Public Policy:
Jurnal Aplikasi Kebijakan Publik dan Bisnis

LPPM STIA Said Perintah

Volume 6, No. 2, September 2025

https://stia-saidperintah.e-journal.id/ppj

Received; 2025 – 07 - 09

Accepted; 2025 – 08 - 05

Published; 2025 – 08 - 12

Application of Single Exponential Smoothing for Sales Forecasting: A Data-Driven Approach to Demand Management

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Abstract

Forecasting is a method used to predict future values based on historical data. This study aims to analyze and apply the Single Exponential Smoothing (SES) method to forecast the sales volume at Cafe Sibu-Sibu 01 for the upcoming period. The data used in this research consist of monthly sales records from January 2022 to December 2023. The forecasting results are then evaluated for accuracy using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The findings indicate that the sales volume for January 2024 is projected to increase to approximately IDR 68,882,000. With a smoothing constant of 0.1, the obtained values are MAD = 8,210.9, MSE = 114,138,110, and MAPE = 11.4%. Based on these results, it is concluded that the Single Exponential Smoothing method can be effectively used to forecast sales volume at Cafe Sibu-Sibu 01.

Keywords : Forecasting, Single Exponential Smoothing

Introduction

In a dynamic business environment, accurate sales forecasting plays a crucial role in strategic decision-making and resource allocation (Ahaggach et al., 2024).). Accurate forecasts can help companies optimize inventory, manage production, and improve supply chain efficiency (Qi et al., 2025). Errors in forecasting can lead to overstocking or understocking, ultimately affecting profitability and customer satisfaction (He et al., 2023).

Cafe Sibu-Sibu 01, a local culinary establishment located in Ambon City, has experienced notable operational challenges in recent years, primarily due to inconsistent sales volumes and a lack of reliable demand forecasting mechanisms. Monthly sales data from January 2022 to December 2023 exhibit significant fluctuations, with some product categories such as food and beverages showing unpredictable peaks and troughs. For instance, sales of the 'Cake' category ranged from as low as 1,220,000 IDR in April 2022 to a high of 4,300,000 IDR in December 2023, indicating a variation of over 250%. This volatility has led to frequent instances of inventory spoilage, particularly for perishable goods, resulting in financial losses estimated at approximately 8% of total monthly revenue. Moreover, overproduction during low-demand periods and understocking during high-demand occasions have further complicated inventory control and customer satisfaction. These issues underscore the urgent need for a systematic, data-driven forecasting approach to stabilize operations and enhance inventory decision-making.

In recent years, forecasting techniques have evolved significantly, shifting from traditional statistical methods to approaches based on machine learning and artificial intelligence (Song et al., 2024). Classical methods such as linear regression and autoregressive models are often less effective in handling the complex, fluctuating, and nonlinear nature of sales data (Park & Yang, 2024). Therefore, adopting modern techniques like Single Exponential Smoothing (SES) is an attractive alternative due to its ability to capture trend patterns and short-term fluctuations with higher accuracy (Ahaggach et al., 2024)

Accurate decision-making in sales strategy is crucial for maximizing profit (Claro et al., 2024; Chaker et al., 2024). Sejak lama (Calvo & Thoumi, 1984) As early as 1984, Calvo and Thoumi warned that demand fluctuations could affect inventory optimization.

Recent studies (He et al., 2023; Qi et al., 2025; Martin et al., 2025), have reported that uncertainties in customer demand often lead to challenges in product control and production processes. Incorrect production quantity decisions can result in significant losses. Hence,(Ahaggach et al., 2024) strengthen the argument that meticulous and strategic planning is required to forecast future sales accurately and adjust raw material stock levels accordingly, thereby avoiding losses.

