

## Forecasting Model using Single Exponential Smoothing Method on PT. Rakha Medika

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### Abstract

*PT. Rakha Medika is a healthcare company with a network of clinics spread across various branches in the city of Palembang. In stock management, the company faces significant challenges related to both overstocking and stock shortages, which impact operational efficiency. These issues arise because inventory orders are made without proper planning. This study aims to optimize stock management by applying the Single Exponential Smoothing forecasting method to analyze usage patterns. The data used includes inventory records spanning a one-year period (April 2023 to April 2024), comprising a total of 4,033 entries. The forecasting results indicate that an alpha value of 0.99 is the most optimal, achieving a forecasting accuracy of MAPE at 14%, MAD at 4, and MSE at 97. These results suggest that the forecasting method performs reasonably well, as the MAPE score does not exceed 20%. However, a comparison between the forecasting results and the actual values reveals a deviation of 38.24% from the total inventory. This deviation is influenced by the characteristics of the data and unavoidable external factors.*

**Keywords :** Data Mining, Forecasting, Single Exponential Smoothing

### INTRODUCTION

In the business sector, inventory serves as a substantial asset; however, improper management can lead to significant organizational issues (Chairunisa et al., 2023). Efficient inventory management is essential to ensure operational continuity and must be systematically organized (Fadilah et al., 2023). Poor oversight increases the risk of product damage and hinders strategic decision-making, which ultimately restricts product turnover rates (Chairunisa et al., 2023). Recognizing the critical nature of inventory systems, PT. Rakha Medika, a healthcare provider in Palembang, has initiated improvements in its management processes.

PT. Rakha Medika operates within the pharmaceutical sector through its pharmacy and clinic sub-units. In its daily operations, the company faces major challenges in medication stock management, particularly frequent product expiration due to "dead stock" from low-turnover items and disorganized data. This issue is further compounded by a lack of specialized staff knowledge in inventory control, leading to substantial financial and time-efficiency losses. Similar difficulties have been documented in other institutions, such as UPT RSUD Ogan Ilir (Vebrianti et al., 2023), Toko Obat Aqilah

(Nuryani et al., 2022), and Apotek Simpang F (Sari et al., 2023)

Addressing these challenges requires a forecasting model to determine minimum stock levels based on identified patterns (Nugraha, 2019). Exponential Smoothing is a widely adopted algorithm for forecasting in pharmaceutical and commodity inventory studies. Although this method has been implemented in previous research (Nuryani et al., 2022; Sari et al., 2023; Vebrianti et al., 2023), the present study offers several fundamental novelties.

First, regarding analytical tooling, while most prior studies relied on ready-to-use software like RapidMiner, this research utilizes the Python programming language. Python enables more precise optimization of smoothing parameters through automated code iteration. Second, in terms of data characteristics, this study handles a higher level of complexity by integrating 4.033 records from two distinct sub-units: the pharmacy and the clinic. Due to limited historical data access, which constrained the study to a one-year period (April 2023 – April 2024), the dataset reveals complexity through indications of seasonal patterns and sharp fluctuations in specific medications. This requires high-precision forecasting to mitigate

dead stock risks while ensuring the availability of essential medical supplies.

Based on these comparisons, this study applies the method to stock consumption data to forecast minimum inventory levels. This research is expected to provide a robust technical justification for forecasting complex datasets, surpassing the conventional methods used in earlier studies. Consequently, this research on PT. Rakha Medika’s inventory aims to refine product turnover and enhance overall management efficiency under the title “Forecasting Model Using Single Exponential Smoothing Method on PT. Rakha Medika.”

**METHOD**

**2.1 Forecasting**

Forecasting is the process of predicting future events based on specific objects, experiences, or historical datasets (Sabarina et al., 2021). It serves as a critical component in strategic decision-making for companies and organizations (Larasati Amalia et al., 2019). Effective planning, encompassing both short-term and long-term horizons, relies heavily on accurate projections of product demand (Heizer et al., 2020). In the field of forecasting, achieving absolute precision is unattainable as errors are inherent to the process; therefore, researchers focus on minimizing these errors to the lowest possible margin (Syakura et al., 2016).

