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Enhancing Demand Forecasting Accuracy for Electronic Components: A Case Study of PT Omron Indonesia

Fadhil Rizqi Az Zahran[1]*
[1]*Industrial Management, College of Vocational Studies, IPB University
fadhil@apps.ipb.ac.id

Agung Prayudha Hidayat[2]
[2]Industrial Management, College of Vocational Studies, IPB University
agungprayudha@apps.ipb.ac.id

In the dynamic realm of manufacturing, precise demand forecasting is crucial for optimizing supply chains and production processes. This study addresses PT Omron Indonesia's challenge of inaccurate demand forecasts leading to production disruptions. Utilizing the Plan-Do-Study-Act (PDSA) cycle, alongside Multiplicative Decomposition methods, the research aims to improve forecasting accuracy. Results indicate that the Multiplicative Decomposition - Centered Moving Average method yields a lower Mean Absolute Percentage Error (MAPE), though refinement is needed to meet set standards. The estimated demand for the next period is 1308 units, with a MAPE of 140%. The study concludes that iterative refinement of the selected method is essential for achieving higher forecasting accuracy. This research contributes to enhancing production efficiency and mitigating the impact of part shortages in the electronics industry.

Keywords: Demand Forecasting, Multiplicative Decomposition, Electronic Components

INTRODUCTION

In the realm of manufacturing, the efficient management of supply chains and production processes is imperative for sustaining competitiveness and meeting ever-evolving consumer demands (Octaviany & Gunawan, 2023). Similarly, in the agricultural sector, particularly in Indonesia, the dynamics of supply and pricing of commodities play a pivotal role in economic stability. Of particular significance is the red chili, or cabai merah, which holds a crucial position within the horticultural market due to its inherent attractiveness in pricing. The fluctuations in red chili prices not only impact consumers but also significantly affect the livelihoods of red chili farmers. Fluctuating prices lead to uncertainties in production profitability, influencing both supply and demand dynamics. Consequently, these fluctuations are influenced by various factors, including production scale, harvest area, production costs, and distribution channels (Dardanella, Hidayat, Santosa, & Siskandar, 2022).

Within the dynamic landscape of the electronics industry, characterized by rapid technological advancements and volatile market fluctuations, the ability to accurately forecast demand and optimize production schedules holds paramount importance (Niaz, 2022). Logistics and supply chain management literature emphasizes the crucial role of innovative tactics in maintaining competitiveness through balancing supply and demand, effective delivery strategy management, and optimizing vehicle routes to minimize costs and ensure customer satisfaction (Hidayat, Santosa, & Siskandar, 2021). The aforementioned challenges resonate with the current discourse in production planning and optimization. The integration of fuzzy logic methodologies proves instrumental in addressing complexities inherent in production decision-making processes. By leveraging fuzzy logic, companies can effectively navigate intricate variables such as product stock, labor allocation, machine capacity, storage space, and time value, thereby enhancing the precision of production planning strategies. This underscores the significance of adopting innovative approaches to align production capabilities with fluctuating market demands, ensuring operational efficiency and sustained competitiveness in the ever-evolving business landscape (Santosa, Sulaeman, Hidayat, & Ardani, 2020). The electronic components industry is a cornerstone of modern technological infrastructure, encompassing a vast array of products ranging from semiconductors to passive electronic devices. As consumer preferences continue to evolve, fueled by the proliferation of automation (Anaam, Hidayat, Pranata, Abdillah, & Putra, 2022) manufacturers face heightened pressure to adapt swiftly to shifting market dynamics while minimizing costs and maximizing resource utilization (Octaviany & Gunawan, 2023).

PT Omron Manufacturing of Indonesia (PT OMI) faces an issue where demand forecasting methods are ineffective, resulting in inaccurate demand forecasts and production line stoppages due to shortages of parts. As a manufacturer of various electronic components, PT OMI confronts market complexity similar to the electronics industry as a whole. The electronics industry has high consumer demand that constantly shifts due to fast technological advancements and unstable market fluctuations. This requires PT OMI to have the ability to forecast demand accurately. However, the lack of effective forecasting methods hinders PT OMI's ability to anticipate part needs on time, leading to production line stoppages due to part shortages. Therefore, PT OMI needs to implement more sophisticated and accurate forecasting methods immediately to increase production efficiency and reduce the impact of part shortages on the company's operations.

