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Forecasting Book Inventory Needs at CV. Irmandiri Pustaka Using Holt-Winters Method

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ABSTRACT

This study aims to forecast inventory needs at CV. Irmandiri Pustaka using the Holt-Winters Multiplicative method. The company distributes Student Worksheets (LKS), with seasonal demand that rises at the start of each semester. Accurate forecasting is crucial to manage inventory efficiently and avoid overstocking or shortages. Holt-Winters was chosen for its ability to capture both trend and seasonal patterns. The forecast uses sales data from January 2024 to June 2025. Forecast accuracy is evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE). Initial parameter settings produced high errors, prompting optimization through Excel's Solver feature. The optimized parameters α = 0.01, β = 0.01, and γ = 0.04 reduced the MAPE to 25.19%. These results show that the Holt-Winters method can provide reliable inventory forecasts, especially after the second seasonal cycle, and serve as a helpful tool for inventory planning decisions.

Keyword: Forecasting, Holt-Winters Multiplicative, Inventory, Microsoft Excel Solver, Seasonal.

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1. INTRODUCTION

Forecasting is an essential aspect of business operations, enabling companies to anticipate future demand and make data-driven decisions [1], [2]. Accurate forecasting minimizes the risk of overstock or understock, which can lead to financial losses and inefficiencies in storage and supply chain management[3].

CV. Irmandiri Pustaka is a book distributor based in Jombang, East Java, specializing in Student Worksheets (Lembar Kerja Siswa or LKS). The company experiences seasonal spikes in demand, particularly at the beginning of each academic semester. Currently, the company relies on simple forecasting methods based on recent sales data, which often fail to account for underlying trends and seasonal fluctuations. This results in mismatches between inventory and actual demand.

Several forecasting methods have been applied in similar studies, such as Simple Moving Average [4], Linear Regression [5], and ARIMA [6]. However, these methods may not be optimal for datasets with both trend and seasonal components. In contrast, the

Holt-Winters Multiplicative method is specifically designed to handle such data characteristics, offering a more accurate solution for seasonal forecasting problems [7].

This study aims to apply the Holt-Winters Multiplicative method to forecast book inventory needs at CV. Irmandiri Pustaka. The research evaluates the method’s ability to capture trends and seasonal patterns in sales data and determine its forecasting accuracy using error metrics such as MAPE, MAD, and MSE.

2. METHODS

This study uses a quantitative descriptive approach to forecast book inventory needs at CV. Irmandiri Pustaka. The research was conducted in Jombang, East Java, from July 2023 to June 2025. The object of the study is monthly sales data of Student Worksheets (Lembar Kerja Siswa or LKS), which exhibit seasonal demand fluctuations, particularly during the beginning of academic semesters. The overall research procedure is outlined in Figure 1.

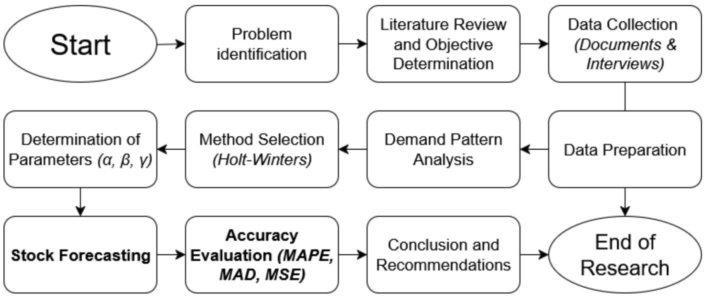

Figure 1. Research Workflow

The research began with identifying the problem of fluctuating stock availability at the company. This was followed by a literature review to determine the most appropriate forecasting method, data collection through company records and interviews, preparation of the time series data, analysis of demand patterns, selection and application of the Holt-Winters Multiplicative method, and evaluation of forecasting accuracy.

2.1 Type and Object of Research

This study is categorized as quantitative descriptive research. The object is the historical sales data of LKS distributed by CV. Irmandiri Pustaka, which serves as the basis for developing a forecasting model that accommodates seasonal variations.