Based on the time horizon, forecasting is classified into three categories (Lawrence & Rombe, 2018):

1. Short-term forecasting  
Typically covers a period of up to one year.
2. Medium-term forecasting  
Generally spans between one and three years.
3. Long-term forecasting  
Usually involves a duration of three years or more

Furthermore, forecasting methodologies are categorized into two primary approaches (Heriansyah & Hasibuan, 2018):

1. Qualitative methods  
An intuitive approach based on experiential judgment and expert opinions.
2. Quantitative methods

A mathematical approach that relies on the analysis of historical data.

**2.2 Exponential Smoothing**

Exponential Smoothing is a forecasting technique based on the moving average principle, where weights are determined through an exponential function (Aji et al., 2022). This method is recognized for being both effective and relatively straightforward to implement (Ahmar et al., 2024). Furthermore, this technique is well-suited for both medium-term and long-term projections (Santoso et al., 2021). Generally, Exponential Smoothing is categorized into three primary types: Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES).

**2.3 Single Exponential Smoothing**

Single Exponential Smoothing (SES) is a quantitative forecasting method designed for historical datasets characterized by instability or lack of a clear trend. This method incorporates a continuous refinement process, adjusting forecasts based on the most recent observational data (Vebrianti et al., 2023). The initial step in its application involves establishing the first forecast value (F1) which can be derived from either the first actual observation (A1) or the average of available historical data. Subsequently, forecasts for following periods are calculated using the Single Exponential Smoothing formula:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \tag{1}$$

Where :

- $F_t$  : Forecast for the current period, t-1
- $F_{t-1}$  : Forecast for the previous period, t-1
- $A_{t-1}$  : Actual value for the previous period, t-1
- $\alpha$  : Smoothing constant

The smoothing constant ( $\alpha$ ) can be assigned any value between 0 and 1. A higher weight is assigned to the most recent data; therefore, selecting an appropriate  $\alpha$  parameter is critical to achieving optimal forecasting with minimal error. Determining the optimal  $\alpha$  involves a trial-and-error process to reach the lowest possible error rate. This selection is conducted by comparing values within the smoothing interval of  $0 < \alpha < 1$ , typically ranging

from 0,1 to 0,9. Once the forecasts are generated, the performance of the model is assessed using forecasting accuracy techniques.

## 2.4 Forecasting Accuracy

In forecasting evaluation, model performance is determined through accuracy measurements. High-accuracy forecasting is characterized by a minimal error rate. There are three primary metrics commonly utilized to evaluate forecasting techniques (Sabarina et al., 2021):

### 2.4.1 MAD (Mean Absolute Deviation Error)

MAD represents the average of absolute errors over a specific period, regardless of whether the forecast values are higher or lower than the actual observations. The highest level of forecasting accuracy is indicated by the lowest achieved error value. Mathematically, the MAD formula is expressed as follows:

$$MAD = \sum \frac{|X_t - F_t|}{n} \quad (2)$$

Where :

- $X_t$  : Actual value for period t
- $F_t$  : Forecasted value
- $n$  : Number of time-series data points

### 2.4.2 MAPE (Means Absolute Percentage Error)

MAPE is a relative error metric that provides more comprehensive information than MAD or MSE, as it expresses the forecasting error as a percentage of the historical data. This metric effectively indicates whether the forecasting deviation is significant or negligible. A model is categorized as "Excellent" if the MAPE score is below 10% and "Good" if it falls within the 10% to 20% range. Mathematically, MAPE is calculated using the following formula:

$$MAPE = \frac{|X_t - F_t|/X_t}{n} \times 100\% \quad (3)$$

Where :

- $X_t$  : Actual value for period t
- $F_t$  : Forecasted value

Table 1. MAPE Interpretation Ranges

No	Range MAPE	Criteria
1	<10%	Excellent
2	10%-20%	Good
3	20%-50%	Feasible
4	>50%	Poor

### 2.4.3 MSE (Mean Square Error)

MSE evaluates forecasting accuracy by calculating the average of the squared differences between predicted values and actual observations. Similar to other metrics, the highest forecasting accuracy is represented by the minimum achieved MSE value.

