Eduvest – Journal of Universal Studies
Volume 4 Number 03, March, 2024
p- ISSN 2775-3735- e-ISSN 2775-3727

APPLICATION OF EXPONENTIAL SMOOTHING METHOD FOR FORECASTING SPARE PARTS INVENTORY AT HEAVY EQUIPMENT DISTRIBUTOR COMPANY

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ABSTRACT

As a heavy equipment distributor company with a widespread population of units across Indonesia, PT. Kobexindo Tractors Tbk holds a significant spare parts inventory to meet their customers' needs. However, efficiently and effectively managing spare parts inventory is a challenge the company faces. Over the period from 2016 to 2023, the company experienced an average annual loss of Rp. 1,176,438,113, due to the inadequate analysis of spare parts demand, which serves as a reference in the procurement process. To address this issue, this research focuses on developing a model that can generate accurate forecasts for spare parts inventory, particularly Jungheinrich parts, to support appropriate management decisions in the procurement process at the company. The Exponential Smoothing method is chosen for its ability to handle data with fluctuating patterns and trends. Based on a review of previous research studies, the Exponential Smoothing method has proven to be the most effective in forecasting spare parts inventory with a high level of accuracy. This study will compare the Simple Exponential Smoothing, Double Exponential Smoothing, and Triple Exponential Smoothing methods. The attributes included in this research are spare parts inventory data collected from the company during the period of 2016-2023, which will be processed using Exponential Smoothing techniques. The results of these calculations will be evaluated using the Root Mean Square Error (RSME) and Mean Absolute Percentage Error (MAPE) techniques to test the accuracy and performance of the forecasting models. The data ratio used in this research is 70% for training data and 30% for testing data. The prototype development is conducted using the Python programming language. The research results indicate that the Holts Winter Exponential Smoothing Model with Multiplicative Seasonality and Multiplicative Trend (Triple Exponential) is the best method among others, as seen from the modeling evaluation results as follows: 1) Train RSME (7.082307), a low RSME value on training data indicates that this model has a small prediction error rate on the data

How to cite:	Budiarto, D.D et al (2024). Application of Exponential Smoothing Meth-Od for Forecasting Spare Parts Inventory at Heavy Equipment Distribu-Tor Company. *Journal Eduvest. 4* (3): 959-976
E-ISSN:	2775-3727
Published by:	https://greenpublisher.id/

used for training. 2) Test MAPE (6.343268), a low MAPE value on test data indicates that this model provides fairly accurate predictions in percentage terms of the actual values on the test data. 3) Test RSME Values (23.160521), a sufficiently low RSME value on test data indicates that this model also successfully generalizes well on unseen data.

KEYWORDS *Kobexindo, Forcasting, Exponential Smoothing, Sparepart, MAPE, RSME, Phyton*

INTRODUCTION

PT Kobexindo Tractors Tbk is a company based in Indonesia. The company is a distributor and provider of heavy equipment services such as construction machinery, logistic equipment, cleaning equipment, and mining equipment. With a widespread unit population across almost all regions of Indonesia, the company also provides spare parts and after-sales services. PT Kobexindo Tractors, Tbk was established in 1994 and has become one of the leading companies in the heavy equipment industry in Indonesia. As a large company, it maintains a significant inventory of spare parts to meet the needs of its customers spread across almost all regions of Indonesia. However, efficiently managing spare parts inventory is a challenge that the company must face.

Efficient inventory management is crucial for companies as it can provide several benefits, including reducing inventory costs. Excessive spare parts inventory can result in unnecessary costs such as storage costs, risk of damage, or loss. Another negative effect of poorly managed spare parts inventory is cash flow imbalance due to the mismatch between the capital used for spare parts procurement and the sales value of those spare parts, which can lead to losses for the company. One of the steps to reduce the risk of poor spare parts inventory management is to accurately forecast customer demand by examining historical spare parts sales data. The expected outcome is that the company can reduce unnecessary inventory and optimize the use of company resources.

However, during the period from 2016 to 2023, PT Kobexindo Tractors, Tbk, especially in the product support division, experienced excess inventory, particularly spare parts for Jungheinrich forklift units, where the inventory value categorized as dead stock, measured by the length of storage in the warehouse of more than 1 year, was significant, as shown in Table 1.1. This occurred because the purchase of spare parts for Jungheinrich forklift units was not based on an analysis of historical sales data and customer demand forecasting. Instead, the purchasing process was solely based on meeting purchase quotas set by the principal regarding the targets set by the principal for PT. Kobexindo Tractors, Tbk. This resulted in suboptimal analysis of spare parts demand forecasting, leading to very low accuracy of spare parts inventory data.

The low accuracy of spare parts demand forecasting also results in management errors in determining which spare parts to purchase, leading to excess inventory stored in the spare parts warehouse for more than 1 year.