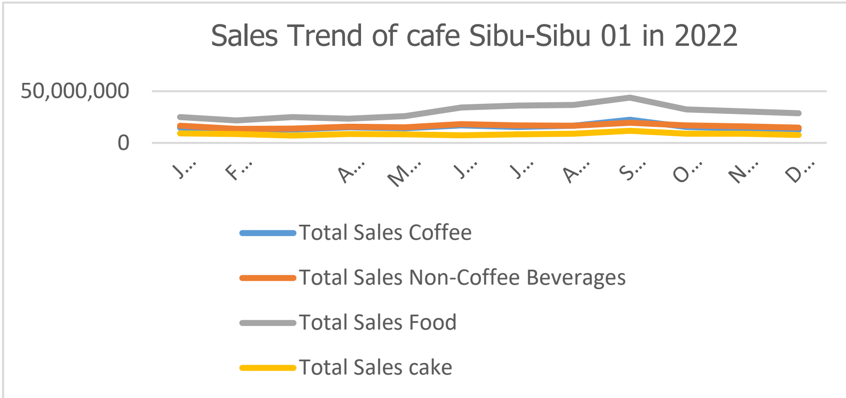
One way to mitigate these risks is through sales forecasting. (Guru et al., 2024; Ahaggach et al., 2024) explain that data-based forecasting methods, which combine historical data with mathematical formulations, are proven to be more accurate and objective than traditional methods based on subjective assessments. Time series modeling is a widely used method in demand analysis and forecasting, as it enables the examination of historical data patterns to gain insights into future behavior (Park & Yang, 2024; Song et al., 2024). In this context, (Gustriansyah et al., 2019; Manalu et al., 2022; Wiedyaningsih et al., 2024), argue that the Single Exponential Smoothing method is particularly relevant for analyzing fluctuating sales data that lack a stable trend. This method effectively produces realistic forecasts and assists entrepreneurs in making inventory-related decisions. Moreover, (Mehdiyev et al., 2016; Saleh et al., 2024), emphasize that forecasting results should be evaluated by comparing predicted values with actual data using various metrics such as MAD, MSE, and MAPE to assess forecasting accuracy.

Sales forecasting is a vital component of business planning because it provides insights into future sales trends, thereby helping organizations make more informed decisions. (Mentzer & Moon, 2004). By combining statistical approaches with managerial judgment, companies can enhance prediction accuracy (Sanders & Ritzman, 2001; Goodwin, 2002; Makridakis et al., 2009; Danese & Kalchschmidt, 2011) Information derived from sales and production planning can assist in setting realistic sales targets, optimizing resource allocation, and supporting business growth. (Grimson & Pyke, 2007; Redman, 2008). Accurate forecasting is essential to ensure more effective resource allocation, particularly in the face of short-term demand fluctuations. (Donaldson & Donaldson, 1998; Majidi, 2019). The information provided in sales and production planning helps establish attainable sales targets, optimize resource allocation, and ultimately drive business growth. (Gupta & Kohli, 2006; Grimson & Pyke, 2007; Oliva & Watson, 2011; Tuomikangas & Kaipia, 2014).