$$MSE = \sum e_i^2 = \frac{\sum (X_t - F_t)^2}{n} \quad (4)$$

Keterangan :

- $e_i^2$  : The squared residual between forecasted and actual values
- $X_t$  : Actual value for period t
- $F_t$  : Forecasted value
- $n$  : Number of time-series data points

## 2.5 Python

Python is a high-level programming language that utilizes dynamic semantics to enhance syntax readability and is capable of executing multiple instructions through object-oriented programming (Athifa et al., 2023). It features extensive libraries for data loading, visualization, statistics, natural language processing, and image processing (Müller & Guido, 2017). The following libraries are instrumental in supporting data mining (Saabith et al., 2020):

### 1. Pandas (Python Data Analysis)

A library for data analysis and cleaning that provides efficient, flexible data structures, such as DataFrames, for managing structured data.

### 2. NumPy (Numerical Python)

The fundamental package for numerical computing in Python, offering powerful N-dimensional array objects for data analysis.

### 3. Statsmodels

A library specifically designed for forecasting and statistical analysis, including high-accuracy Exponential Smoothing methods.

### 4. Skicit-Learn

A comprehensive library for machine learning and data analysis, providing various algorithms and tools to build, train, and evaluate forecasting models.

## 2.6 Data Collection Techniques

The data collection techniques employed to support the objectives of this study include observation, interviews, and documentation. Observation was conducted directly at PT. Rakha Medika to obtain a comprehensive overview of the research object's conditions. Interviews were held with the company owner and the warehouse manager to acquire data regarding inventory management. Furthermore, documentation was carried out by collecting PT. Rakha Medika's stock data in Excel format.

## 2.7 Framework

This research adopts the Knowledge Discovery in Databases (KDD) framework to forecast inventory levels at PT. Rakha Medika. The process encompasses several stages, including data preparation, data processing, and evaluation, as illustrated in Figure 1.

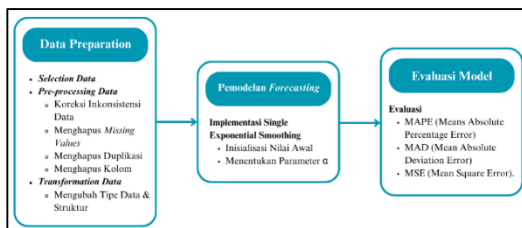


Figure 1. Adoption of KDD Stages in the Research

### 1. Data Selection

This stage involves identifying and selecting relevant variables and records from the database for the inventory forecasting process. This study utilizes historical stock data from PT. Rakha Medika spanning a 13-month period (April 2023 – April 2024).

### 2. Data Pre-processing

This step focuses on data cleaning to address issues such as duplication and missing values. Subsequently, the data undergoes re-verification and correction to ensure integrity.

### 3. Data Transformation

The cleaned data is transformed into a format more suitable for analysis. This involves adjusting data types and restructuring the dataset as required by the forecasting model.

### 4. Data Mining

The Single Exponential Smoothing (SES) forecasting method is implemented using Google Colab, the Python

programming language, and the Statsmodels library to generate the forecasts.

### 5. Evaluation

This final stage involves assessing the forecasting accuracy and translating the patterns generated by the model into a format that is easily interpretable for relevant stakeholders.

## RESULTS AND DISCUSSION

### 3.1 Data Preparation

In the initial stage of this research, data preparation was conducted, consisting of three sub-stages: data selection, data pre-processing, and data transformation.