Table 1 Trends in Spare Parts Storage Life for the 2016-2023 Period
(Source: Document Warehouse Dept. PT. Kobexindo Tractors Tbk)

Tahun	Kategori Umur Penyimpanan											
	1-90 Hari		91-180 Hari		181-360 Hari		> 1 Tahun		> 2 Tahun		> 3 Tahun	
2016	Rp	740,263,466	Rp	760,481,473	Rp	651,384,271	Rp	513,861,535	Rp	982,656,152	Rp	902,646,052
2017	Rp	976,647,058	Rp	823,565,985	Rp	825,647,898	Rp	1,025,634,854	Rp	720,336,525	Rp	816,954,823
2018	Rp	1,919,745,477	Rp	1,314,299,750	Rp	2,235,008,184	Rp	902,646,052	Rp	622,294,201	Rp	1,202,649,713
2019	Rp	2,923,146,916	Rp	1,407,825,842	Rp	1,244,376,006	Rp	1,391,270,141	Rp	623,181,606	Rp	1,558,552,080
2020	Rp	1,996,476,099	Rp	948,370,144	Rp	740,263,466	Rp	1,860,896,343	Rp	651,384,271	Rp	1,708,223,984
2021	Rp	2,151,006,096	Rp	513,861,535	Rp	1,198,010,282	Rp	691,307,974	Rp	1,150,750,150	Rp	1,271,804,388
2022	Rp	4,731,897,378	Rp	1,441,158,725	Rp	588,917,582	Rp	760,481,473	Rp	349,599,871	Rp	1,674,039,857
2023	Rp	3,621,597,386	Rp	1,365,623,589	Rp	825,365,942	Rp	1,032,651,202	Rp	900,225,642	Rp	1,205,690,155
Total	**Rp**	**19,060,779,876**	**Rp**	**8,575,187,043**	**Rp**	**8,308,973,631**	**Rp**	**8,178,749,574**	**Rp**	**6,000,428,418**	**Rp**	**10,340,561,053**

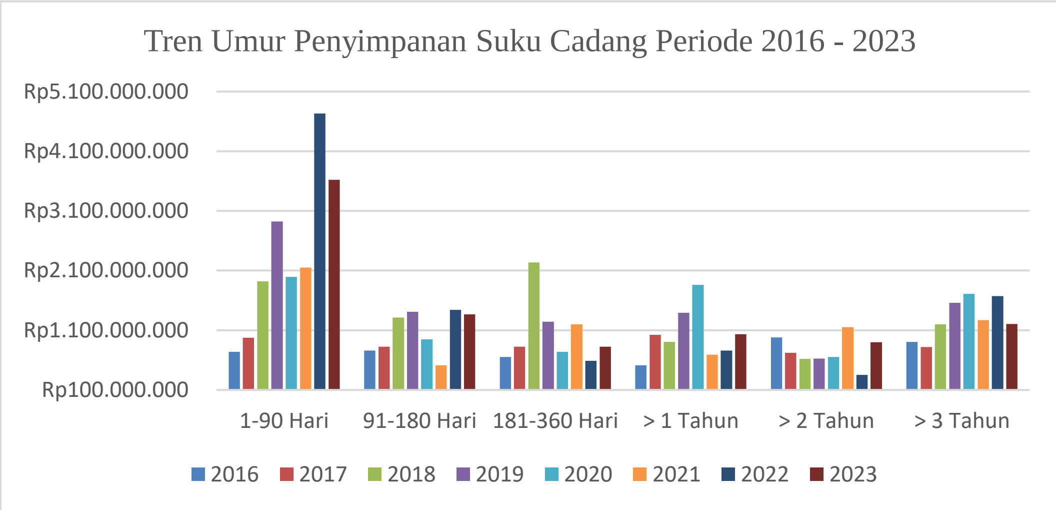

Figure 1. Storage Age Trend of Spare Parts Period 2016-2023
(Source: SQL Server Database, PT. Kobexindo Tractors Tbk)

The graph in Figure 1.1 depicts the trend of spare parts storage age over the period from 2016 to 2023, grouping them into 6 storage age categories: 1-90 Days, 91-180 Days, 181-360 Days, > 1 Year, > 2 Years, and > 3 Years. The total inventory value of the storage age category exceeding 1 year is Rp. 24,519,739,045, with the highest value occurring in 2020 at Rp. 4,220,504,598. This total value represents potential losses for the company as the spare parts have remained unsold for more than one year since purchase and have been stored in the spare parts warehouse. In the financial statements published by the company, it is recorded that over the period from 2016-2023, the average annual loss amounted to Rp1,176,438,113 due to unsold spare parts. The Product Support Division categorizes types of spare parts based on the brand of heavy equipment sold by the company, and the spare parts for Jungheinrich forklifts fall into the dead stock category.

Dead stock is typically associated with items that do not move or remain unsold within a specified inventory turnover period. The inventory turnover period can vary depending on the type of business, industry, and products sold. Inventory Management Review (IMR) defines dead stock as items that remain inactive or unsold for a long period, usually within the range of 12 to 24 months. Dead stock often becomes a financial burden for companies as it requires storage costs and can reduce space for more active inventory. Dead stock also poses a problem in inventory management as it can lead to financial losses and hinder the company's cash flow. Therefore, it is important for companies to identify and manage dead stock effectively to optimize resource utilization and minimize the risk of loss. The management of PT. Kobexindo Tractors, Tbk has a policy in determining the dead stock category for unsold spare parts using a 12-month inventory turnover period with a tolerance of 20% of the total value of spare parts inventory, meaning that any spare parts inventory with an age category exceeding 12 months has the potential to cause losses for the company.