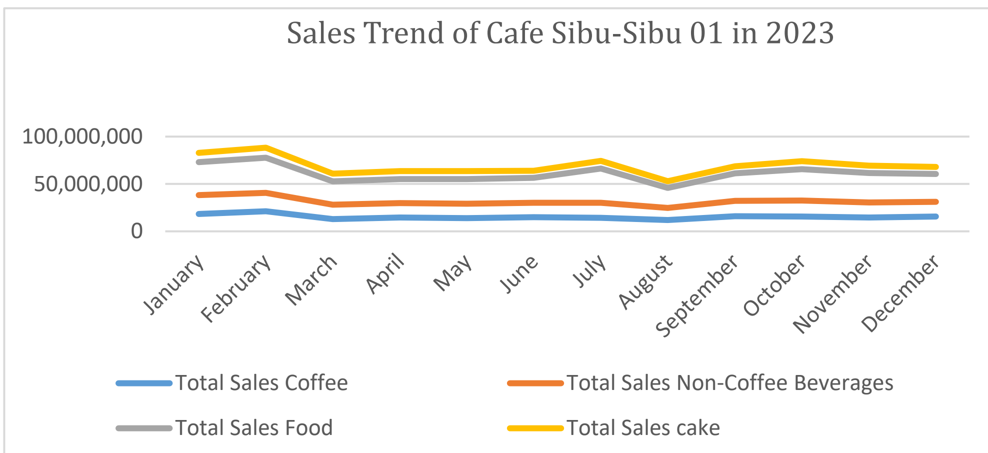
This study aims to apply the Single Exponential Smoothing method to forecast sales at Cafe Sibu-Sibu 01, located in Ambon City, Maluku Province. The urgency to implement reliable sales forecasting methods at Cafe Sibu-Sibu 01 has grown significantly in response to recent contextual developments. Following the COVID-19 pandemic, the local food and beverage sector in Ambon City has become increasingly competitive, marked by the emergence of numerous small-scale culinary businesses. This growing competition has placed pressure on existing enterprises to manage supply and demand more efficiently. Simultaneously, supply chain volatility particularly for perishable ingredients sourced from outside the Maluku region has made inventory planning more complex and risk-laden. Moreover, the gradual recovery of consumer purchasing power has led to erratic consumer behavior, including unpredictable demand spikes during holidays and festive periods. Under these conditions, intuition-based or experience-driven planning is no longer sufficient. These challenges necessitate the adoption of data-driven forecasting tools to support operational stability, reduce waste, and enhance business competitiveness.

This issue aligns with previous research indicating that customer orientation requires service innovation to enhance marketing performance (Racela, 2014; Heng et al., 2020; Thoumrungroje & Racela, 2022; Yagoub Abker & Gebreil Musa, 2024). In the context of Cafe Sibu-Sibu 01, the application of sales forecasting methods is expected to help the owner determine more accurate raw material quantities, reduce potential losses, and improve future *sales* performance.

Sales Trend of Cafe Sibu-Sibu 01 in 2022



Sales Trend of Cafe Sibu-Sibu 01 in 2023



Source: Processed by the researcher

Based on the trend analysis of sales data for 2022 and 2023 (Figures 1 and 2), the sales pattern at Cafe Sibu-Sibu 01 does not exhibit a consistent trend or steady movement. Therefore, the Single Exponential Smoothing method is chosen as the analytical tool to provide quick, clear, and directed information for the owner to determine business strategies for the coming months. This study is expected to assist the owner of Cafe Sibu-Sibu 01 in making informed strategic decisions regarding raw material inventory management, aiming to minimize losses and increase sales in the upcoming period.

This study has two main contributions that distinguish it from previous research. First, it highlights a local context that has received little attention in academic studies. By choosing Cafe Sibu-Sibu 01 in Ambon as the unit of analysis, this research offers a unique perspective compared to broader national or international studies (Chaowai & Chutima, 2024; Muth et al., 2024; Fose et al., 2024; Sharifhosseini et al., 2024) While Single Exponential Smoothing (SES) is a well-established method in sales forecasting, this study contributes novelty by situating its application within the unique operational context of a small-scale food and beverage enterprise in Ambon, Eastern Indonesia—a region that remains underrepresented in empirical forecasting research. Unlike prior studies that applied SES in more developed or densely commercialized areas, businesses in Ambon face distinct challenges, including volatile supply chains, infrastructure constraints, limited digital integration, and unpredictable consumer behavior following the COVID-19 pandemic. These factors make forecasting particularly complex, justifying the need for adaptive yet straight forward models like SES.

Additionally, this study extends the practical evaluation of SES by comparing two smoothing constants ($\alpha = 0.1$ and $\alpha = 0.2$), and analyzing their forecasting accuracy across different product categories. Although SES is not compared with alternative forecasting models in this version of the study, its operational value is demonstrated through direct implications for inventory management, waste reduction, and demand planning. Future research is encouraged to build on this work by comparing SES with more complex models (e.g., ARIMA, Holt-Winters), or by embedding SES within a hybrid forecasting or managerial decision-making framework to enhance strategic relevance.