2.2 Data Source and Collection

The data used are secondary data obtained through internal documentation and interviews. The dataset consists of 18 periods of monthly sales from January 2024 to June 2025. The data were organized into a time series format to facilitate pattern recognition and model fitting.

2.3 Forecasting Method

The Holt-Winters Multiplicative method was selected because of its ability to handle data with both trend and seasonal components that vary proportionally with the data level [8], [9]. The method involves three smoothing constants: alpha (α) for the level component, beta (β) for the trend component, and gamma (γ) for the seasonal component. These parameters are used to iteratively update the forecast model as new data becomes available.

The general form of the equations used in this method is as follows:

Level $: L_t = \alpha \cdot (\frac{Yt}{St-m}) + (1 - \alpha) \cdot (L_t - 1 + T_t - 1)$ (1)

Trend $: T_t = \beta \cdot (L_t - L_t - 1) + (1 - \beta) \cdot T_t - 1$ (2)

Seasonality $: S_t = \gamma \cdot (\frac{Yt}{Lt}) + (1 - \gamma) \cdot S_t - m$ (3)

Forecast $: F_t = (L_t - 1 + T_t - 1) \cdot S_t - s$ (4)

Where Y_t is the actual data at time t, and s is the seasonal length (in this case, 6 months).

2.4 Parameter Estimation and Analytical Tools

Initial values for the level, trend, and seasonal components were estimated manually using early periods of the data. Optimization of the smoothing constants was performed using Microsoft Excel's Solver feature [10]. Solver adjusts α, β, and γ to minimize forecasting errors based on specified objective functions.

2.5 Forecast Evaluation

To assess model performance, three standard accuracy metrics were used:

1. **Mean Absolute Percentage Error (MAPE)**
   Measures the average percentage deviation between actual and forecasted values.
   $$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{Yt-Ft}{Yt}\right)x100\% \quad (5)$$

2. **Mean Absolute Deviation (MAD)**
   Calculates the average magnitude of absolute errors.
   $$MAD = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - F_t\right) \quad (6)$$

3. **Mean Squared Error (MSE)**
   Computes the average of squared forecast errors, giving more weight to large deviations.
   $$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2 \quad (7)$$

These three metrics provide a comprehensive evaluation of the forecasting model's precision and reliability in capturing actual demand patterns [7], [11].

3. RESULTS AND DISCUSSION

This section presents the results of the forecasting process using the Holt-Winters Multiplicative method and discusses the accuracy and implications of the findings. The analysis follows a structured sequence, beginning with an overview of the observed data, continuing with the estimation of initial components, the forecasting process itself, and concluding with an evaluation of forecast accuracy and optimization results.

3.1 Data Description

This study uses monthly sales data of Student Worksheets (LKS) from CV. Irmandiri Pustaka for the period January 2024 to June 2025, consisting of 18 time series observations.

The data were collected from internal company records and represent the number of LKS units sold per month.

To understand the demand behavior across the observed period, Table 1 presents the monthly sales data recorded by the company.

Table 1. Monthly Sales Data from January 2024 – June 2025

Year	Month	Sales
2024	January	5.279
	February	6.361
	March	24.299
	April	44.687
	May	60.230
	June	31.707
	July	2.904
	August	16.236
	September	20.331
	October	40.545
	November	40.086
	December	56.857
2025	January	4.332
	February	6.361
	March	24.299
	April	45.110
	May	58.907
	June	33.280

As shown in Table 1, sales volumes vary significantly across months. Demand tends to peak in May and December 2024, coinciding with the end of school semesters. In contrast, lower sales are observed during off-peak periods such as February, August, and January. This fluctuation suggests a recurring seasonal pattern influenced by the academic calendar.

To further illustrate the monthly fluctuations and identify potential seasonal trends, the data is visualized in a time series line chart, as shown in Figure 2.