To address these challenges, this paper proposes the use of the cycle of PDSA (Plan, Do, Study, Act) in the implementation of forecasting analysis. The PDSA cycle is utilized for continuous improvement and enhancing teamwork in implementing process change (Laverentz & Kumm, 2017). By utilizing the powerful PDSA cycle in the forecasting activities, you can adopt a structured and systematic approach towards continuous improvement, which can significantly enhance your team's collaboration and ensure that you remain adaptable to the ever-changing market dynamics. With PDSA, you can empower your team to achieve greater success in your forecasting activities and stay ahead of the competition. Forecasting in manufacturing has been predominantly reliant on traditional methods such as time series analysis, regression analysis, and exponential smoothing. While these approaches have provided a foundation for demand prediction, they often fall short of capturing the intricate interplay of factors influencing electronic component demand, including technological obsolescence, seasonality, and supply chain disruptions (Petropoulos et al., 2022).

This paper advocates for the suitability of multiplicative decomposition in time series analysis for forecasting sales data in manufacturing industries. By breaking down seasonal and trend patterns in large datasets, multiplicative decomposition offers clarity and insight into underlying patterns, making it an ideal method for analyzing sales data (Sohrabbeig, Ardakanian, & Musilek, 2022). However, it's important to remain adaptable to fluctuations in market demand and consumer behavior throughout the forecasting process, despite the robustness provided by multiplicative decomposition (Rayo, Inaray, & Lule, 2023).

This study aims to demonstrate the effectiveness of multiplicative decomposition in improving forecasting accuracy for manufacturing sales, providing a more comprehensive understanding compared to traditional methods. The approach integrates historical sales data, seasonal factors, and trend analysis to generate reliable forecasts, facilitating informed decision-making and strategic planning in manufacturing operations (Pratama, Karim, & Hertadi, 2023). By showcasing the potential of multiplicative decomposition in manufacturing forecasting, this research aims to contribute to advancements in manufacturing analytics and enhance forecasting methodologies.

Previous research using time series forecasting methods, such as Moving Average and Exponential Smoothing (Zukri, Widyaningrum, & Aini, 2020) (Wildan & Asy'ari, 2023), has proven its effectiveness in overcoming the problem of imbalance between production and demand in various industries. However, to increase the accuracy and precision of forecasting, future research will present a new approach by applying the multiplicative decomposition method. The novelty of this research lies in the application of a multiplicative decomposition approach to understand more deeply the factors that influence trends, seasonality and fluctuations in time series data, as well as enabling the identification of more complex patterns. Thus, the research will explore the potential of this method in improving forecasting capabilities, as well as optimizing production planning and inventory management processes more accurately and efficiently.

This study recommends using multiplicative decomposition in time series analysis to predict sales data in the manufacturing industry, specifically in electronic components. It provides a structured approach to analyzing datasets and generating reliable forecasts. The study highlights the superior performance of multiplicative decomposition in forecasting manufacturing sales compared to traditional methods and contributes to advancements in manufacturing analytics and forecasting methodologies.

METHODS

The Cycle of Plan, Do, Study, Act (PDSA)

The author uses the cycle of PDSA, the cycle that utilized for continuous improvement and enhancing teamwork in implementing process change (Laverentz & Kumm, 2017). The PDSA cycle originates from the Stewhart Cycle which was later reintroduced by W. Edwards Deming in 1993 as the PDSA Cycle (Moen, 2009).

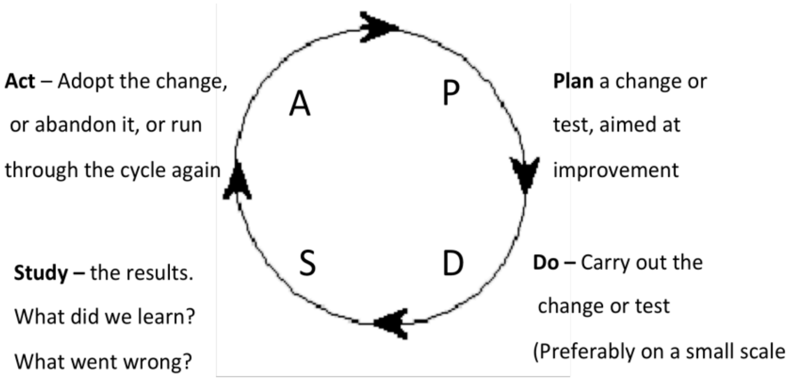


Figure 1 PDSA Cycle by Deming

The PDSA cycle can be linked to forecasting methods in the context of responsive planning and decision making. The systematic activities described in the PDSA cycle below will be carried out as part of the methodology outlined in this journal, which also includes the application of the multiplicative decomposition method for forecasting calculations.