By integrating the forecasting results into strategic business planning, the owner of Cafe Sibu-Sibu 01 is expected to optimize inventory management and enhance sales performance. In light of the identified research gaps, this study aims to make a significant contribution to both theoretical advancements and practical implementations. The findings are anticipated to offer substantial benefits to small and medium-sized enterprises in Indonesia particularly within the Cafe sector by providing a systematic and data-driven approach to sales forecasting.

Method

This study employs a quantitative approach to analyze numerical data and apply statistical methods in the forecasting process. The research design focuses on forecasting sales at Cafe Sibu-Sibu 01 using the Single Exponential Smoothing (SES) method.

Metode Single Exponential Smoothing dalam memprediksi penjualan Cafe Sibu-SibuMetode yang akan digunakan untuk mencari nilai stabilitas dengan menggunakan data Cafe Sibu-Sibu dari tahun 2022 – 2023 untuk diberi fungsi exponential.

Y^_(t+1)=ɑ.Yt+(1- ɑ).Y^_t

Information:

$\hat{Y}_{t+1}$ = forecast for period t+1

ɑ = smoothing constant (0 ≤ ɑ ≤ 1)

Yt = actual value at period t+1

$\hat{Y}_t$ = forecast value for period t

The research is conducted using historical sales records from Cafe Sibu-Sibu 01 in Ambon. The population comprises the sales reports of Cafe Sibu-Sibu 01, while the sample includes monthly sales data for sub-categories coffee, non-coffee beverages, snacks, and food over the last two years (January 2022 to December 2023).

The data used in this study are historical sales records collected from January 2022 to December 2023. This approach enables the researcher to identify patterns and trends in sales across various product categories such as coffee, non-coffee beverages, snacks, and food.

Sales data of cafe Sibu-Sibu 01, January – December 2022 (Rupiah)

Month	Total sales				Total
	Coffee	Non-Coffee Beverage	Food	Cake	
January	14,869,000	16,707,000	25,026,000	9,232,000	65,834,000
February	12,776,000	13,542,000	21,717,000	8,591,000	56,626,000
March	13,050,000	13,902,000	24,849,000	7,092,000	58,893,000
April	15,200,000	15,768,000	23,279,000	8,448,000	62,695,000
May	14,060,000	15,152,000	25,893,000	8,409,000	63,514,000
June	17,001,000	18,244,000	34,373,000	7,328,000	76,946,000

Month	Total sales				Total
	Coffee	Non-Coffee Beverage	Food	Cake	
July	15,291,000	16,880,000	36,187,000	8,191,000	76,549,000
August	16,741,000	16,485,000	36,587,000	8,742,000	78,555,000
September	22,394,000	19,472,000	43,812,000	11,683,000	97,361,000
October	15,504,000	16,983,000	32,486,000	8,859,000	73,832,000
November	13,826,000	15,902,000	30,418,000	8,987,000	69,133,000
December	12,710,000	14,619,000	28,599,000	7,626,000	63,554,000
Total	183,422,000	193,656,000	363,226,000	103,188,000	843,492,000
Average	15,285,167	16,138,000	30,268,833	8,599,000	70,291,000

Source: Cafe Sibu-Sibu 01, (2022)

Tabel 2. Sales data of cafe Sibu-Sibu 01, January – December 2023 (Rupiah)

