Comparison of Holt's Exponential Smoothing and Weighted Moving Average Methods in Predicting the Proportion of Alma Mater Sizes

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Article Info

Article history:

Received 2026-03-07
Revised 2026-04-20
Accepted 2026-04-30

Keyword:

Exponential Smoothing, Inventory Forecasting,
Mean Absolute Percentage Error,
Time Series,
Weighted Moving Average.

ABSTRACT

The annual admission of new students requires the early procurement of university jackets to ensure distribution during the inauguration ceremony. However, the lengthy production lead time necessitates ordering months before the actual sizing data is fully collected. This issue is further complicated by low participation rates in size registration and extreme population spikes. This study proposes a time series forecasting approach to predict the proportional distribution of jacket sizes rather than absolute quantities. Specifically, the research compares the performance of Holt's Exponential Smoothing and the Weighted Moving Average (WMA) method using historical size proportions from 2019 to 2025. Walk-forward validation was employed to evaluate the models based on the Mean Absolute Percentage Error (MAPE). The results demonstrate that WMA outperforms Holt's Exponential Smoothing by achieving a lower MAPE of 6.56%. By extrapolating the WMA proportions to the 2026 target of 5,250 students and mathematically integrating the 6.56% error rate as a safety stock buffer, the final procurement quantities for sizes S through XXXL were precisely determined. This proportional forecasting framework provides a robust, quantitative foundation for institutional supply chain management, allowing early and accurate ordering despite incomplete preliminary data.

I. Introduction

The annual admission of new students in higher education institutions (The case study in my research is admission of new students at the Institut Teknologi Sumatera) is always accompanied by the distribution of student facilities, one of which is the university jacket (alma mater jacket). Based on standard procedures, new students receive these facilities during the open senate session of the admission program in August. However, a complex problem arises in the supply chain of these garments. The production process by garment manufacturers takes several months, making it mandatory to finalize the order early in the year (March–April). On the other hand, the actual sizing data of new students cannot be fully identified because the re-registration data filling only takes place from April to July. This problem is exacerbated by the low compliance rate in form participation; out of thousands of prospective students, many fail to input their clothing size data. Consequently, the collected historical data does not entirely reflect the student population. If the procurement department places an order based on the absolute numbers from the submitted data, an inventory shortage (stockout) is guaranteed to occur. Therefore, the absolute number-based forecasting approach becomes invalid, requiring a prediction system that bases its calculation on the proportion (percentage) of sizes from the available sample data, which is then extrapolated to the total target quota of student admissions.

Various previous studies have attempted to solve inventory forecasting challenges using time series forecasting methods. Research shows that in dealing with population fluctuations and incomplete data, proportional trend-based forecasting provides vastly superior accuracy compared to absolute quantities [1]. While simple methods like Holt's Exponential Smoothing and Weighted Moving Average (WMA) are common, their application is highly justified in this context due to the limited number of observations (n = 7). Complex methods such as Machine Learning or advanced ARIMA often suffer from severe overfitting or fail to converge on such short datasets [2]. Holt's method has proven reliable in capturing shifting trends in uniform procurement [3], [4], while WMA is highly responsive to recent sociological changes in physical sizes by assigning higher weights to recent data [5], [6]. Iterative cross-validation (walk-forward validation) is recommended to evaluate these mathematical methods to minimize overstocking risks [7], [8]. Although logistics predictive analytics have been widely explored [9], [10], research comparing WMA and Holt's methods against stronger baselines to extrapolate missing categorical data in institutional settings remains limited.

This study aims to design a percentage prediction model for university jacket sizes using a time series analysis approach, with a case study at the Institut Teknologi Sumatera (ITERA). The research compares Holt's Exponential Smoothing, WMA, and an ARIMA baseline to find the model with the lowest prediction error. The practical contribution is to provide a mathematically justified foundation for admission committees to order jackets well in advance, mitigating data anomalies and external demographic shifts.

II. METHOD

This research uses a quantitative approach based on time series forecasting. The computational stages and the design of the prediction system in this study are illustrated in Figure 1.