#### 3.1.1 Data Selection

Data selection is the primary phase aimed at identifying relevant and representative data. The dataset used in this study comprises inventory records obtained directly from the Warehouse Manager of PT. Rakha Medika, spanning the period from April 2023 to April 2024.

```

[11]: [11] df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4033 entries, 0 to 4032
Data columns (total 11 columns):
 #   Column                                     Non-Null Count  Dtype
---  ---
 0   Bulan                                     4033 non-null   object
 1   NAMA OBAT/BARANG                          4033 non-null   object
 2   JENIS BARANG                               4033 non-null   object
 3   STOCK AWAL PERIODE                        4033 non-null   int64
 4   UNIT                                       4033 non-null   object
 5   PENERIMAAN BARANG BULAN BERJALAN (OBAT MASUK)  4033 non-null   int64
 6   STOCK OPNAME (Jumlah Fisik Terhitung)     4033 non-null   int64
 7   BARANG YANG TERPAKAI (STOCK OPNAME)      4033 non-null   int64
 8   BARANG TERPAKAI (CATATAN OBAT KELUAR)    4033 non-null   int64
 9   STOCK AKHIR PERIODE (SELISIH)            4033 non-null   int64
10  STOCK SISA HARIAN                         4033 non-null   int64
dtypes: int64(7), object(4)
memory usage: 346.7+ KB
    
```

Figure 2. PT. Rakha Medika Inventory Data for the 13-Month Period

As illustrated in Figure 2, the dataset consists of 4.033 rows and 11 columns. These attributes include the month, item/medicine name, item category, initial stock level, unit, incoming stock received during the current month, stock opname, stock consumption based on stock opname, stock consumption based on outgoing records, final stock discrepancy, and daily remaining stock.

#### 3.1.2 Data Pre-processing

This stage involves data cleaning and preparation, which includes checking for data duplication, missing values, and inconsistencies. Upon examination, no duplicate records or missing values were found; however, inconsistencies were identified within the "UNIT" column headers and entries.

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4033 entries, 0 to 4032
Data columns (total 3 columns):
#   Column                Non-Null Count  Dtype
---  ---                ---
0   BULAN                  4033 non-null   object
1   NAMA OBAT/BARANG      4033 non-null   object
2   BARANG YANG TERPAKAI (STOCK OPNAME)  4033 non-null   int64
dtypes: int64(1), object(2)
memory usage: 94.64 KB
```

Figure 3. Research Dataset Post-Cleaning

Figure 3 illustrates the results of the data cleaning process. This procedure included correcting data inconsistencies and selecting relevant columns. The final dataset remains unchanged in size, containing 4.033 rows, and has been narrowed down to three essential columns:

1. BULAN: Month
2. NAMA OBAT/BARANG: Item/Medicine Name
3. BARANG YANG TERPAKAI (STOCK OPNAME): Stock Opname

### 3.1.3 Data Transformation

Prior to forecasting, the cleaned data must undergo transformation. First, the data type of the "BULAN" column was converted from "category" to "datetime." This adjustment is necessary to meet the requirements of Python modeling, specifically for the Single Exponential Smoothing method within the Statsmodels library, which requires time-format data to function. The results of this conversion are shown in Figure 4.