Month	Total sales				Total
	Coffee	Non-Coffee Beverage	Food	Cake	
January	18,256,000	19,917,000	34,852,000	9,957,000	82,982,000
February	21,192,000	19,425,000	37,084,000	10,595,00 0	88,296,000
March	13,050,000	14,902,000	24,849,000	8,092,000	60,893,000
April	14,682,000	15,017,000	25,279,000	8,448,000	63,426,000
May	14,060,000	15,152,000	25,893,000	8,409,000	63,514,000
June	15,001,000	15,244,000	26,373,000	7,328,000	63,946,000
July	14,291,000	15,880,000	36,187,000	8,191,000	74,549,000
August	11,940,000	12,764,000	21,117,000	7,086,000	52,907,000
September	16,048,000	16,200,000	28,817,000	7,547,000	68,612,000
October	15,733,000	16,732,000	33,247,000	8,172,000	73,884,000
Novembe	14,520,000	15,900,000	31,109,000	7,694,000	69,223,000
December	15,602,000	15,704,000	29,169,000	7,461,000	67,936,000
Total	184,375,00 0	192,837,00 0	353,976,00 0	98,980,00 0	830,168,00 0
Average	15,364,583	16,069,750	29,498,000	8,248,333	69,180,667

Source: Cafe Sibu-Sibu 01, (2023)

In the analysis process, the study uses forecasting techniques to estimate future sales based on past data patterns. The accuracy of the forecasting model is tested using evaluation metrics such as MAD, MSE, and MAPE. This design aims to provide data-driven insights to support business decision-making, particularly in planning and managing product stock at Cafe Sibu-Sibu 01.

Data Analysis

The analysis method employed in this study is time series analysis using the Single Exponential Smoothing method. The historical sales data are first organized and then processed using the forecasting method. The subsequent steps include selecting the appropriate number of periods (n) for calculation and determining the forecast value using the formula: $\hat{Y}_{(t+1)}=\alpha.Y_t+(1-\alpha).\hat{Y}_t$

Since every forecasting method has its level of error, error measurements are calculated using MAD (Mean Absolute Deviation) and MAPE (Mean Absolute Percentage Error) as follows:

MAD (Mean Absolute Deviation)

$MAD = (\sum_{t=1}^{n}|Y_t-F_t|)/n$

Y_t : Actual data at period t

F_t : Forecast for period t

n : Number of forecasting periods

The lower the value obtained from the MAD calculation, the higher the accuracy. The results derived from the computations of MAD (Mean Absolute Deviation), MSE (Mean Squared Error), and MAPE (Mean Absolute Percentage Error) reveal the degree of error, which can be used to select the most appropriate method characterized by superior accuracy for monthly forecasting by identifying the method with the smallest MAD and MAPE values.

Discussion

For the sales forecasting of Cafe Sibu-Sibu 01, two smoothing constants, $\alpha = 0.1$ and $\alpha = 0.2$, were used for comparison. The forecasting process was initiated by setting the first forecast equal to the first observation. The results are presented in the following table:

Forecasting Results using α = 0.1 dan α = 0.2

Year	Month	Actual Sales Data (Yt)	Smoothed Value Y_t α = 0.1	*Error*	Smoothed Value Y_t α = 0.2	*Error*
2022	1	65,834	-	-	-	-
	2	56,626	65,834.0	-9,208.0	65,834.0	-9,208.0
	3	58,893	64,913.2	-6,020.2	63,992.4	-5,099.4
	4	62,695	64,311.2	-1,616.2	62,972.5	-277.5
	5	63,514	64,149.6	-635.6	62,917.0	597.0
	6	76,946	64,086.0	12,860.0	63,036.4	13,909.6
	7	76,549	65,372.0	11,177.0	65,818.3	10,730.7
	8	78,555	66,489.7	12,065.3	67,964.5	10,590.5
	9	97,361	67,696.2	29,664.8	70,082.6	27,278.4
	10	73,832	70,662.7	3,169.3	75,538.3	-1,706.3
	11	69,133	70,979.6	-1,846.6	75,197.0	-6,064.0
	12	63,554	70,795.0	-7,241.0	73,984.2	-10,430.2
2023	1	82,982	70,070.9	12,911.1	71,898.2	11,083.8
	2	88,296	71,362.0	16,934.0	74,114.9	14,181.1
	3	60,893	73,055.4	-12,162.4	76,951.1	-16,058.1
	4	63,426	71,839.2	-8,413.2	73,739.5	-10,313.5
	5	63,514	70,997.8	-7,483.8	71,676.8	-8,162.8
	6	63,946	70,249.5	-6,303.5	70,044.3	-6,098.3
	7	74,549	69,619.1	4,929.9	68,824.6	5,724.4
	8	52,907	70,112.1	-17,205.1	69,969.5	-17,062.5
	9	68,612	68,391.6	220.4	66,557.0	2,055.0
	10	73,884	68,413.6	5,470.4	66,968.0	6,916.0
	11	69,223	68,960.7	262.3	68,351.2	871.8
	12	67,936	68,986.9	-1,050.9	68,525.6	-589.6
Σ		**1,673,660**	**1,577,347.907**	**30,478**	**1,594,957.8**	**12,868.2**