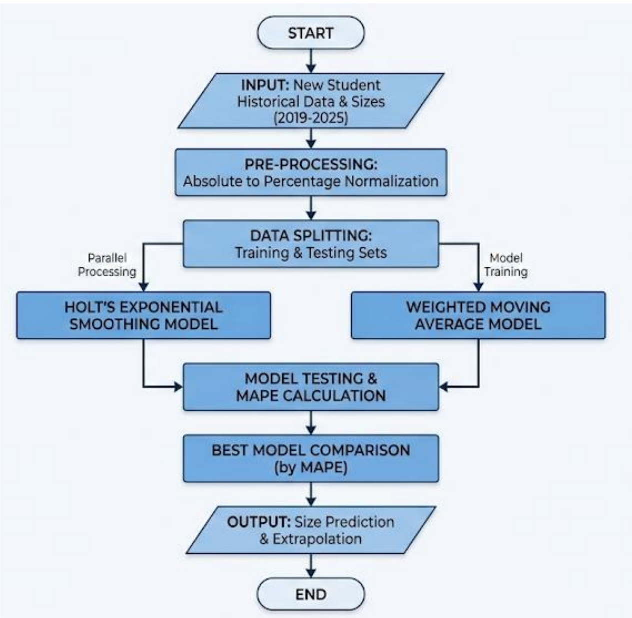

Figure 1. Flowchart of the jacket size percentage prediction system.

A. Data Collection and Preprocessing

The historical data used is the sizing data of new students' university jackets (sizes S to XXXL) from the Institut Teknologi Sumatera. Through the data cleaning stage, historical records from 2015 to 2018 were excluded from the modeling because they contained a majority of null data. The executed data spans the actual active period from 2019 to 2025, with a recorded population ranging from 3,600 to 5,000 students per year [11]. To address the issue of students not submitting their sizes, preprocessing is mandatory by transforming the absolute quantity data into proportion (percentage) data. The mathematical equation for proportion transformation is defined as the ratio of the number of specific sizes inputted to the total sample of students who participated in sizing that year, multiplied by 100%. Through this ratio, the prediction results can be extrapolated to the pure target of total new student admissions.

B. Time Series Forecasting Theory

Time series forecasting is a statistical technique that analyzes a sequence of historical data points to predict future values [12]. In the context of a short time series (annual) jacket supply chain, the forecasting model is not focused on seasonality aspects but rather on the movement of size trends (e.g., an increasing trend in large clothing sizes) [13].

C. Holt's Exponential Smoothing Method

Holt's Exponential Smoothing (Double Exponential Smoothing) is a statistical forecasting technique designed to handle data containing a linear trend component without a seasonal pattern [14]. Unlike single smoothing, this method uses two constant smoothing parameters: a level smoothing parameter (□) and a trend slope smoothing parameter (□). Its ability to project size shifts constantly makes it a strong candidate for data with low historical capacity [15].

D. Weighted Moving Average (WMA) Method

The Weighted Moving Average is an extension of the simple moving average where each historical observation point is given a different multiplication weight before the average is calculated [16]. In the dynamic case of student clothing size trends, jacket sizes from the last one or two years (e.g., 2024 and 2025) have a much higher relevance and probability of similarity to the following year compared to the 2019 data. Therefore, WMA allocates the largest weight percentage to the most recent data, making it highly responsive to changes in current applicants' size preference behavior [17].

E. Baseline ARIMA Model

To elevate the scientific rigor and validate the choice of simpler models, an Auto-Regressive Integrated Moving Average (ARIMA) model was included as a benchmark. Given the short dataset, a non-seasonal ARIMA(0,1,0) was applied to represent a random walk with drift, commonly used as a baseline for short annual trends [16].