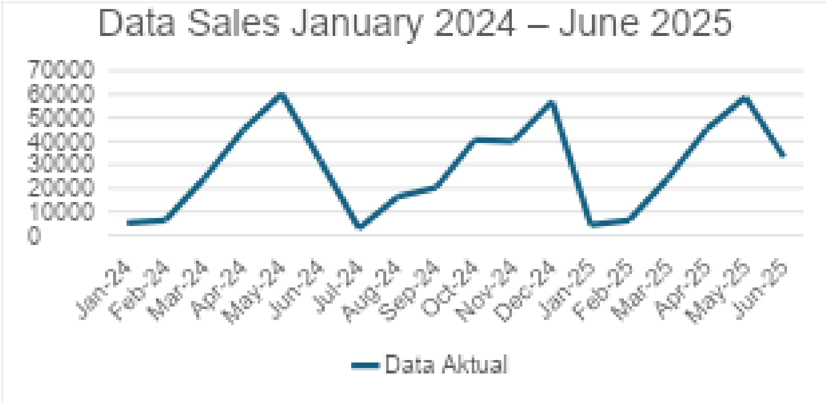

Figure 2. Line Graph of Sales Data from January 2024 - June 2025

Figure 2 clearly displays the cyclical nature of LKS demand over the 18-month period. The X-axis represents the time sequence in months, while the Y-axis indicates the number of units sold. The recurring peaks validate the existence of a biannual seasonal pattern, supporting the selection of the Holt-Winters Multiplicative method for forecasting.

3.2 Initial Component Estimation

The initial stage of the Holt-Winters Multiplicative method involves calculating the three core components: level, trend, and seasonal indices. These components were calculated using the first six months of the time series data (January to June 2024) and are used to initialize the forecasting model.

The initial level component (L_0), was calculated by averaging the sales values from the first six periods (January–June 2024). This value represents the baseline estimate of demand before any trend or seasonal adjustments are applied. The initial level was calculated using the following formula:

$$L_0 = \frac{Y_1 + Y_2 + Y_3 + Y_4 + Y_5 + Y_6}{6} \tag{8}$$

$$L_0 = \frac{5279+6361+24299+44687+60230+31707}{6}$$

$$L_0 = \frac{172563}{6} = 28760,5$$

The result indicates that the average monthly demand during the initial six months was 28,760.5 units. This value serves as the initial level (L_0) in the Holt-Winters Multiplicative model and becomes the foundation for calculating both the initial trend and seasonal components, as well as for generating forecasts in subsequent periods.

After determining the initial level, the next step is to calculate the initial trend (T_o), which represents the average monthly change in demand. The trend component helps capture the directional movement in the data, whether it is increasing, decreasing, or relatively stable. To estimate the initial trend, sales data from the first six months were paired with their corresponding values six months later. These pairs were used to calculate the average increase in sales across the seasonal gap.

$$T_o = \frac{1}{m} \sum_{i=1}^{m} \left(\frac{Y_{m+i} - Y_i}{m} \right) \tag{9}$$

Here is the value of Y_i and Y_{m+i}:

Table 2. Count results for Y_i and Y_{m+i}

i	Y_i **(i -th month)**	**Value**	Y_{6+1} **((6 + i)-th month)**	**Value**
1	Jan 2024	5.279	Jul 2024	2.904
2	Feb 2024	6.361	Agu 2024	16.236
3	Mar 2024	24.299	Sep 2024	20.331
4	Apr 2024	44.687	Okt 2024	40.545
5	May 2024	60.230	Nov 2024	40.086
6	Jun 2024	31.707	Des 2024	56.857

Table 2 presents the sales values from January to June 2024 along with the corresponding values from July to December 2024. These pairs are used to calculate the change in demand over time.

So the calculation for $\frac{Y_{6+i} - Y_i}{i}$ is as in Table 3.