After obtaining the smoothed values, forecasting errors are calculated using MSE (Mean Squared Error), MAD (Mean Absolute Deviation), and MAPE (Mean Absolute Percentage Error) with the formulas provided earlier.

For Yt wiht Constant α = 0.1:

MAD $= \frac{1}{n}\sum_{t=1}^{n}|Yt - \widehat{Yt}| = \frac{188850.9}{23} = 8{,}210.9$

MSE $= \frac{1}{n}\sum_{t=1}^{n}(Yt - \widehat{Yt})^2 = \frac{2625176529}{23} = 114{,}138{,}110$

MAPE $= \frac{1}{n}\sum_{t=1}^{n}|\frac{Yt - \widehat{Yt}}{Yt \times 100}| = \frac{264}{23} = 11.4\%$

For Yt with a constant α = 0.2:

MAD $= \frac{1}{n}\sum_{t=1}^{n}|Yt - \widehat{Yt}| = \frac{195008.5}{23} = 8{,}478.6$

MSE $= \frac{1}{n}\sum_{t=1}^{n}(Yt - \widehat{Yt})^2 = \frac{2593659064.9}{23} = 112{,}767{,}785.4$

MAPE $= \frac{1}{n}\sum_{t=1}^{n}|\frac{Yt - \widehat{Yt}}{Yt \times 100}| = \frac{276.2}{23} = 12\%$

Furthermore, the moving average method was applied by using the first observation as the initial estimate with a k-value of 6. The formula is provided below:

$$\hat{Y}_{t+1} = \frac{Y_t + Y_{t-1} + \cdots + Y_{t-k+1}}{k}$$

Information:

$\hat{Y}_{t+1}$= the estimated value for the next period

Y_t = actual value in period t

k = Total Values in Moving Average

$$\hat{Y}_{t+1} = \frac{Y_t + Y_{t-1} + \cdots + Y_{t-k+1}}{k}$$

$$= \frac{76{,}946 + 63{,}514 + 62{,}695 + 58{,}893 + 56{,}626 + 65{,}834}{6}$$

$$= 64{,}084.6 \approx 64{,}085$$

The results of the MAD, MAPE, and MSE calculations will be shown in table 4. and 5.

MAD, MSE, MAPE Results for α = 0.1

Month	Sales Data Y_t	Smoothed Values Y_t α = 0.1	|Error|	Error²	Error%
1	65,834	-	-	-	-
2	56,626	65,834.0	9,208.0	84,787,264.0	16.3
3	58,893	64,913.2	6,020.2	36,242,808.0	10.2
4	62,695	64,311.2	1,616.2	2,612,037.8	2.6
5	63,514	64,149.6	635.6	403,939.1	1.0