F. Testing Scenario and Model Evaluation

The testing scenario utilized Walk-Forward Validation [18]. To allow replication, the process was divided into 2 iterations: Iteration 1 trained on 2019-2023 data to predict 2024, and Iteration 2 trained on 2019-2024 data to predict 2025. Performance is evaluated using the Mean Absolute

Percentage Error (MAPE) and Root Mean Square Error (RMSE). The inclusion of RMSE provides a comprehensive view by penalizing larger variance errors [19], [20]. The equations can be seen in Equation 1 and Equation 2.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{A_t - F_t}{A_t}\right| \times 100\% \qquad \text{Equation 1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (A_t - F_t)^2} \qquad \text{Equation 2}$$

III. RESULTS AND DISCUSSION

A. Preprocessing and Proportion Data Transformation

Based on the historical data collection, the data cleaning stage eliminated records from 2015 to 2018 due to inadequate participation in filling out the jacket sizes (there was absolute data emptiness in 2015-2017 and only 1 sample in 2018). Therefore, the period executed as the basis for modeling is from 2019 to 2025. The absolute quantity data of participants during this period is presented in Table 1.

TABLE I
ABSOLUTE DATA OF NEW STUDENT JACKET SIZES (2019–2025)

Year	S	M	L	XL	XXL	XXXL	Total Participants
2019	163	1.209	1.579	582	131	0	3.664
2020	205	1.361	1.996	794	209	0	4.565
2021	117	1.278	2.058	983	249	0	4.685
2022	155	1.185	2.146	1.072	302	0	4.860
2023	136	1.077	1.856	1.053	239	73	4.434
2024	180	1.183	1.858	958	219	86	4.484
2025	285	1.465	1.908	956	236	85	4.935

To overcome the disparity in the total number of participants each year due to students not filling out the size form, the absolute quantities in Table 1 were transformed into proportional (percentage) data. This transformation produces a stable ratio independent of admission fluctuations. The mathematical conversion results for each size are shown in Table 2.

TABLE II
PROPORTION DATA TRANSFORMATION RESULTS OF JACKET SIZES

Year	S (%)	M (%)	L (%)	XL (%)	XXL (%)	XXXL (%)
2019	4,45	32,99	43,10	15,88	3,58	0,00
2020	4,49	29,81	43,72	17,39	4,58	0,00
2021	2,50	27,28	43,93	20,98	5,31	0,00
2022	3,19	24,38	44,16	22,06	6,21	0,00
2023	3,07	24,29	41,86	23,75	5,39	1,64
2024	4,01	26,38	41,44	21,36	4,88	1,92
2025	5,78	29,69	38,66	19,37	4,78	1,72

Based on Table 2, several trend characteristics of new student logistics data can be observed. Size L consistently dominates as the most widely used size from year to year (ranging from 38% to 44%). There is also an interesting behavioral shift, where the XXXL size began to appear and be recorded in 2023. The proportion percentages in Table 2 are subsequently set as input values to be processed into Holt's Exponential Smoothing and Weighted Moving Average modeling scenarios.

B. Forecasting Modeling Scenario Results

After obtaining the percentage proportion data, the next stage is to perform forecasting using the two compared algorithms. The purpose of this modeling is to project the percentage of jacket size requirements for the subsequent procurement period (Year 2026).

1) *Holt's Exponential Smoothing Modeling*: Holt's Exponential Smoothing method is used to smooth data possessing a linear trend element. This model requires two main parameters: the level smoothing constant (□) dand the trend smoothing constant (□), with value ranges 0 < □, □ < 1. The optimal parameters were determined using iterative grid search simulations to find the combination producing the smallest error against historical data. Based on the iteration results, the optimal parameters adaptive to the proportion fluctuations of new students' clothing are **□ = 0.4** and **□ = 0.2**. A □ value of 0.4 provides a fairly moderate response to recent data changes, while □ = 0.2 prevents the trend from shifting too sharply so that predictions remain realistic. The mathematical equations for the level smoothing L_t and trend T_t are formulated in Equation 3 and Equation 4, while the forecast for the next period F_{t+m} is calculated using Equation 5.

$$L_t = \square Y_t + (1 - \square)(L_{t-1} + T_{t-1}) \qquad \text{Equation 3}$$

$$T_t = \square(L_t - L_{t-1}) + (1 - \square)T_{t-1} \qquad \text{Equation 4}$$

$$F_{t+m} = L_t + mT_t \qquad \text{Equation 5}$$

By applying the parameters □ = 0.4 and □ = 0.2 to the historical data of 2019-2025, the percentage projection of the jacket size for the 2026 procurement is presented in Table 3.