```
#Buat tipe data BULAN menjadi datetime
df['BULAN'] = pd.to_datetime(df['BULAN'])
df.head()
```

BULAN	NAMA OBAT/BARANG	BARANG YANG TERPAKAI (STOCK OPNAME)
2023-04-01	Actlar 300mg	0
2023-04-01	Actlar 600mg	200
2023-04-01	Actlar Kim	2
2023-04-01	Acyclovir Kim	0
2023-04-01	Acyclovir 400mg Tablet	1200

Figure 4. Time Data Type Transformation

Once the data types were aligned, the data structure was converted from a long format (where each record is a separate row) to a wide format (where each record becomes a separate column) using pivoting techniques. This transformation facilitates the analysis of item consumption patterns across different months.

	Bulan	2023-01-01	2023-02-01	2023-03-01	2023-04-01	2023-05-01	2023-06-01	2023-07-01	2023-08-01	2023-09-01	2023-10-01	2023-11-01	2023-12-01	2024-01-01	2024-02-01	2024-03-01
Nama Obat/Barang																
Actlar 300mg		50	15	21	20	0	20	5	15	12	20	10	24	10	0	0
Actlar 600mg		100	100	0	800	200	0	0	400	600	0	0	0	0	0	0
Actlar Kim		10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Acyclovir Kim		1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200
Acyclovir Tablet		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Actlar 300mg		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Actlar 600mg		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Actlar Kim		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Acyclovir Kim		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Acyclovir Tablet		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
All 2024 Dashboard		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 5. Data Structure Transformation

The resulting columns in Figure 5 are consistent with the time-series nature of the Single Exponential Smoothing method, which focuses exclusively on the primary variables: time and the measured value. Furthermore, Single Exponential Smoothing is designed to focus on these internal patterns without incorporating the influence of other external variables in the dataset.

## 3.2 Data Processing

### 3.2.1 Implementation of Single Exponential Smoothing

Forecasting is a vital endeavour for companies to enhance the effectiveness of inventory management. By utilizing historical data, specific patterns can be identified as a reference for implementing forecasting models. The insights gained from the monthly stock consumption patterns are shown in Figure 6.

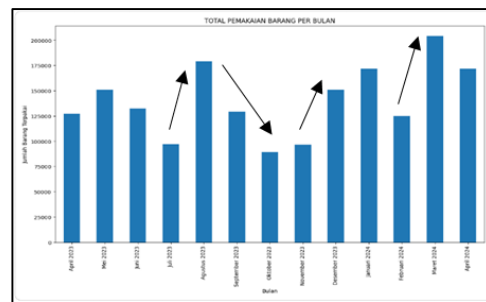


Figure 6. Total Monthly Item Consumption Diagram

As illustrated in Figure 6, item consumption data exhibits significant fluctuations. Notable trends include a rapid increase of 84,27% from July to August 2023, a decrease of 50,04% from August to October 2023, a rise of 55,88% between November and December 2023, and a sharp spike of 63,76% from February to March 2024. Such fluctuations suggest that the dataset is better suited for a high alpha ( $\alpha$ ) value approaching 1 (Nugus, 2009), as data characteristics directly influence the optimal smoothing constant.

The initial stage of Single Exponential Smoothing involves initializing the first forecast value, typically by using the actual value of the first period if no prior forecasting has been conducted (Vebrianti et al., 2023). The subsequent step is determining the smoothing constant ( $\alpha$ ) within the range of  $0 < \alpha < 1$  through a trial-and-error approach to identify the value that yields the minimum forecasting error. In this

study,  $\alpha$  values of 0,1; 0,5; and 0,99 were selected for comparison, representing low, medium, and high parameters respectively. This trial-and-error approach aims to determine the optimal value that produces the lowest error rate. A similar methodology was employed in a study titled "Production Planning Forecasting System Using the Single Exponential Smoothing Method in the Putera Sejahtera Tempe Home Industry" which tested various alpha values to identify optimal parameters (Audinasyah & Solehudin, 2024). The results of the Single Exponential Smoothing application with  $\alpha$  values of 0,1; 0,5; and 0,99 are shown in Figure 7.

the criteria in Table 1, where a MAPE range of 10%–20% is categorized as a reliable forecasting level. The relatively low MAPE, MAD, and MSE values for  $\alpha$ : 0,99 demonstrate strong overall model performance.

Barang	Forecast $\alpha=0.1$	Forecast $\alpha=0.5$	Forecast $\alpha=0.99$
Abocath No. 24	35.7269	53.9936	79.4424
Acifar 300mg	99.5711	46.6568	0.000395
Acifar 400mg	267.473	458.394	742.525
Acifar Krim	16.1896	11.5632	1.16924
Acylovir 400mg Tablet	956.997	1131.64	1687.07
Acylovir Krim	16.6226	32.4799	49.6783
Adacel	0.98	0.98	0.98
Adiframol Sirup	2.83187	1.86482	0.98
Akita Tablet	634.885	584.611	482.971
Alat GCU Easytouch	1.38214	2.8216	2.9798
Alat Nebulizer	0.9818	0.985	0.000398
Alerzin Sirup	31.2177	43.8361	38.2515
Alkohol Onemed 1 Liter	3.42672	1.94481	1.8182
Alkohol Sumb	0.98	0.98	0.98
Alleron Tablet	318.752	61.3297	0.580485
Allofar 100mg Tablet	96.6794	3.14926	0.98
Allofar 300mg Tablet	189.332	38.8373	0.000395
Alphamol 600mg Tablet	1856.99	1472.98	474.828
Amlodipin 5mg Tablet	186.983	298.815	283.248
Anacortine Sirup	0.98	0.98	0.98
Anelet Tablet	56.1758	32.4894	1.9604
Antasida Doan Sirup	6.14647	1.21441	0.98
Antasida Doan Tablet	1381.96	3382.81	4488.9
Aquadest Injeksi	82.6196	112.887	119.829
Asconex Rakha	31.1932	26.311	18.5805
Aspilex Chewable	45.9533	68.1474	2.8791
Attapulgite Tablet	148.136	4.56528	0.98
Avaxim 100	0.98	0.98	0.98
Avaxim 80	0.98	0.98	0.98
Betamethasone Krim	5.86581	0.99417	0.98
Bimaflox 500mg Tablet	0.98	0.98	0.98
Bio IT	0.98	0.98	0.98
Bloviton Sirup	25.8242	1.00296	0.98
Bisoprolol 2,5mg Tablet	0.98	0.98	0.98
Bisoprolol 5mg Tablet	149.538	451.277	891.81

Figure 7. Forecasting Results with Various  $\alpha$  Values

Figure 7 presents the forecasted inventory values for the upcoming period (May 2024) based on  $\alpha$  values of 0,1; 0,5; and 0,99.

### 3.3 Evaluation

Following the generation of forecasts, the subsequent stage involves measuring forecasting accuracy. Performance is evaluated using three metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Square Error (MSE). The application of these three methods facilitates a comprehensive assessment and enhances precision in identifying the optimal alpha value. These calculations were performed utilizing the Scikit-Learn library, which provides the necessary evaluative metrics.

Based on the error calculations for various alpha ( $\alpha$ ) values as shown in Figure 8, the parameter  $\alpha$ : 0,99 yielded the highest accuracy. This parameter produced the lowest error rates, with a MAPE of 14%, a MAD of 4, and an MSE of 97, outperforming the other alpha values. The achieved MAPE value (14%) indicates that the forecast possesses "Good" accuracy according to