Month	Sales Data Y_t	Smoothed Values Y_t $\alpha = 0.1$	|Error|	Error^2	Error%
6	76,946	64,086.0	12,860.0	165,379,450.8	16.7
7	76,549	65,372.0	11,177.0	124,925,212.3	14.6
8	78,555	66,489.7	12,065.3	145,571,350.7	15.4
9	97,361	67,696.2	29,664.8	879,998,328.3	30.5
10	73,832	70,662.7	3,169.3	10,044,394.0	4.3
11	69,133	70,979.6	1,846.6	3,410,078.3	2.7
12	63,554	70,795.0	7,241.0	52,431,729.8	11.4
13	82,982	70,070.9	12,911.1	166,697,066.7	15.6
14	88,296	71,362.0	16,934.0	286,760,682.5	19.2
15	60,893	73,055.4	12,162.4	147,923,762.7	20.0
16	63,426	71,839.2	8,413.2	70,781,129.8	13.3
17	63,514	70,997.8	7,483.8	56,007,815.8	11.8
18	63,946	70,249.5	6,303.5	39,733,523.2	9.9
19	74,549	69,619.1	4,929.9	24,303,835.7	6.6
20	52,907	70,112.1	17,205.1	296,015,368.0	32.5
21	68,612	68,391.6	220.4	48,581.7	0.3
22	73,884	68,413.6	5,470.4	29,924,962.2	7.4
23	69,223	68,960.7	262.3	68,819.2	0.4
24	67,936	68,986.9	1,050.9	1,104,389.2	1.5
Σ			**188,850.9**	**2,625,176,529.9**	**264**
			MAD = 8,210.9	**MSE = 114,138,110**	**MAPE = 11.4**

MAD, MSE, MAPE Results for α = 0.2

Month	Sales Data Y_t	Smoothed Values Y_t $\alpha = 0.2$	|Error|	Error^2	Error%
1	65,834	-	-	-	-
2	56,626	65,834.0	9,208.0	84,787,264.0	16.3
3	58,893	63,992.4	5,099.4	26,003,880.4	8.7
4	62,695	62,972.5	277.5	77,017.4	0.4
5	63,514	62,917.0	597.0	356,389.9	0.9
6	76,946	63,036.4	13,909.6	193,476,616.1	18.1
7	76,549	65,818.3	10,730.7	115,147,273.5	14.0
8	78,555	67,964.5	10,590.5	112,159,448.7	13.5
9	97,361	70,082.6	27,278.4	744,112,669.4	28.0

Month	Sales Data Y_t	Smoothed Values Y_t $\alpha = 0.2$	|Error|	Error^2	Error%
10	73,832	75,538.3	1,706.3	2,911,313.2	2.3
11	69,133	75,197.0	6,064.0	36,772,164.7	8.8
12	63,554	73,984.2	10,430.2	108,789,166.6	16.4
13	82,982	71,898.2	11,083.8	122,851,428.8	13.4
14	88,296	74,114.9	14,181.1	201,102,720.8	16.1
15	60,893	76,951.1	16,058.1	257,864,011.9	26.4
16	63,426	73,739.5	10,313.5	106,368,607.7	16.3
17	63,514	71,676.8	8,162.8	66,631,509.9	12.9
18	63,946	70,044.3	6,098.3	37,188,654.2	9.5
19	74,549	68,824.6	5,724.4	32,768,754.5	7.7
20	52,907	69,969.5	17,062.5	291,128,225.9	32.2
21	68,612	66,557.0	2,055.0	4,223,090.6	3.0
22	73,884	66,968.0	6916.0	47,831,232.5	9.4
23	69,223	68,351.2	871.8	760,053.0	1.3
24	67,936	68,525.6	589.6	347,571.4	0.9
Σ			**195,008.5**	**2,593,659,064.9**	**276.2**
			MAD = 8,478.6	**MSE = 112,767,785.4**	**MAPE = 12**

Using a smoothing constant of 0.1 yielded a Mean Absolute Deviation (MAD) of 8,210.9, a Mean Squared Error (MSE) of 114,138,110, and a Mean Absolute Percentage Error (MAPE) of 11.4%. In contrast, with a smoothing constant of 0.2, the MAD was 8,478.7, the MSE was 112,767,785.4, and the MAPE was 12%. When compared to the initial estimation approach where the first observation served as the initial estimate the results indicate that the method using a smoothing constant of 0.1 is preferable, as it produces lower MAD and MAPE values. Consequently, the constant of 0.1 was selected for its superior performance. Based on these findings, the forecast for January 2024 will be generated using the single exponential smoothing method with α = 0.1.