Table 3. Count results for $\frac{Y_{6+i} - Y_i}{i}$

i	$Y_{6+1} - Y_i$	**Value**	$\frac{Y_{6+i} - Y_i}{i}$
1	2.904 – 5.279 =	-2.375	-2.375
2	16.236 – 6.361 =	9.875	49.375
3	20.331 – 24.299 =	-3.968	-13.227
4	40.545 – 44.687 =	-4.142	-10.355
5	40.086 – 60.230 =	-20.144	-40.288
6	56.857 – 31.707 =	25.150	41.917

The difference between the two periods is divided by the index for i-th month and then added together. The results are then averaged to obtain the final value. The calculated result for the initial trend (T_o) is as follows:

$$\sum = -2375 + 49375 - 13277 - 10355 - 40288 - 41917 = 0,3672$$

$$T_o = \frac{1}{6}.0,3672 = 0,0612$$

The differences between the paired values were divided by their respective indices and then averaged. The result of the initial trend calculation is approximately –0.0612, indicating a slight downward trend in monthly LKS sales. This value is used as the trend component for forecasting in subsequent periods.

The final step in initializing the Holt-Winters model is to calculate the seasonal indices (S_t) for each month in the first seasonal cycle. These values quantify how much each month's demand deviates from the average level and serve as adjustment factors in the forecasting model. Each seasonal index was calculated by dividing the actual sales of a given month by the initial level value obtained earlier.

$$S_t = \frac{Y_t}{L_6} \tag{10}$$

As a result, the seasonal index value for ($S_1 - S_6$) is calculated as:

Table 4. Count results for ($S_1 - S_6$)

Month	Y_t	$S_t = \frac{Y_t}{L_6}$
Jan 2024	5.279	0,18355
Feb 2024	6.361	0,221171
Mar 2024	24.299	0,844874
Apr 2024	44.687	1,553763
May 2024	60.230	2,094192
Jun 2024	31.707	1,10245

Table 4 presents the seasonal indices calculated for January to June 2024. These values represent the seasonal patterns within the dataset and are assumed to repeat every six months in future periods. The resulting indices serve as the seasonal adjustment factors in the Holt-Winters Multiplicative model and will be applied to all forecasted periods accordingly.

3.3 Forecast Calculation

After all initial components were estimated, the forecasting process was initiated. Forecasting began from the 7th period (July 2024), since the Holt-Winters Multiplicative method requires a full seasonal cycle (six months in this case) to perform the initial forecast. This is due to the seasonal nature of the data, which exhibits a clear six-month periodic pattern.

Based on the characteristics of the dataset, which showed relatively stable patterns and low volatility, the smoothing parameters for level (α), trend (β), and seasonality (γ) were set close to 1. This configuration allows the model to remain responsive to actual data while maintaining stability, as there were no significant shifts in trend or seasonal structure observed in the early periods. The selected smoothing constants are as follows:

Table 5. Smoothing Parameters α, β, γ

$\alpha = 0.3$ (level)	$\beta = 0.2$ (trend)	$\gamma = 0.7$ (seasonal)

These parameters were then applied in calculating the forecasted value for July 2024 (Period 7), as presented in the following section.

Forecast for Period 7 (July 2024)

With all initial components obtained namely the initial level (L_0), trend (T_o), and seasonal indices (S_t) along with the selected smoothing parameters (α, β, γ), the forecasting process begins in period 7 (July 2024).

The Holt-Winters Multiplicative method requires full seasonal information to compute the forecast, and thus the model first generates a prediction for the first month after the initial seasonal cycle. To calculate the forecast for period 7, the model incorporates the last known level and trend, and multiplies the result by the corresponding seasonal index. In this case, the seasonal index used corresponds to that of January, as the seasonal cycle restarts every 6 months. The level value for period 7 (L_7) was computed using the level smoothing equation.

$$L_7 = \alpha \cdot \frac{Y_7}{S_{7-6}} + (1-\alpha)\left(L_{7-1} + T_{7-1}\right) \tag{11}$$

$$L_7 = 0,3 \cdot \frac{2904}{0,18355} + (1-0,3)(28760,5 + 0,0612) = 24878,78284$$

Since this is the first forecast period, the previously estimated values for level (L_6) and trend (T_6) were used as the baseline for the update. The resulting value of L_7 will serve as input for both the next trend calculation and the subsequent forecasting steps. The level value for period 7 (L_7) was computed using the level smoothing equation. The trend component for period 7 (T_7) was updated using the following trend smoothing equation.