```

[38] @menghitung rata-rata dari MAPE, MAD, dan MSE
average_mape = results_df[['col' for col in results_df.columns if 'MAPE' in col]].mean()
average_mad = results_df[['col' for col in results_df.columns if 'MAD' in col]].mean()
average_mse = results_df[['col' for col in results_df.columns if 'MSE' in col]].mean()

print("\nPerbandingan rata-rata MAPE pada setiap nilai alpha (%):")
print(average_mape)

print("\nPerbandingan rata-rata MAD pada setiap nilai alpha (%):")
print(average_mad)

print("\nPerbandingan rata-rata MSE pada setiap nilai alpha (%):")
print(average_mse)

Perbandingan rata-rata MAPE pada setiap nilai alpha (%):
MAPE  $\alpha=0.1$ : 1.580
MAPE  $\alpha=0.5$ : 7.50
MAPE  $\alpha=0.99$ : 14
dtype: float64

Perbandingan rata-rata MAD pada setiap nilai alpha (%):
MAD  $\alpha=0.1$ : 288
MAD  $\alpha=0.5$ : 172
MAD  $\alpha=0.99$ : 4
dtype: float64

Perbandingan rata-rata MSE pada setiap nilai alpha (%):
MSE  $\alpha=0.1$ : 472.482
MSE  $\alpha=0.5$ : 17.484
MSE  $\alpha=0.99$ : 97
dtype: float64
    
