et al. 2026). Such accurate quantitative forecasting acts as a fundamental instrument to mitigate the risk of operational halts due to utility shortages, while simultaneously preventing financial waste from unutilized capacity (Krajewski dan Malhotra 2022).

Furthermore, in the context of sustainable manufacturing, this projected data provides an empirical foundation for evaluating green operations policies on the shop floor (Aulia et al. 2025; Leon-medina et al. 2025). With a significantly estimated surge in energy consumption by June 2026, management is compelled to implement efficient power distribution strategies or consider the integration of renewable energy sources to offset the additional load (Dubey 2025; Zahan dan Kenett 2013). Therefore, the application of Holt's method in this study transcends mere mathematical estimation; it transforms into a strategic decision-making parameter for maintaining cost efficiency and reducing operational carbon emissions sustainably.

Error Method

Table 3. Error Method Result With Double Exponential Smoothing by Holt

No	Method	Result
1	MAD	20,79
2	MSE	690,396
3	MAPE	1,26%

The performance evaluation of the Double Exponential Smoothing by Holt forecasting model demonstrated a very high level of accuracy. The error metric calculation yielded a Mean Absolute Deviation (MAD) of 20,79, a Mean Square Error (MSE) of 690,40, and a Mean Absolute Percentage Error (MAPE) of 1.26% (0.0126).

The MAPE value of 1.26% clearly fulfills the primary objective of the study, which is to reduce the error ratio well below the maximum threshold of 10%. In the time series analysis literature, MAPE values below 10% are universally classified as "very accurate" forecasts (Box et al. 2016; Hyndman 2014; Kusuma et al. 2026; Makridakis, Wheelwright, dan Hyndman 1998). Furthermore, the MAD value of 20.79 MWh indicates that the average absolute deviation between predicted and actual energy consumption is very small, especially when compared to the facility's total monthly load, which ranges from 1,500 to 1,900 MWh. Meanwhile, the controlled MSE value proves the absence of extreme deviations or significant outliers during the 24-month observation period, confirming that the smoothing parameters are working optimally (Aulia et al. 2025; Montgomery 2015).

From a managerial and sustainable manufacturing perspective, this extremely low error rate has massive strategic implications. High forecasting accuracy acts as a shield against the bullwhip effect and ensures that utility planning does not result in excess capacity, which results in financial waste and excessive carbon emissions, or supply shortages, which can trigger sudden production line shutdowns. (Chopra 2019; Oil et al. 2023). With an error ratio of nearly 1%, the Holt model in this study goes beyond mere mathematical estimation functions, and proves to be highly reliable for direct integration into the green operations decision-making system of manufacturing companies to achieve robust supply chain efficiency. (Dubey 2025; Zahan dan Kenett 2013).

CONCLUSION

This study confirms the high efficacy of Holt's Double Exponential Smoothing method for forecasting non-stationary electrical energy demand within a dynamic manufacturing environment. Based on the 24-month historical data analysis, the model achieved exceptional predictive precision with a Mean Absolute Percentage Error (MAPE) of 1.26%, alongside

minimal structural deviations (MAD = 20.79, MSE = 690.40). The six-month projection reveals a steady linear escalation, with energy requirements expected to reach 2,020.72 MWh by mid-2026. The primary novelty and advantage of this research lie in proving that Holt's dual-smoothing algorithm provides a mathematically robust yet computationally simple solution for shop-floor implementation. It successfully isolates and models continuous linear trends without seasonal noise, significantly outperforming conventional moving average techniques. This offers industrial practitioners a highly accurate, practical tool that bridges theoretical forecasting with the immediate strategic mandates of green operations and utility management.

Based on these findings, the following recommendations are proposed for practical action and future studies: 1) Practical Implication: Facility managers are strongly advised to integrate this precise predictive model into standard capacity planning procedures. Utilizing these forecasts will proactively prevent production bottlenecks, mitigate the financial waste of overcapacity, and support sustainable operations; 2) Theoretical Implication: This research reinforces the established knowledge that trend-specific smoothing parameters are strictly necessary when forecasting continuously growing industrial utilities; 3) Future Research: Subsequent studies should incorporate exogenous variables—such as specific production volumes, climate fluctuations, or machine-hour utilization rates—into the forecasting framework. Furthermore, benchmarking Holt's method against advanced artificial intelligence or hybrid machine learning algorithms (e.g., Artificial Neural Networks or LSTM) is highly recommended to handle complex, multi-variable energy datasets in modern smart factories.

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