Table 2 Table of Dead Stock Percentage in the Period 2016 -2023
(Source : Document Warehouse Dept. PT. Kobexindo Tractors Tbk)

Tahun	Total Nilai Inventory > 1 Tahun	Total Nilai Inventory	Persentase Dead Stock
2016	Rp 2,399,163,739	Rp 4,551,292,950	53%
2017	Rp 2,562,926,202	Rp 5,188,787,143	49%
2018	Rp 2,727,589,966	Rp 8,196,643,378	33%
2019	Rp 3,573,003,827	Rp 9,148,352,590	39%
2020	Rp 4,220,504,598	Rp 7,905,614,308	53%
2021	Rp 3,113,862,511	Rp 6,976,740,424	45%
2022	Rp 2,784,121,202	Rp 9,546,094,887	29%
2023	Rp 3,138,566,999	Rp 8,951,153,916	35%
Total	**Rp 24,519,739,045**	**Rp 60,464,679,595**	**41%**

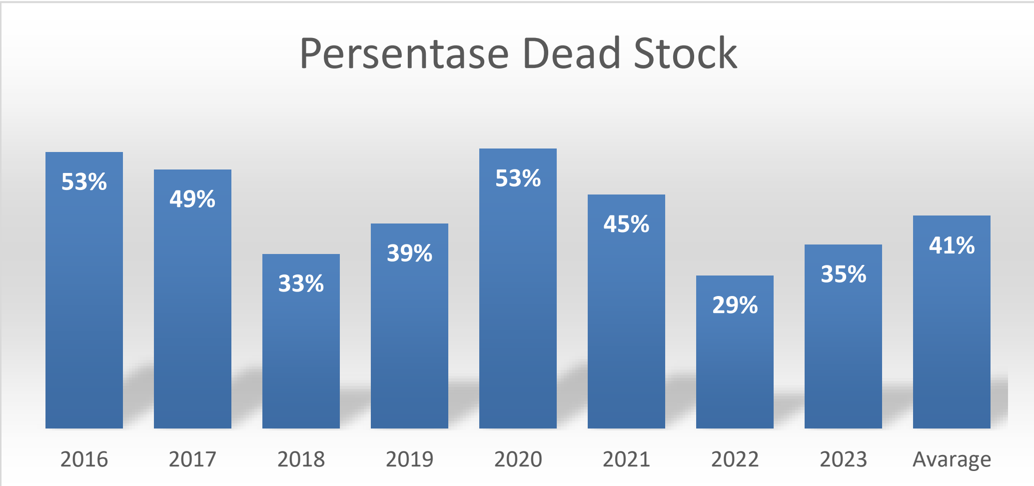

Figure 2 Percentage of Dead Stock
(Source : Database *SQL Server*. PT. Kobexindo Tractors Tbk)

The graph in Figure 1.2 illustrates the percentage value of dead stock each year within the period range of 2016 – 2023. This percentage value is obtained by summing up the inventory values of 3 storage age categories, namely > 1 Year, > 2 Years, and > 3 Years, compared to the total value of inventory across all storage age categories.

Based on the business understanding analysis, the researcher will develop a method that can forecast the demand for spare parts in the future, thus minimizing potential losses for the company due to errors in the analysis of spare parts procurement that ultimately fall into the dead stock category.

In developing the spare parts inventory forecasting method at PT. Kobexindo Tractors Tbk, the author bases the ideas and thoughts on research discussing problems and problem-solving methods that have been previously conducted. Several previous studies that have used Exponential Smoothing methods include one by May Shinta Putri, Fujiati (2022), titled "Application of Winter Exponential Smoothing Method in Forecasting Spare Parts Procurement at PT. Sumatera Sarana Sekar Sakti", which discusses forecasting spare parts procurement for 985 units of company transport fleets.

Another study by Ariadi Retno Tri Hayati Ririd, Elok Nur Hamdana, Edo Julyanto (2020), titled "Information System and Spare Parts Sales Forecast Using Triple Exponential Smoothing Method (Case Study of Lancar Jaya Motor Workshop)", discusses forecasting motorcycle spare parts sales to address errors in inventory management in motorcycle workshops.

A study titled "Inventory Forecasting System Using Brown Exponential Smoothing Method", written by Yulvia Nora Marlim, Alyauma Hajjah (2021), discusses the accumulation of goods leading to changes in production costs and fluctuations in demand over time, with occasional stock shortages.

From these previous studies, the author identifies similar problems that form the basis for this research, including the time series nature of the data. While these studies also use similar methods to address the problems, such as Exponential Smoothing, the author identifies areas for further development, including considering the Additive and Multiplicative nature of trends and seasonal patterns in the data.

Considering the nature of the spare parts procurement data at PT. Kobexindo Tractors Tbk, which is a time series data with seasonal patterns, the Exponential Smoothing method incorporating Additive and Multiplicative properties will be used in this study.

One of the main objectives of the Exponential Smoothing method is to forecast or predict future data values. By modeling patterns and seasonality in historical data, a time series model can be used to generate forecasts that approximate the expected values in the future.

By using the Exponential Smoothing method, a spare parts inventory forecasting model can be developed to assist PT Kobexindo Tractor, Tbk in forecasting future spare parts demand with high accuracy, enabling the company to make better decisions in inventory management.