```

Figure 8. Final Results of MAPE, MAD, and MSE

After identifying the optimal alpha value (0.99) through evaluation, the resulting forecast is presented in Figure 9. This selection aligns with Gasperz's theory, which states that "The parameter  $\alpha$  can be determined freely, and the forecast with the smallest error is the result of selecting the lowest error rate" (Gasperz, 2015).

1	Barang	Forecast $\alpha=0.99$
327	Vitamin B Kompleks St	2595.030596
328	Vitamin B Kompleks isi	0.98
329	Vitamin B Kompleks isi	0.98
330	Vitamin C Pot isi 100	2970.141579
331	Vivaxim	0.98
332	Wing Needle Onemed	109.960297
333	Yusimox 125mg Sirup	54.46310429
334	Yusimox Forte 250mg S	65.10990544
335	Yusimox Tablet	2389.970486
336	Zevask 10mg	1290.960493
337	Zevask 5mg	1188.01069
338	Zinc Sirup	0.98
339	Zinc Sirup	0.98
340	Zinc Tablet	905.089795

Figure 9. Forecasting Results with  $\alpha$  : 0,99

These analytical results are further supported by previous research titled "Warranty Part Inventory Control System Using Exponential Smoothing Forecasting Method", which demonstrated that an  $\alpha$  value of 0,9 provided the most optimal inventory forecast with a MAPE of less than 20% (Suratun et al., 2017). Conversely, another study titled "Forecasting Drug Needs Using the Single Exponential Smoothing Method" showed different results, where an  $\alpha$  of 0,5 was the best fit, though still maintaining a MAPE below 20% (Vebrianti et al., 2023). These discrepancies emphasize that  $\alpha$  adjustments must be tailored to the specific characteristics of the dataset.

Consequently, the company can optimize inventory management by referencing these forecast values, thereby mitigating the risks of stock outs or overstocking.

### 3.3.1 Comparison of Forecasting and Actual Data

This sub-section aims to validate the forecasting results by comparing the actual data, the forecasts generated using the optimal alpha parameter (0,99), , and manual calculations. The following demonstrates the manual calculation of Single Exponential Smoothing for a specific item at PT. Rakha Medika, namely Cefadroxil 500mg, which yielded a forecast value of 6.313,839519 using the Python implementation.

Initialization of initial value for April 2023:

$$F_1 = A_1 = 5.100$$

Calculation for May 2023 ( $\alpha: 0,99$ ):

$$F_2 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_2 = 5.100 + 0,99 \times (5300 - 5100)$$

$$F_2 = 5.298$$

Calculation for June 2023 ( $\alpha: 0,99$ ):

$$F_3 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_3 = 5.298 + 0,99 \times (4.600 - 5.298)$$

$$F_3 = 4.606,98$$

Calculation for July 2023 ( $\alpha: 0,99$ ):

$$F_4 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_4 = 4.606,98 + 0,99 \times (3.400 - 4.606,98)$$

$$F_4 = 3.411,07$$

Calculation for August 2023 ( $\alpha: 0,99$ ):

$$F_5 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_5 = 3.411,07 + 0,99 \times (6.600 - 3.411,07)$$

$$F_5 = 5.580,11$$

Calculation for September 2023 ( $\alpha: 0,99$ ):

$$F_6 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_6 = 5.580,11 + 0,99 \times (5.100 - 5.580,11)$$

$$F_6 = 5.104,80$$

Calculation for October 2023 ( $\alpha: 0,99$ ):

$$F_7 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_7 = 5.104,80 + 0,99 \times (2.200 - 5.104,80)$$

$$F_7 = 2.225,05$$

Calculation for November 2023 ( $\alpha: 0,99$ ):

$$F_8 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_8 = 2.225,05 + 0,99 \times (4.600 - 2.225,05)$$

$$F_8 = 4.575,25$$

Calculation for December 2023 ( $\alpha: 0,99$ ):

$$F_9 = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_9 = 4.575,25 + 0,99 \times (7.500 - 4.575,25)$$

$$F_9 = 7.470,76$$

Calculation for January 2024 ( $\alpha: 0,99$ ):

$$F_{10} = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_{10} = 7.470,76 + 0,99 \times (5.600 - 7.470,76)$$

$$F_{10} = 5.260,77$$

Calculation for February 2024 ( $\alpha: 0,99$ ):

$$F_{11} = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_{11} = 5.620,77 + 0,99 \times (6.100 - 5.620,77)$$

$$F_{11} = 6.095,20$$

Calculation for March 2024 ( $\alpha: 0,99$ ):

$$F_{12} = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_{12} = 6.095,20 + 0,99 \times (7.700 - 6.095,20)$$

$$F_{12} = 7.685,95$$

Calculation for April 2024 ( $\alpha: 0,99$ ):

$$F_{13} = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

$$F_{13} = 7.685,95 + 0,99 \times (6.300 - 7.685,95)$$

$$F_{13} = 6.314,85$$