$$T_7 = \beta \cdot (L_7 - L_{7-1}) + (1-\beta) \cdot T_{7-1} \tag{12}$$

$$T_7 = 0,2 \cdot (24878,78284 - 28760,5) + (1-0,2) \cdot 0,0612 = -776,294472$$

As in the level calculation, the reference values are L_6 and T_6. Since values from the previous period are not yet available, the trend and seasonal calculations for the 7th month rely on the initial component estimates. The seasonal index for July (S_7) was recalculated based on the ratio between actual sales and the updated level.

$$St = \gamma \cdot \left(\frac{Y7}{L7}\right) + (1-\gamma) \cdot S_{7-6} \tag{13}$$

$$S_7 = 0,7 \cdot \left(\frac{2904}{24878,78284}\right) + (1-0,7) \cdot 0,18355 = 0,1367732$$

The updated seasonal index for July represents the adjusted seasonal effect for that period, replacing the initial value from the first cycle. This updated index is then used as part of the forecast calculation for the same month, as shown in the following computation.

$$F_7 = (L_{7-1} + T_{7-1}) \cdot S_{7-6} \tag{14}$$

$$F_7 = (28760,5 + 0,0612) \cdot 0,1835 = 5280,33$$

The forecasted value for July 2024 completes the calculation for the first prediction period, using all initialized components of the model. This forecast combines the most recent level and trend estimates with the seasonal index corresponding to the same month in the seasonal cycle. To summarize the outcome of this calculation, Table 6 presents the actual sales figure for July 2024 along with the forecasted value and the supporting components used in the prediction.

Table 6. Forecast Result for Period 7

Component	Results
Y_t (Actual)	2.904
F_7 (Forecast)	5.280,33
L_7 (Level)	24.880,52
T_7 (Trend)	-775,95
S_7 (Seasonal)	0,1367

This table serves as a concise reference point before continuing with forecasts for the remaining periods. The accuracy of this initial result, along with subsequent forecasts, was later evaluated to assess the overall performance of the model across time.

After forecasting period 7, the same Holt-Winters calculation process was applied iteratively to generate forecasts for periods 8 through 18, using the updated level, trend, and seasonal values from each previous period. In Table 7, the actual sales values are presented starting from January 2024, as they serve as the basis for forming the initial components. Meanwhile, forecast results are only available beginning in July 2024, after one full seasonal cycle (six months) has been completed and used to initiate the forecasting process.

Table 7. Forecast Results for January 2024 – July 2025

Month	Actual (Y_t)	Forecast (F_t)	Level (L_t)	Trend (T_t)	Seasonal (S_t)
Jan 2024	5.279	—	—	—	—
Feb 2024	6.361	—	—	—	—
Mar 2024	24.299	—	—	—	—
Apr 2024	44.687	—	—	—	—
May 2024	60.230	—	—	—	—

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Jun 2024	31.707	—	—	—	—
Jul 2024	2.904	5.301,41	24.964,21	-661,57	0,3575
Aug 2024	16.236	5.375,05	39.034,59	2.182,24	0,6472
Sept 2024	20.331	34.909,69	36.142,77	1.249,49	13,008
Oct 2024	40.545	58.098,71	34.003,00	571,64	15,653
Nov 2024	40.086	72.405,91	29.944,70	-354,35	14,306
Dec 2024	56.857	32.621,87	36.185,25	964,63	0,1263
Jan 2025	4.332	5.070,72	35.526,23	639,90	0,2525
Feb 2025	6.361	12.929,70	30.654,07	-462,51	0,7192
Mar 2025	24.299	19.540,75	32.397,09	-21,41	13,452
Apr 2025	45.110	42.114,46	33.066,53	116,76	16,642
May 2025	58.907	51.942,64	34.518,04	383,71	11,709
Jun 2025	33.280	49.931,42	31.409,98	-314,64	0,3575

The table above summarizes the forecasting results across all periods, which serve as the foundation for evaluating the model's accuracy. To further illustrate the comparison between forecasted and actual sales, a line chart is presented below. This visualization highlights the trend alignment and any deviations across time, before the model's performance is assessed in the next section.