This research aims to address issues in the management of spare parts inventory for Jungheinrich forklift units at PT Kobexindo Tractors Tbk. Identified problems include inaccuracies in spare parts procurement decision-making and the absence of an effective mechanism for spare parts provisioning decision-making. This research is limited to the scope of using historical data on spare parts purchases and sales from 2016 to 2018. The problem statement is how to develop an accurate forecasting model to improve the management of Jungheinrich forklift spare parts inventory.

The research objectives include the development of an Exponential Smoothing method to forecast spare parts inventory, optimization of inventory management based on forecasting results, and evaluation of Simple Exponential Smoothing, Double Exponential Smoothing, and Triple Exponential Smoothing forecasting methods. The benefits include helping to reduce the risk of financial losses due to incorrect spare parts inventory, improving the effectiveness of the company's inventory management system, and making academic contributions to research in similar fields.

RESEARCH METHOD

This research utilizes a scientific method with both descriptive and quantitative approaches, applying statistical methods for forecasting. The research methodology follows the steps of CRISP-DM, starting from business understanding to monitoring the results. The research object is PT. Kobexindo Tractors Tbk with the goal of achieving the highest level of accuracy in forecasting spare parts inventory.

The sampling method used is Stratified Random Sampling to ensure good representation from each spare parts group. Data collection steps involve data identification, gathering from the SQL Server database, verification, processing, and storage. Important instruments in this research include spare parts inventory data, forecasting software, Exponential Smoothing techniques, model validation, historical data, forecasting performance evaluation methods, and documentation.

Analysis techniques include descriptive analysis, system design based on problem analysis, and testing using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) methods. The strategic plan includes data collection, implementation of Exponential Smoothing methods, testing, interpretation of results, and formulation of conclusions and recommendations.

The research steps include business understanding, data understanding, data preparation, modeling, evaluation, implementation, and monitoring. The research schedule is organized in a table showing a series of activities from 2023 to 2024, including stages of business understanding, data preparation, modeling, evaluation, implementation, and monitoring.

RESULT AND DISCUSSION

Business Understanding

In this stage, the researcher analyzes data to identify and formulate problems in order to gain a comprehensive understanding of the company's business needs related to forecasting spare parts inventory. The goal is to improve inventory efficiency, reduce inventory costs, and decrease the number of Jungheinrich spare parts classified as dead stock. The researcher analyzes data on the trend of

Jungheinrich part storage age by comparing the total value of inventory > 1 year to the overall total value of inventory in the period from 2016 to 2023.

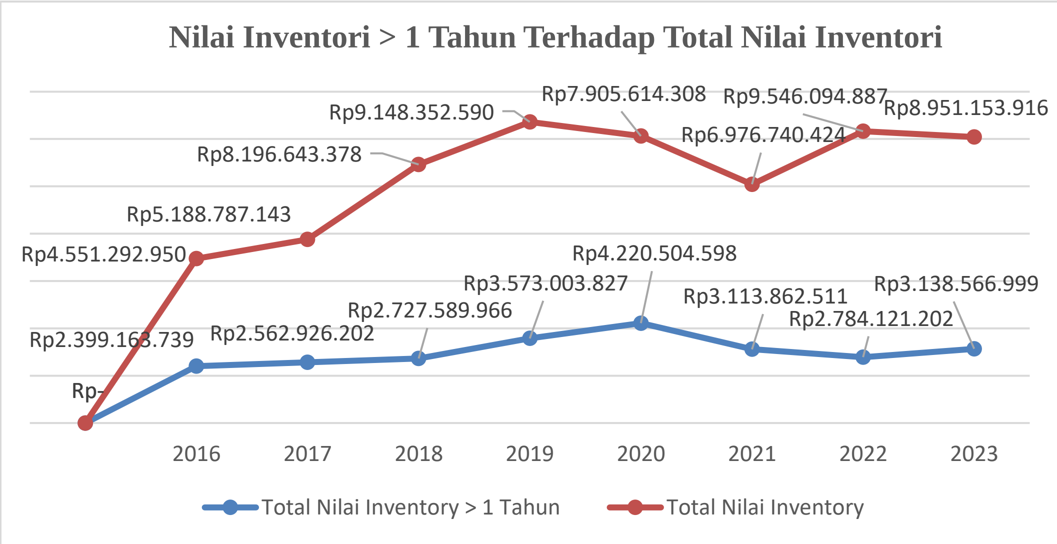

Figure 3. Inventory Value > 1 Year Compared to Total Inventory Value
(Source: SQL Server Database. PT. Kobexindo Tractors Tbk)

The graph in Figure 3. illustrates the comparison of inventory values in the > 1 Year storage age category, which consists of 3 categories: > 1 Year, > 2 Years, and > 3 Years. The inventory values in these three categories are summed and then compared to the total value of all storage age categories to obtain the percentage value of the storage age category to be classified as dead stock.

In the background discussion in Chapter 1, it was found that the average percentage of dead stock over the period 2016-2023 reached 41%. PT. Kobexindo Tractor, Tbk adopts a policy to categorize dead stock based on a 12-month inventory rotation period, with a tolerance of 20% of the total value of spare parts inventory. Spare parts with an age of more than 12 months are considered potentially causing losses to the company. Therefore, the researcher intends to develop a method for forecasting spare parts demand to reduce the potential loss due to errors in spare parts purchase analysis that end up as dead stock.