1. Plan

A plan is setting goals and a process for achieving results certain. The planning stage is the stage for identifying problems, establishing certain quality standards and quality control on an ongoing basis and sustainable (Isniah, Purba, & Debora, 2020).

2. Do

The do is the stage of implementing or carrying out everything that has been planned at the planning stage including explaining the process, producing and carry out subsequent data collection will be used for the check and action stages (Bastuti, 2017).

3. Study

Study is the process of evaluating information or documents related to the results planned improvements. This study aims to determine the success of plans that have been implemented. Data from evaluation results is also necessary compared with predictions that have been prepared in a series of plans (Zahroti & Chalidyanto, 2018).

4. Act

The term Act refers to a repetitive sequence of actions or events that are aimed towards accomplishing future goals or objectives. It involves a process of continuous iteration, where each cycle builds on the previous one, leading to a series of achievements over time (Taylor et al., 2013)

Multiplicative Decomposition Method

The decomposition method involves breaking down a periodic series into its main components. This method is widely used to predict outcomes and to generate information about the various factors that contribute to periodic and visible series, such as trends, cycles, seasonality, and randomness. When using the multiplicative method, it is assumed that the seasonal pattern increases as the data value increases. On the other hand, the additive method assumes that data values are centered around a constant width of trends (Gunaryati & Suhendra, 2015).

There are two ways to categorize the method of multiplicative decomposition forecasting, which are Multiplicative Decomposition - Average All and Multiplicative Decomposition - Centered Moving Average (Kristiyanti & Sumarno, 2020). These two types can be explained as follows,

1. Determination of Season Range

   A seasonal pattern refers to the repetition of data within a specific period of time, such as a day, week, month, or quarter. This pattern can occur every three months (quarterly), every four months (four-monthly), every six months (semi-annually), or every twelve months (annually).
2. Calculate the Average Demand (CTDMA)

   Average All

$$Average\ All = \frac{y_1 + y_2 + y_3 + ... + y_n}{n}$$

   Centered Moving Average (CMA)

   Odd Season (eg 3 months)

$$CMA = \frac{y_{n-1} + y_n + y_{n+1}}{3}$$

   Even Season (eg 4 months)

$$CMA = \frac{(0,5 * y_{n-2}) + y_{n-1} + y_n + y_{n+1} + (0,5 * y_{n+2})}{4}$$

3. Determine the Ratio

$$Ratio = \frac{Actual\ Demand}{CTDMA}$$

4. Determine Seasonal Values

$$Seasonal = \frac{\Sigma ratio\ (i)}{n}$$

5. Determine Smoothed Values

$$Smoothed = \frac{Actual\ Demand}{Seasonal}$$

6. Determine Unadjusted Values

$$\hat{Y}(Unadjusted) = a + b(x)$$

   The values a and b can be obtained through the following calculations

   - calculate x value (period)

$$X = \frac{\Sigma x}{n}$$

   - calculate y value (demand)

$$Y = \frac{\Sigma y}{n}$$

- after getting the x and y values, then you can find the value of b

$$b = \frac{\Sigma xy - nxy}{\Sigma x^2 - nx^2}$$

- after getting the b values, then you can find the value of a

$$a = y - b(x)$$

7. Determine Adjusted Values

$$\hat{Y}(Adjusted) = \hat{Y}(Unadjusted) * Seasonal$$

Calculation of Forecasting Error

To be able to overcome problems where the forecasting error value is positive and negative neutralize each other, several alternative methods for measuring Forecasting errors have been widely used, such as Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE) (Purba & Bakhtiar, 2022)

1. Mean Absolute Deviation (MAD)

MAD, or Mean Absolute Deviation, quantifies the forecast error of a model by summing up the absolute values of each error and then dividing by the total number of data points (Samari, Kurniawan, & Ratnanto, 2022)

$$MAD = \frac{\Sigma|At - Ft|}{n}$$

Note :
At = Actual Value in a period of time
Ft = Forecasting Value at t-period
n = Numbers of period