In addition to the tabular data, a line chart was created to visually compare the forecasted and actual sales over the observed periods, as shown in Figure 3. This graph helps illustrate the extent to which the Holt-Winters model captures the demand pattern across time and highlights any deviations that may not be immediately obvious in the numerical table.

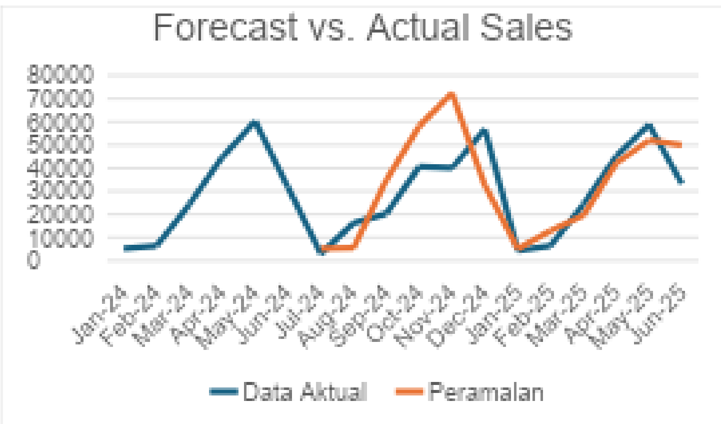

Figure 3. Forecast vs. Actual Sales Chart

The visualization confirms the overall alignment between the forecasted and actual sales trends, with only minor deviations occurring in certain periods. This graphical representation complements the tabular results and provides a clearer picture of how well the model follows real demand fluctuations. These results provide the basis for evaluating the model's overall accuracy, which will be analyzed in the following section using MAPE, MAD, and MSE error metrics.

3.4 Evaluation of Forecasting Results

To assess the reliability of the forecasting results produced by the Holt-Winters Multiplicative method, three commonly used error metrics were applied: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE). These metrics quantify the difference between the forecasted values and the actual observed sales, providing insight into the model's accuracy and consistency across multiple periods.

MAPE is useful for interpreting the average forecast error as a percentage, making it intuitive for performance comparison.

$$MAPE = \left|\frac{Y_t - F_t}{Y_t}\right| x\,100\% \tag{15}$$

$$MAPE = \left|\frac{2904 - 5301,41}{2904}\right| x\,100\% = 82,56\%$$

The MAPE result in this study indicates a moderate level of error, suggesting that the model's predictions were not consistently close to the actual sales figures across all periods. To complement this, another perspective on accuracy is provided by MAD, as calculated below. MAD offers the average absolute deviation between forecasted and actual values, serving as a straightforward measure of error magnitude.

$$MAD = \left|Y_t - F_t\right| \tag{16}$$

$$MAD = |2904 - 5301,41| = 2397,41$$

The MAD value shows the average absolute difference between forecasted and actual sales across the evaluated periods, highlighting the typical scale of deviation. To further examine the presence of larger or extreme errors, the Mean Squared Error (MSE) is used. This metric is more sensitive to outliers, as it penalizes larger deviations more heavily, as shown in the calculation below.

$$MSE = \left(Y_t - F_t\right)^2 \tag{17}$$

$$MSE = (2904 - 5301,41)^2 = 5751352,79$$

The MSE result emphasizes periods with larger deviations, drawing attention to outliers that may have skewed the overall forecast performance. This final metric completes the evaluation of the model's predictive accuracy across all forecasting periods. The overall results are summarized in Table 8, which compiles the MAPE, MAD, and MSE values calculated from July 2024 to December 2025 (Periods 7 to 18).