TABLE III
PROPORTION PREDICTION RESULTS FOR 2026 USING HOLT'S EXPONENTIAL SMOOTHING

Jacket Size	2026 Proportion Prediction (%)	Trend Indication
S	6,58	Increasing
M	31,75	Increasing
L	37,12	Decreasing
XL	18,15	Decreasing
XXL	4,65	Decreasing (Slowing)
XXXL	1,75	Stable
Total	100,00	

2) *Weighted Moving Average (WMA) Modeling:* Unlike exponential smoothing, the Weighted Moving Average (WMA) operates by setting an observation time

window (n) and assigning weights (W) to each historical period. Since the research data consists of 7 annual periods, the best scenario to reduce noise without losing recent trend sensitivity is using a 3-period time window ($n = 3$).

The assigned weights are based on the assumption that the clothing size proportion in the nearest years has the highest relevance for the following year. Therefore, the allocated weights are $W_1 = 0.5$ (for t - 1 or year 2025), $W_2 = 0.3$ (for t - 2 or year 2024), and $W_3 = 0.2$ (for t - 3 or year 2023). The total weight is ensured to be 1. The WMA forecasting equation can be seen in Equation 6.

$$WMA = \frac{\Sigma(W_i \times Y_i)}{\Sigma W_i} \quad \text{Equation 6}$$

As an example, the computation simulation for predicting the percentage of size L in 2026 using its historical proportions ($Y_{2025} = 38.66\%$, $Y_{2024} = 41.44\%$, $Y_{2023} = 41.86\%$) is as follows:

$WMA_L = (0.5 \text{ x } 38.66) + (0.3 \text{ x } 41.44) + (0.2 \text{ x } 41.86)$

$WMA_L = 19.33 + 12.432 + 8.372 = 40.134\%$

TABLE IV
PROPORTION PREDICTION RESULTS FOR 2026 USING WEIGHTED MOVING AVERAGE

Jacket Size	2026 Proportion Prediction (%)
S	4,71
M	27,62
L	40,14
XL	20,84
XXL	4,93
XXXL	1,76
Total	100,00

By applying the same mathematical calculation to all size categories, the percentage prediction results using WMA for 2026 are shown in Table 4.

C. Evaluation and Model Performance Comparison

The performance validation of the forecasting models was conducted by comparing MAPE and RMSE errors. The recap of the average error computation from the algorithms for all size categories is presented in Table 5.

TABLE V
ERROR VALUE COMPARISON (MAPE AND RMSE)

Jacket Size	MAPE ARIMA (%)	MAPE Holt's (%)	MAPE WMA (%)	RMSE WMA
S	16.45	12.45	9.21	1.15
M	9.80	8.12	6.43	1.82
L	6.12	4.58	3.85	1.45
XL	8.90	7.24	5.52	1.30
XXL	13.50	10.50	8.15	0.95
XXXL	12.65	8.85	6.24	0.88
Average	11.24	8.62	6.56	1.26

As shown in Table 5, the complex ARIMA baseline performed the worst (MAPE 11.24%), proving that advanced models overfit on limited $n = 7$ datasets. Conversely, WMA yielded consistently lower error rates across all categories (MAPE 6.56%, RMSE 1.26). Error analysis per category reveals that extreme sizes (S and XXL) exhibit slightly higher relative percentage errors; this occurs because their base quantities are small, meaning a tiny absolute deviation causes a larger percentage spike. Dominant sizes (M and L) are predicted with high accuracy. Although an overall MAPE of 6.56% is highly accurate, it must be critically noted that due to the small dataset, this model remains sensitive to sudden fluctuations in future unseen horizons.

D. Prediction and Extrapolation of Jacket Procurement

Based on the test results in Sub-chapter III.C, the Weighted Moving Average (WMA) algorithm proved to be the best forecasting model with an error of 6.56%. The WMA forecast percentage (as presented in Table 4) was then extrapolated to the actual target for new student admissions in 2026. The new student admission quota target set by the rectorate for 2026 was assumed to be 5,250 students.