Sales forecasting results using a smoothing constant of 0.1 in the $\boldsymbol{\widehat{Y}_{25}}$ (January):

$\widehat{Y}_{25} = \propto Y_t + (1- \propto)\widehat{Y}_t$

$\widehat{Y}_{25} = \ 6{,}793.6 + 62{,}088.2$

$\widehat{Y}_{25} = \ 68{,}882$ **≈** ±Rp. 68,882,000,-

In this study, the Single Exponential Smoothing method was employed to forecast sales across four sub-categories: coffee, non-coffee beverages, food, and cake at Cafe Sibu-Sibu. The analysis was conducted using two alpha values, 0.1 and 0.2, to examine the impact of the smoothing constant on the accuracy of the predictions. The following are the monthly sales forecasts for each sub-category over the study period.

MAD, MSE, MAPE, MPE Results for the Coffee, Non-Coffee, Food, and Cake Sub Categories for α = 0.1 and α = 0.2

Sub-Category	Alpha	MAD	MSE	MAPE (%)
Kopi	0,1	2,092,824.23	7,819,260,860,817.68	12.95
Kopi	0,2	2,081,918.25	6,994,744,352,338.54	13.27
Non-kopi	0,1	1,504,416.27	3,553,244,878,828.91	9.52
Non-kopi	0,2	1,514,634.57	3,653,528,341,803.56	9.55
Makanan	0,1	4,770,928.77	38,928,575,921,972.20	15.16
Makanan	0,2	4,714,771.91	35,413,886,392,773.40	15.44
Kue	0,1	945,899.46	1,389,807,192,684.59	11.38
Kue	0,2	869,452.02	1,326,468,091,866.57	10.31

From Table 6, it is evident that the cake sub-category, with α = 0.2, exhibits the lowest MAD and MSE values, indicating the highest prediction accuracy. In contrast, the food sub-category records the highest MAPE, suggesting lower forecasting reliability. The forecasted sales value for January 2024 will be provided to the management of Cafe Sibu-Sibu 01 for further adjustments based on actual sales data.

This study has important implications for the financial management of Cafe Sibu-Sibu, particularly in cash flow management, cost control, and budget planning. By incorporating sales forecasting using the Single Exponential Smoothing (SES) method, the financial management team can make more data-driven decisions regarding fund allocation and operational efficiency, ultimately contributing to the long-term sustainability of the business

Conclusion

Based on the results of the study, the Single Exponential Smoothing method has proven to be effective in forecasting sales at Cafe Sibu-Sibu 01, considering metrics such as MAD, MSE, MAPE, and MPE. The analysis revealed that the cakes category, with α = 0.2, provided the most accurate prediction, as indicated by the lowest MAD and MSE values compared to the other sub-categories. Conversely, the food category exhibited the highest MAPE, indicating a higher level of forecasting inaccuracy.

Recommendation

The implications of this study are highly relevant for the financial management and business strategy at Cafe Sibu-Sibu, especially in managing cash flow, budget planning, and operational cost control. By applying a more accurate forecasting method, the Cafe management can optimize raw material inventory levels and minimize potential losses due to overstocking or understocking. Furthermore, the findings of this research may serve as a reference for developing data-driven sales forecasting approaches for small and medium-sized enterprises in Indonesia, particularly in the Cafe sector.

Future Research

While the SES method yields satisfactory results, specific limitations exist in terms of forecasting accuracy for some sub-categories, particularly food. Future research may consider employing more complex forecasting methods or hybrid techniques to enhance the accuracy of sales predictions further.

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