Data Understanding

In this stage, the researcher collects relevant data related to spare parts inventory by understanding the data needed for forecasting, such as historical inventory data and historical sales data. The data will be extracted from the SQL Server database on Epicor Kinetic, which is the information system used by PT. Kobexindo Tractors Tbk within the period of 2016 – 2023. The researcher gathers data using SQL syntax by creating stored procedures to extract data from several tables in the SQL Server database, such as the Master Item table, Purchase Order, Purchase Order Receiving, Goods Receiving Note, Sales Order, Invoice, and Delivery Order. The data obtained from this extraction process is exported to Excel format. Subsequently, this data will be used for forecasting modeling using the Exponential Smoothing method.

Table 3. Jungheinrich *Part Purchase Dataset* Per Month Period 2016 - 2023
(Source: SQL *Server Database*. PT. Kobexindo Tractors Tbk)

Month	Order	Month	Order	Month	Order	Month	Order
Jan-16	136	Jan-18	169	Jan-20	220	Jan-22	266
Feb-16	142	Feb-18	174	Feb-20	220	Feb-22	257
Mar-16	156	Mar-18	202	Mar-20	260	Mar-22	291
Apr-16	153	Apr-18	187	Apr-20	259	Apr-22	293
May-16	145	May-18	196	May-20	253	May-22	294
Jun-16	159	Jun-18	202	Jun-20	267	Jun-22	339
Jul-16	172	Jul-18	223	Jul-20	288	Jul-22	388
Aug-16	172	Aug-18	223	Aug-20	296	Aug-22	371
Sep-16	160	Sep-18	208	Sep-20	261	Sep-22	336
Oct-16	143	Oct-18	186	Oct-20	235	Oct-22	298
Nov-16	128	Nov-18	170	Nov-20	204	Nov-22	261
Dec-16	142	Dec-18	190	Dec-20	225	Dec-22	302
Jan-17	139	Jan-19	195	Jan-21	228	Jan-23	308
Feb-17	150	Feb-19	204	Feb-21	212	Feb-23	301
Mar-17	165	Mar-19	217	Mar-21	259	Mar-23	341
Apr-17	159	Apr-19	205	Apr-21	251	Apr-23	337
May-17	149	May-19	207	May-21	258	May-23	342
Jun-17	173	Jun-19	242	Jun-21	288	Jun-23	398
Jul-17	194	Jul-19	254	Jul-21	326	Jul-23	437
Aug-17	194	Aug-19	266	Aug-21	317	Aug-23	429
Sep-17	182	Sep-19	233	Sep-21	283	Sep-23	379
Oct-17	157	Oct-19	215	Oct-21	253	Oct-23	330
Nov-17	138	Nov-19	196	Nov-21	227	Nov-23	295
Dec-17	164	Dec-19	218	Dec-21	253	Dec-23	330

Table 3. illustrates the results of data mining using *a store procedure* in a *SQL Server* database that generates a monthly parts purchase dataset for the period 2016 – 2023. The dataset consists of 2 *fields: Month* which is the month data in each year of purchase and *Order* is the quantity data of purchasing spare parts each month.

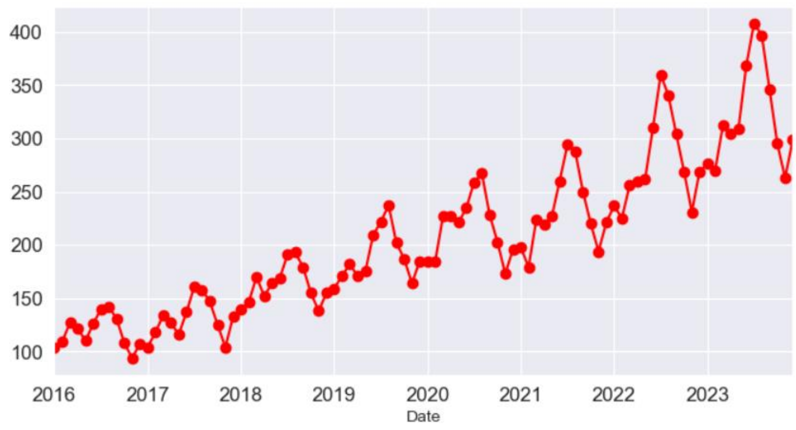

Figure 4. ***Jungheinrich Part Purchase Chart*** **for the 2016-2023 Period**
(Source: *SQL Server Database*. PT. Kobexindo Tractors Tbk)

Figure 4 shows a graph of the trend of purchasing spare parts every month in the period 2016 – 2023, from the chart it can be seen that the quantity of spare parts purchases increases each year.

Data Preparation

The data cleansing process is conducted during the data mining from the SQL Server database by creating stored procedures using SQL syntax. In this process, empty or invalid data is removed to ensure that it does not affect the accuracy when the data is used in the modeling process. In this process, the researcher creates SQL syntax by combining/joining several master tables with transaction tables with the aim of obtaining a summary of the total quantity of spare parts purchase and sales data per month for each year within the period of 2016 – 2023. From a total of 27,127 rows and 48 columns, after undergoing the data cleansing process, it becomes 92 rows and 2 columns of data, which are then exported to Excel format.

The data cleansing process is carried out to ensure that the data is ready to be used according to the needs of analysis and modeling. In the next stage, the researcher imports the dataset that has been mined in the previous stage into the Jupyter Notebook application, then performs data cleansing again to address missing or invalid values. By performing data transformation, such as converting date formats or standardizing data scales into formats suitable for use in the Exponential Smoothing method. All activities in this stage use the Python programming language.