2. Mean Square Error

This method of error calculation imposes a greater penalty on substantial discrepancies relative to minor variations, utilizing quadratic computations to achieve this smoother assessment (Lusiana & Yuliarty, 2020)

$$MSE = \frac{\Sigma(At - Ft)^2}{n}$$

Note :
At = Actual Value in a period of time
Ft = Forecasting Value at t-period
n = Numbers of period

3. Mean Absolute Percentage Error

MAPE is computed by dividing the absolute error value for each period by the actual value for that period, followed by calculating the average percentage of the absolute values (Hajjah & Marlim, 2021).

$$MAPE = \left(\frac{\sum_{t=1}^{n} |At - Ft|}{At}\right)\left(\frac{100\%}{n}\right)$$

Note :
At = Actual Value in a period of time
Ft = Forecasting Value at t-period
n = Numbers of period

The MAPE utilized can assess the effectiveness of different forecasting models. The forecasting model yielding the lowest MAPE value indicates the most favorable outcome. Presented below is a table illustrating the determination of the MAPE value (Ramadhani, Eltivia, & Riwajanti, 2023).

Table 1 Significance Level of MAPE Value

MAPE Value	Significance Level
<10%	Excellent forecasting ability
10 – 20%	Food forecasting ability
20 – 50%	Reasonable forecasting ability
>50%	Poor forecasting ability

RESULTS AND DISCUSSION

The Cycle of Plan, Do, Study, Act (PDSA)

1. Plan

The author intends to meticulously explore seasonal fluctuations using a methodical strategy, based on statistical data. The objective is to gain a comprehensive understanding of the complexities involved in seasonal variations.

2. Do

To conduct the necessary calculations, including forecasting and analysis, the author requires reference data, particularly historical data. This historical data encompasses a series of orders over a sufficient number of periods to effectively illustrate fluctuations and trends within the dataset.

3. Study

Through the process of 'study', the author will engage in the application and simulation of forecasting techniques, specifically utilizing seasonal theories or methods. Among the methodologies available, the author intends to employ multiplicative decomposition as a suitable approach. This method involves dissecting the time series data into various components such as trend, seasonal, and irregular components, thereby facilitating a more comprehensive understanding of the underlying patterns and fluctuations. The outcome of these forecast calculations will be the generation of forecasted values.

4. Act

Through 'act', the author establishes an objective centered around the implementation of forecast calculations to aid the Production Planning and Inventory Control (PPIC) department in formulating the version of PT OMI's master plan. This master plan is envisioned as the cornerstone or blueprint guiding the company's production processes. The envisaged transformation entails equipping PPIC with a mechanism to systematically compare values derived from raw forecast inputs. By providing this means of comparison, it is anticipated that the production process will evolve towards greater efficiency and optimization, thereby aligning with organizational objectives and enhancing overall operational performance.

Multiplicative Decomposition

A. Manual Calculation

During the calculation procedure, demand data for the product type LY4N DC24 at PT Omron Manufacturing of Indonesia will be utilized, spanning a period of three years from 2021 to 2023. Presented below are the demand figures for LY4N DC24 products recorded during the aforementioned period.

Table 2 Demand of LY4N DC24 from 2021 - 2023

Months	Years		
	2021	**2022**	**2023**
January	3.406	1.232	522
February	1.790	1.136	690
March	4.767	3.711	1.567
April	2.760	5.765	961
May	2.333	2.048	1.528
June	2.835	4.047	3.840
July	4.320	3.300	3.660
August	2.341	2.193	589
September	3.910	3.244	2.716
October	1.754	391	40
November	3.368	3.100	2.344
December	2.490	246	1.038

1. Determination of Season Range

   The seasonal component of this research is calculated using multiplicative decomposition with a value of 4.

2. Calculate the Average Demand (CTDMA)

   After determining how many seasons that divided, then the next process is to calculate average sales. Average All :

$$\text{CTDMA} = \frac{3.406+1.790+4.767+\ldots+40+2.344+1.038}{36}$$

$$\text{CTDMA} = \frac{85.982}{36} = 2.388$$

   Then we get the average sales value for LY4N DC24 product type is 2,388.