Table 8. Forecast Accuracy Evaluation Summary (Periods 7–18)

Month	Actual (Y_t)	Forecast (F_t)	MAPE (%)	MAD	MSE
Jul 2024	2.904	5.301,41	82,56%	2.397,41	5.751.352,79
Aug 2024	16.236	5.375,05	66,89%	10.860,95	139.955.595,80
Sept 2024	20.331	34.909,69	71,71%	14.578,69	212.563.176,79

Oct 2024	40.545	58.098,71	43,29%	17.553,71	308.078.026,52
Nov 2024	40.086	72.405,91	80,63%	32.019,91	1.025.271.726,38
Dec 2024	56.857	32.621,87	42,62%	23.678,87	560.843.874,38
Jan 2025	4.332	5.070,72	17,05%	738,72	545.707,81
Feb 2025	6.361	12.929,70	103,27%	6.568,70	43.147.816,69
Mar 2025	24.299	19.540,75	19,58%	4.758,25	22.640.967,06
Apr 2025	45.110	42.114,46	6,64%	2.995,54	8.966.807,30
May 2025	58.907	51.942,64	11,82%	6.964,36	48.361.180,88
Jun 2025	33.280	49.931,42	50,03%	16.651,42	277.444.713,23
		Mean =	49,67%	11.718,54	223.114.745,47

Note: Forecast begins in July 2024 after initial components are established in the first six months.

The evaluation shows that the highest forecasting errors occurred in February 2025, July 2024, and November 2024, as indicated by the MAPE values exceeding 80% in those months. These deviations highlight the model's limitations in certain periods. However, lower error rates in the final months, such as April and May 2025, suggest that the model improved as it adjusted to the data pattern. Overall, the Holt-Winters Multiplicative method was able to capture the seasonal trend, although some refinements are needed for greater short-term accuracy.

After evaluating the forecasting performance using standard accuracy metrics, the next step involves optimizing the Holt-Winters parameters through Microsoft Excel Solver to improve the model's fit.

3.5 Optimization Using Excel Solver

To enhance the accuracy of the forecasting results, Microsoft Excel's Solver tool was used to optimize the smoothing parameters (α, β, and γ) of the Holt-Winters Multiplicative method. Solver allows the user to define an objective function, which in this case is to minimize the Mean Squared Error (MSE), and adjust the parameter values within a specified range, typically between 0 and 1.

The need for this optimization arose because the initial forecast results, based on manually selected parameters, produced relatively high error levels in several periods. Therefore, a systematic optimization was conducted using Solver by assigning MSE as the objective function to minimize, and designating α, β, and γ as the variable cells. Constraints were set to ensure all parameter values remained between 0 and 1.

After several iterations, Solver identified the optimal parameter combination that yielded the lowest MSE: $\alpha = 0.01$, $\beta = 0.01$, and $\gamma = 0.04$. These optimized values were then applied to the Holt-Winters Multiplicative model to generate the final forecast results for each period.

With the optimized smoothing parameters obtained from the Solver process, the Holt-Winters Multiplicative method was then reapplied to the sales data. Table 9 below presents the updated forecasting results, including the level, trend, and seasonal components, along with the final forecast values for each period.

Table 9. Forecasting Results Using Optimized Parameters

Month	Actual (Y_t)	Level (L_t)	Trend (T_t)	Seasonal (S_t)	Forecast (F_t)
Jan 2024	5.279	28.760,5	0,0612	0,18355	—
Feb 2024	6.361	28.760,5	0,0612	0,221171	—
Mar 2024	24.299	28.760,5	0,0612	0,844874	—
Apr 2024	44.687	28.760,5	0,0612	1,553763	—
Mei 2024	60.230	28.760,5	0,0612	2,094192	—
Juni 2024	31.707	28.760,5	0,0612	1,10245	—
Juli 2024	2.904	28.631,17	-1,23273	0,180265	5.279,011
Agust 2024	16.236	29.077,73	3,245191	0,234659	6.332,123
Sept 2024	20.331	29.030,8	2,743487	0,839092	24.569,76
Okt 2024	40.545	29.004,16	2,449604	1,547529	45.111,25
Nov 2024	40.086	28.907,96	1,463095	2,065891	60.745,40
Des 2024	56.857	29.136,06	3,729487	1,136409	31.871,18
Jan 2025	4.332	29.088,7	3,21863	0,179012	5.252,897
Feb 2025	6.361	29.072,08	3,020178	0,234025	6.826,686
Mar 2025	24.299	29.073,93	3,008537	0,838959	24.396,68
Apr 2025	45.110	29.077,67	3,015813	1,547682	44.997,40
Mei 2025	58.907	29.075,02	2,959154	2,064297	60.077,53
Juni 2025	33.280	29.080,05	2,97988	1,13673	33.044,47

The updated forecast outputs reflect the application of the optimized smoothing parameters. As shown in the table, the level, trend, and seasonal components adjust over time to accommodate the observed fluctuations in the sales data. These component-based adjustments contribute to more responsive and representative forecast values across periods.