Based on the manual calculations, it can be concluded that the forecasting results generated using Python are highly accurate, showing a negligible discrepancy of only 0,016% between the Python forecast (6.313,839519) and the manual calculation (6.314,85). This minimal variance indicates that the implemented model provides consistent and reliable projections.

Furthermore, a comparison was conducted between the forecasting results ( $\alpha: 0,99$ ) and the actual field data for May 2024. During this period, changes in the inventory data occurred due to the discontinuation of certain items, reducing the total item count from 340 to 318. This comparison serves to analyse the extent to which the forecasting results ( $\alpha: 0,99$ ) align with real-world conditions and to identify any significant deviations. The comparative results for selected items are presented in Table 2.

Table 2. Comparison between Actual Values and Forecast Results

Item Name	Actual Value	Forecast Result ( $\alpha:0,99$ )	Difference
Caviplex Tablet	2.800	3.214	12,87%
Cetirizin Tablet	2.100	2.508	16,26%
Dexamethason Tablet	11.400	3.522	-223,62%
Holimox Sirup 125mg/5ml	60	61	1,03%
Ketoconazole Krim	50	54	7,22%
Methyl Prednisolon 4mg	4.800	5.008	4,15%

Based on the comprehensive analysis, significant variations exist between the forecasted results and the actual data.

Specifically, 98 items showed a difference of less than 30%, while no items (0) fell within the 31%–50% difference range. The largest segment consisted of 220 items with a difference exceeding 50%; however, 98 of these instances involved a discrepancy of only a single unit, which is not considered a significant deviation. Consequently, 122 out of 318 items (38,24%) exhibited a difference greater than 50% and are categorized as substantial deviations. Although the overall MAPE was recorded at 14%, which remains within the "Good" category, these deviations reflect the inherent uncertainty in historical data.

The actual conditions at the clinic are influenced by external factors, such as seasonal demand shifts, patient fluctuations, and sudden medical trends. For instance, the surge in Dexamethasone usage in Palembang during May 2024 occurred during the transitional season (*pancaroba*) (Multimedia, 2024). According to interviews, this spike was driven by an increase in allergy cases resulting from extreme weather fluctuations. Despite these external factors causing data deviations, forecasting remains essential for projecting future trends and supporting inventory planning to mitigate the risks of overstocking or stock outs. This knowledge facilitates more informed decision-making even when forecasting results are not perfectly precise.

This aligns with the fundamental principle of forecasting: that all forecasts inherently contain errors, meaning no prediction is 100% accurate or perfectly reflective of actual conditions due to unpredictable variables (Anisah & Hadita, 2024). Therefore, continuous evaluation of forecasting errors is imperative to improve accuracy for future projections (Tampi et al., 2023).

## CONCLUSION

Based on the research conducted on inventory forecasting at PT. Rakha Medika using the Single Exponential Smoothing method, several conclusions have been drawn. The optimal alpha ( $\alpha$ ) value identified in this study is 0,99, which represents an increase compared to previous research due to data characteristics exhibiting high fluctuations and intermittent patterns. This model achieved a MAPE of 14% (categorized as "Good"), a MAD of 4, and an MSE of 97, demonstrating reliable accuracy at the selected alpha level. However, a deviation of

38.24% was observed across the total inventory compared to actual results, primarily driven by unavoidable external factors. These findings suggest that Single Exponential Smoothing is less effective in addressing datasets with extreme fluctuations and potential seasonal patterns.

As a reference for future work, it is recommended to utilize a longer historical timeframe, ideally a minimum of two years, to accurately validate the persistence of annual seasonal patterns and overcome the historical data limitations encountered in this study. Furthermore, subsequent research should consider employing more complex models, such as Double or Triple Exponential Smoothing, and integrating external variables to further reduce deviation levels and improve forecasting precision.

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