Modeling

In this stage, the researcher performs calculations to analyze data using the Exponential Smoothing method to develop a forecasting model based on historical data. The researcher will compare each method that is part of Exponential Smoothing, aiming to measure how accurate the forecasting results are for each model. From the calculations made by each model, the researcher will apply the best model that has a high level of forecasting accuracy for use in forecasting spare parts inventory at PT. Kobexindo Tractors Tbk. The methods in Exponential Smoothing to be used in this modeling are as follows:

1. Simple Exponential Method
2. Holt Method (Double Exponential)
3. Holts Winter Exponential Smoothing with Additive Seasonality and Additive Trend (Triple Exponential)
4. Holts Winter Exponential Smoothing with Multiplicative Seasonality and Additive Trend (Triple Exponential)
5. Holts Winter Exponential Smoothing with Additive Seasonality and Multiplicative Trend (Triple Exponential)
6. Holts Winter Exponential Smoothing with Multiplicative Seasonality and Multiplicative Trend (Triple Exponential)

In modeling with forecasting methods, dividing data into two main parts, namely training data and testing data, is common practice. The main reason for this division is to measure how well the developed model can predict unseen data. The data ratio used in this study is 70% for training data and 30% for testing data. With a sufficiently large amount of data, allocating 70% of the data as training data aims to train the model to analyze patterns and trends in the data, allowing the model to learn from the variations and dynamics of the data.

Then, by separating 30% of the data for testing, this study has a large enough dataset to test how well the model can forecast unseen data. The total data used in this modeling is 92 rows of data with 2 columns, namely Month and Sales. This data represents monthly spare parts sales within the period of 2016-2023 (9 years). If detailed, there are 92 months with quantities for each month.

Figure 5. Training and Testing Data *Graph*

(Source: PT. Kobexindo Tractors Tbk)

Figure 5 is a graph illustrating the amount of data to be used for training. Based on the division into two main parts, the data allocated for training constitutes 70% of the entire dataset available, meaning the data used for training includes spare parts sales data for 6 years or 72 months from the period of 2016 to 2021. Within this period, there are 14,897 quantities of spare parts purchased.

In forecasting modeling using the Exponential Smoothing method, the training data aims to train the model to recognize patterns, trends, and seasonality in historical data. The training data is used to estimate model parameters, enabling the model to accurately reflect the behavior of the observed system. In other words, the training data helps the Exponential Smoothing model adjust weights or other parameters to provide accurate predictions of future values.

The training process involves adjusting model parameters based on the differences between the model's predictions and the actual values in the training data. The model is then tested and evaluated using data not involved in the training to ensure its performance can be relied upon when applied to new data.

By utilizing training data, the Exponential Smoothing method can produce a model capable of providing accurate estimates for future conditions based on patterns and trends detected in the historical data.

Figure 5 also illustrates the amount of data to be used for testing. Based on the division into two main parts, the data allocated for testing constitutes 30% of the entire dataset available, meaning the data used for testing includes spare parts purchase data for the last 2 years or 24 months from the period of 2022 to 2023. Within this period, there are 7,823 quantities of spare parts purchased.

In forecasting modeling using the Exponential Smoothing method, the purpose of testing data is to evaluate the performance of the model obtained through the training process using the training data. The testing data is used to assess the extent to which the model can provide accurate predictions, testing its ability to apply patterns and trends from historical data to unseen data.

The testing process involves applying the model to the testing data and comparing the predictions generated by the model with the actual values in the testing data. This assessment aims to ensure that the model can not only generate estimates consistent with the training data but also provide reliable estimates for previously unseen situations.

Through testing using separate data, we can determine the reliability of the model and whether it can recognize variations in data not involved in the training process. The results of testing help validate the quality of the model and provide confidence in using the model to make predictions in the future.

Simple Exponential Method

Simple Exponential Smoothing will be optimized to obtain the best Smoothing level (alpha) parameter, and the values generated by the model on the trained data will be stored in the variable "train_pred_ses." Then, predictions will be made for the next 24 months in the test data. The model will then be evaluated by calculating the RMSE on the test data and training data, and calculating MAPE to evaluate the percentage of average absolute errors between actual values and predictions on the test data.

This Simple Exponential Smoothing model attempts to represent data with full smoothing without considering trends or seasonality. With a maximum smoothing level (1.0), this model gives the greatest weight to historical data to make predictions. Optimized model parameters help the model adapt to the observed data.

If viewed from the criterion of SSE (Sum of Square Errors) values produced, this model is less effective in fitting the data compared to other models because it has the highest value. Meanwhile, if viewed from the values of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and AICC (Corrected Akaike Information Criterion), this model also has the highest value, indicating a less favorable balance between the fit with the tested data and model complexity compared to other models.

Holt Method (Double Exponential)

The Double Exponential Smoothing model will be optimized to obtain the best Smoothing level (alpha) and trend smoothing (beta) parameters, and the values generated by the model in the trained data will be stored into the variable "train_pred_dexp" and then make predictions for the next 24 months period in the test data. Then the model will be evaluated by calculating RSME on the test data and training data, and calculating MAPE to evaluate the absolute mean error percentage between the actual value and the prediction on the test data.