To evaluate the model's performance after optimization, the forecasted values were then compared to the actual sales data using three standard error metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE). The results of this accuracy evaluation are presented in Table 10.

Table 10. Forecast Accuracy Using Optimized Parameters

Month	Actual (Y_t)	Forecast (F_t)	MAPE (%)	MAD	MSE
Juli 2024	2.904	5.279,011	81.78%	2.375,011	5.640.678,358
Agust 2024	16.236	6.332,123	61.00%	9.903,877	98.086.781,944
Sept 2024	20.331	24.569,76	20.85%	4.238,759	17.967.078,508

Okt 2024	40.545	45.111,25	11.26%	4.566,249	20850626,242
Nov 2024	40.086	60.745,40	51.54%	20.659,4	426.810.626,467
Des 2024	56.857	31.871,18	43.95%	24.985,82	624.291.398,085
Jan 2025	4.332	5.252,897	21.26%	920,8972	848.051,721
Feb 2025	6.361	6.826,686	7.32%	465,6858	216.863,281
Mar 2025	24.299	24.396,68	0.40%	97,68301	9.541,971
Apr 2025	45.110	44.997,40	0.25%	112,6039	12.679,634
Mei 2025	58.907	60.077,53	1.99%	1.170,526	1.370.130,936
Juni 2025	33.280	33.044,47	0.71%	235,5314	55.475,039
		Mean =	25,19%	5.811,004	99.679.994,35

Based on the evaluation results, the forecasting model using the optimized parameters demonstrated improved accuracy across most periods when compared to the initial configuration. While the optimized model significantly reduced the overall forecast error, a few months still showed noticeable forecast deviations, indicating that further refinement could enhance its performance.

Nevertheless, the Holt-Winters Multiplicative method combined with Solver-based parameter tuning proved effective in capturing the underlying trend and seasonality of the sales data. These findings confirm that parameter optimization plays a crucial role in improving the predictive power of time series models in practical applications.

3.6 Forecast Projection for the Next Six Months (July – December 2025)

After the model was optimized and its performance validated, it was further utilized to generate sales projections for the next six months. This extended forecast provides a practical outlook that can assist in future inventory planning and strategic decision-making. Table 11 presents the projected sales values from July to December 2025, derived using the adjusted forecasting model.

Table 11. Forecast Results for the Next 6 Months (Jul – Dec 2025)

Month	Forecast Results
July 2024	5.206,205
August 2024	6.738,106
September 2024	23.911,62
October 2024	43.661,45
November 2024	57.635,75
December 2024	31.407,62

The projection results offer valuable insights into anticipated demand trends for the upcoming semester. These figures highlight the model’s practical relevance in supporting planning activities, particularly in business environments characterized by seasonal fluctuations.

CONCLUSION

This study aimed to forecast the future demand for book inventory at CV. Irmandiri Pustaka using the Holt-Winters Multiplicative method. The forecasting process revealed that the model was capable of capturing both trend and seasonal patterns in the sales data. However, initial results using manually selected smoothing parameters showed relatively high forecast errors in several periods.

To address this issue, Microsoft Excel Solver was employed to optimize the smoothing parameters (α, β, and γ) by minimizing the Mean Squared Error (MSE). The optimized model yielded improved accuracy, as indicated by a significant reduction in error metrics such as MAPE, MAD, and MSE. Although some forecast deviations remained in specific months, the model demonstrated a better overall fit.

The extended forecast for the next six months provided a practical projection of future demand and highlighted the model's usefulness in supporting inventory planning decisions. These results affirm the importance of parameter optimization in enhancing the performance of time series forecasting methods in real business settings.

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