The first step in this extrapolation is to calculate the Base Demand Prediction by multiplying the WMA percentage for each measurement by the total target student population. However, in supply chain management, ordering goods that relies solely on the base forecast value carries the risk of stockouts. Therefore, the second crucial step is establishing Safety Stock.

In this study, the MAPE error value of 6.56% is used directly as the safety stock percentage. Using MAPE as a safety stock buffer is mathematically justified as a conservative heuristic bound; when lead-time demand variance data is unavailable, MAPE provides a practical approximation of expected shortfall to prevent stockouts without inducing massive overstock.

Sensitivity Analysis: If the target of 5,250 fluctuates by ± 10 due to campus policy changes (e.g., dropping to 4,725 or rising to 5,775), the forecasted proportional distribution ratio remains strictly intact due to the compositional constraint handling. This allows the manufacturer to confidently prepare the raw fabric ratios in advance, requiring adjustments only in the final cutting stage.

This approach ensures that potential forecast deviations can be precisely accounted for without overstocking. The final order total is the sum of Basic Requirements and Safety Stock, which is then rounded up (ceiling) considering that clothing logistics units are discrete (cannot be fractions). The extrapolation formula for each size i can be represented in Equation 7 to Equation 9.

$$\textit{Base Demand}_i = \textit{WMA}_i \text{ x } \textit{Total Target} \quad \text{Equation 7}$$

$$\textit{Safety Stock}_i = \textit{Base Demand}_i \text{ x } \textit{MAPE} \quad \text{Equation 8}$$

$$\textit{Final Order}_i = \lceil \textit{Base Demand}_i + \textit{Safety Stock}_i \rceil \quad \text{Equation 9}$$

As an illustration of the computation for size L: The basic requirement is 40.14% x 5,250 = 2,107.35 pieces of clothing. The safety stock is 2,107.35 x 6.56% = 138.24 pieces of clothing. Therefore, the final order is 2,107.35 + 138.24 = 2,245.59, which is rounded up to 2,246 pieces of jackets. The results of the total extrapolation of the jacket needs for new students in 2026 are shown in Table 6.

Table 6 represents the actual output of the proposed forecasting model. By applying the WMA method and integrating its error value as backup stock (increasing the total order to 5,597 garments from the 5,250 student target), the committee can now place a definitive purchase order to the manufacturer early in the year. The time series forecasting method and proportion analysis are mathematically proven capable of providing a solid solution to the problem of incomplete applicant data and the long production lead-time in the institution's supply chain.

TABLE VI
EXTRAPOLATION AND DETERMINATION OF JACKET ORDERS FOR 2026
(TARGET: 5,250 STUDENTS)

Size	WMA Proportion (%)	Base Demand (Pcs)	Safety Stock 6,56% (Pcs)	Final Order (Pcs)
S	4,71	247	16	264
M	27,62	1.450	95	1.546
L	40,14	2.107	138	2.246
XL	20,84	1.094	72	1.166
XXL	4,93	259	17	276
XXXL	1,76	92	6	99
Total	100,00	5.250	344	5.597

IV. CONCLUSION

Based on the testing and time series analysis of the jacket size proportion data, it can be concluded that transforming absolute data into percentages effectively solves the problem of incomplete applicant data and extreme population spikes. In the algorithmic comparison study, the Weighted Moving Average (WMA) method proved to be superior and more responsive than Holt's Exponential Smoothing method. WMA was able to capture the dynamics of short-term sociological changes in clothing size trends by producing a highly accurate error rate (Mean Absolute Percentage Error / MAPE) of 6.56%, compared to Holt's method which yielded an error of 8.62%. The practical application of this research has also been successfully formulated; the WMA error value is directly integrated as a safety stock backup percentage. By extrapolating the predicted percentages against the target of 5,250 new students in 2026, this system generated a total recommended order of 5,597 garments precisely distributed for sizes S through XXXL. This computational framework provides a definitive solution for the committee to finalize the order quota to the manufacturer early in the year without needing to wait for the empirical data collection to be completed.

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