Holt's model indicates that trends have an additive impact on the Sales variable. With maximum smoothing levels (1.0) and trend smoothing (0), this model may give the most weight to historical data to make accurate trend predictions. The optimized parameters will help the model to adapt to the observed data.

When viewed from the criteria of the SSE (Sum of Square Errors) value produced, this model is better at fitting data than the Simple Exponetial Method model because it has a smaller value. Meanwhile, when viewed from the value of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and AICC (Corrected Akaike Information Criterion), this model also has a smaller value so that the balance between suitability with the data tested and the complexity of the model, is better than the Simple Exponetial Method model.

Holts Winter Exponential Smoothing with Additive Seasonality and Additive Trend (Triple Exponential)

The model considers additive trend and seasonality effects with 12 seasonal periods. The model will be optimized to obtain the best smoothing level (alpha), best trend smoothing (beta) and best seaseonal smoothing (gamma) parameters, and the values generated by the model in the trained data will be stored into the variable "train_pred_ad_texp" then make predictions for the next 24 months period in the test data. Then the model will be evaluated by calculating RSME on the test data and training data, and calculating MAPE to evaluate the absolute mean error percentage between the actual value and the prediction on the test data.

This Triple Exponential Smoothing model attempts to model data by considering additive trends and additive seasonal components. Optimized parameters help the model to adapt to the observed data. Note that the values of trend smoothing and seasonal smoothing are very small, which indicates that the model gives low weight to seasonal trends and components, possibly due to data that does not show very significant seasonal trends or patterns.

When viewed from the criteria of the SSE (Sum of Square Errors) value produced, this model is better at fitting data than the Holt Method (Double Exponetial) model because it has a smaller value. Meanwhile, when viewed from the value of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and AICC (Corrected Akaike Information Criterion), this model also has a smaller value so that the balance between suitability with the data tested and the complexity of the model, is better than the Holt Method (Double Exponetial) model.

Holts Winter Exponential Smoothing with Multiplicative Seasonality and Additive Trend (Triple Exponential)

This model considers the effects of trends are Additive and seasonal which are Multiplicative with 12 seasonal periods. The model will be optimized to obtain the best smoothing level (alpha), best smoothing trend (beta) and best seasonal smoothing (gamma) parameters , and the values generated by the model in the trained data will be stored into the variable "train_pred_mul_ad_texp" and then make predictions for the next 24 months period in the test data. Then the model will be evaluated by calculating RSME on the test data and training data, and calculating MAPE to evaluate the absolute mean error percentage between the actual value and the prediction on the test data.

This Triple Exponential Smoothing model attempts to model the data by considering additive trends and multiplicative seasonal components. Optimized parameters help the model to adapt to the observed data. Note that the values of trend smoothing and seasonal smoothing are very small, which indicates that the model gives low weight to seasonal trends and components, possibly due to data that does not show very significant seasonal trends or patterns.

When viewed from the criteria of the SSE (Sum of Square Errors) value produced, this model is best at fitting data compared to other models because it has the smallest value. Meanwhile, when viewed from the value of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and AICC (Corrected Akaike Information Criterion), this model also has the smallest value so that the balance between suitability with the data tested and the complexity of the model, is better than other models.

Holts Winter Exponential Smoothing with Additive Seasonality and Multiplicative Trend (Triple Exponential)

This model considers the effects of trends are multiplicative and seasonality are additive with 12 seasonal periods. The model will be optimized to obtain the best smoothing level (alpha), best smoothing trend (beta) and best seasonal smoothing (gamma) parameters , and the values generated by the model in the trained data will be stored into the variable "train_pred_ad_mul_texp" then make predictions for the next 24 months period in the test data. Then the model will be evaluated by calculating RSME on the test data and training data, and calculating MAPE to evaluate the absolute mean error percentage between the actual value and the prediction on the test data.

This Triple Exponential Smoothing model attempts to model data by considering multiplicative trends and additive seasonal components. Most of the model-parameters have been optimized.

When viewed from the criteria of the SSE (Sum of Square Errors) value produced, this model is better at fitting data than the Triple Exponential Additive Seasonality and Trend model because it has a smaller value. Meanwhile, when viewed from the value of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and AICC (Corrected Akaike Information Criterion), this model also has a smaller value so that the balance between conformity with the tested data and model complexity is better than the Triple Exponential Additive Seasonality and Trend model.

***Holts Winter Exponential Smoothing with Multiplicative Seasonality* and *Multiplicative Trend* (*Triple Exponential*)**

This model considers the effects of trends are Multiplicative and seasonal are Multiplicative with 12 seasonal periods. The model will be optimized to obtain the best smoothing level (alpha), best smoothing trend (beta) and smoothing seasonal (gamma) parameters, and the values generated by the model in the trained data will be stored into the variable "train_pred_mul_texp" and then make predictions for the next 24 months period in the test data. Then the model will be evaluated by calculating RSME on the test data and training data, and calculating MAPE to evaluate the absolute mean error percentage between the actual value and the prediction on the test data.

This Triple Exponential Smoothing model attempts to model data by considering only multiplicative trends and not considering seasonal components. Optimized parameters help the model to adapt to the observed data. Note that trend smoothing and seasonal smoothing are set to 0, which means that these models ignore trends and seasonality in their modeling.

When viewed from the criteria of the SSE (Sum of Square Errors) value produced, this model is better at fitting data than the Triple Exponential Additive Seasonality and Multivicative Trend model because it has a smaller value. Meanwhile, when viewed from the value of AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and AICC (Corrected Akaike Information Criterion), this model also has a smaller value so that the balance between suitability with the tested data and model complexity is better than the Triple Exponential Additive Seasonality and Multivicative Trend model.

Evaluation

At this stage, researchers evaluate the performance of the Exponential Smoothing model using cross-validation techniques or dividing data into training data and test data. Then measure the level of accuracy and accuracy of the forecasting model with methods, Root Mean Squared Error (RSME) and Mean Absolute Percentage Error (MAPE), as well as identify potential problems or biases that need to be corrected.

Table 4. RSME and MAPE Evaluation Results
(Source: Jupyter Notebook Modeling)

Model	Train *RSME*	Test *MAPE* (%)	Test *RSME* Value
Triple_Exp_mul	7.082307	6.343268	23.160521
Triple_Exp_mul_ad	7.065019	9.925810	35.446347
Triple_Exp_ad_mul	8.361800	10.535260	42.006432
Triple_Exp_ad	8.325393	12.597693	48.284372
Double_Exp	19.523254	17.730427	72.677166
Simple_Exp	19.591310	24.130498	91.903256

Based on the performance evaluation results of the Exponential Smoothing models on the training and testing datasets recorded in Table 4.9, the researcher made several interpretations as follows:

1. Holts Winter Exponential Smoothing with Multiplicative Seasonality and Multiplicative Trend (Triple Exponential):
   - Train RSME (7.082307): The low RSME value on the training data indicates that this model has a small prediction error rate on the data used for training.
   - Test MAPE (6.343268): The low MAPE value on the test data indicates that this model provides fairly accurate predictions in terms of the percentage of actual values on the test data.
   - Test RSME Values (23.160521): The relatively low RSME value on the test data indicates that this model also generalizes well to unseen data.
2. Holts Winter Exponential Smoothing with Multiplicative Seasonality and Additive Trend (Triple Exponential):
   - Train RSME (7.065019): The low RSME value on the training data indicates good performance on that data.
   - Test MAPE (9.92581): The higher MAPE value on the test data may indicate overfitting, where the model does not generalize well to new data.
   - Test RSME Values (35.446347): The higher RSME value on the test data also indicates that this model may not perform as well on unseen data.
3. Holts Winter Exponential Smoothing with Additive Seasonality and Multiplicative Trend (Triple Exponential):
   - Train RSME (8.3618): The high RSME value on the training data indicates poor performance on that data.
   - Test MAPE (10.53526): The lower MAPE value on the test data compared to the previous model, but still high, indicates poor prediction accuracy.

- Test RSME Values (42.006432): The high RSME value on the test data indicates that this model may not be effective in generalizing to new data.

4. Holts Winter Exponential Smoothing with Additive Seasonality and Additive Trend (Triple Exponential):
    - Train RSME (8.325393): The high RSME value on the training data indicates poor performance on that data.
    - Test MAPE (12.597693): The lower MAPE value on the test data compared to the previous model, but still high, indicates poor prediction accuracy.
    - Test RSME Values (48.284372): The high RSME value on the test data indicates that this model may not be effective in generalizing to new data.
5. Holt Method (Double Exponential):
    - Train RSME (19.523254): The high RSME value on the training data indicates that this model may not fit well to that data.
    - Test MAPE (17.730427): The high MAPE value on the test data indicates that this model provides less accurate predictions in terms of the percentage of actual values.
    - Test RSME Values (72.677166): The high RSME value on the test data indicates that this model may not be effective in predicting new data.
6. Simple Exponential Method:
    - Train RSME (19.59131): The high RSME value on the training data indicates that this model may not fit well to that data.
    - Test MAPE (24.130498): The high MAPE value on the test data indicates that this model provides less accurate predictions in terms of the percentage of actual values.
    - Test RSME Values (91.903256): The high RSME value on the test data indicates that this model may not be effective in predicting new data.

Thus, based on these evaluation results, the Holts Winter Exponential Smoothing with Multiplicative Seasonality and Multiplicative Trend (Triple Exponential) model is a better choice as it performs well on both training and testing data. The Holts Winter Exponential Smoothing with Multiplicative Seasonality and Additive Trend (Triple Exponential) model also performs well on the training data but tends to overfit on the testing data. Other models, such as Holts Winter Exponential Smoothing with Additive Seasonality and Additive Trend (Triple Exponential), Holts Winter Exponential Smoothing with Additive Seasonality and Multiplicative Trend (Triple Exponential), Holt Method (Double Exponential), and Simple Exponential Method, have poorer performance, especially on the testing data.

CONCLUSION

Research at PT Kobexindo Tractors Tbk in the Warehouse division found that the Holts Winter Exponential Smoothing with Multiplicative Seasonality and Multiplicative Trend (Triple Exponential) model is the best method based on modeling evaluation. This model shows low RSME values in training data, low MAPE in test data, and low RSME in test data, indicating a good level of accuracy in predicting parts sales. This model will be applied in the spare parts procurement process to ensure purchases according to customer needs and reduce losses due to dead stock. The advice given is to review the spare parts purchase policy using forecasting data to minimize losses.

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