Centered Moving Average :

$$\text{CTDMA } 4\ (3) = \frac{(0{,}5*3.406)+1.790+4.767+2.760+(0{,}5*2.333)}{4}$$

$$\text{CTDMA } 4\ (3) = \frac{12.186{,}5}{4} = 3.046{,}62$$

$$\text{CTDMA } 4\ (34) = \frac{(0{,}5*589)+2.716+40+2.344+(0{,}5*1.038)}{4}$$

$$\text{CTDMA } 4\ (34) = \frac{5.913{,}5}{4} = 1.478{,}37$$

   Then we get the average sales value in the 3rd and 34th period for LY4N DC24 product type is 3.046,62 and 1.478,37.

3. Determine the Ratio

   Following the determination of the demand's average value, this figure will serve as a divisor to obtain the ratio. Example of calculating the ratio in the 3rd and 34th periods.

Average All :

Ratio (3) = $\frac{Actual\ Demand}{CTDMA}$

Ratio (3) = $\frac{4.767}{2.388}$ = 2,00

Ratio (34) = $\frac{Actual\ Demand}{CTDMA}$

Ratio (34) = $\frac{40}{2.388}$ = 0,02

Centered Moving Average :

Ratio (3) = $\frac{Actual\ Demand}{CTDMA}$

Ratio (3) = $\frac{4.767}{3.046,62}$ = 1,56

Ratio (34) = $\frac{Actual\ Demand}{CTDMA}$

Ratio (34) = $\frac{40}{1.478,37}$ = 0,03

4. Determine Seasonal Values

The established ratio will aid in identifying seasonal values by categorizing them based on the recurrence of seasons. Example of calculating the seasonal in the 3rd and 34th periods.

Average All :

Seasonal (3) = $\frac{\sum Seasonal\ Ratio\ of\ 3}{9}$

Seasonal (3) = $\frac{(2,00+1,81+1,41+1,55+1,38+1,30+0,66+1,53+0,98)}{9}$ = 1,40

Seasonal (34) = $\frac{\sum Seasonal\ Ratio\ of\ 2}{9}$

Seasonal (34) = $\frac{(0,75+1,19+0,73+0,48+1,69+0,16+0,29+1,61+0,02)}{9}$ = 0,77

Centered Moving Average :

Seasonal (3) = $\frac{\sum Seasonal\ Ratio\ of\ 3}{9}$

Seasonal (3) = $\frac{(1,56+1,37+1,32+1,21+1,08+2,21+1,48+1,43+0)}{9}$ = 1,46

Seasonal (34) = $\frac{\sum Seasonal\ Ratio\ of\ 2}{9}$

Seasonal (34) = $\frac{(0+0,94+0,61+0,45+1,21+0,20+0,82+1,57+0,03)}{9}$ = 0,73

5. Determine Smoothed Values

The subsequent stage involves calculating the smoothed value through an equation combining demand and seasonality. These resultant values are then utilized to derive the regression equation for subsequent stages. Example of calculating the seasonal in the 3rd and 34th periods.

Average All :

Smoothed Value (3) = $\frac{Demand}{Seasonal}$

Smoothed Value (3) = $\frac{4.767}{1,40}$ = 3.400,10

Smoothed Value (34) = $\frac{Demand}{Seasonal}$

Smoothed Value (34) = $\frac{40}{0,77}$ = 52,03

Centered Moving Average :

Smoothed Value (3) = $\frac{Demand}{Seasonal}$

Smoothed Value (3) = $\frac{4.767}{1,46}$ = 3.268,04

Smoothed Value (34) = $\frac{Demand}{Seasonal}$

Smoothed Value (34) = $\frac{40}{0,73}$ = 55,01

6. Determine Unadjusted Values

After getting the smoothed value, this value will become the y variable (demand data), and the period will become the x variable. These two variables are used to calculate trends then the unadjusted equation value is obtained as follows,

Average All : a = 3.430

b = -56

$\hat{Y}(Unadjusted) = 3.430 + (-56)(x)$

Centered Moving Average : a = 3.548

b = -59

$\hat{Y}(Unadjusted) = 3.548 + (-59)(x)$

Example of calculating the unadjusted value in the 37th period.

Average All :

$\hat{Y}(Unadjusted) = 3.430 + (-56)(x)$

$\hat{Y}(Unadjusted) = 3.430 + (-56)(37) = 1.346,78$

Centered Moving Average :

$\hat{Y}(Unadjusted) = 3.548 + (-59)(x)$

$\hat{Y}(Unadjusted) = 3.548 + (-59)(37) = 1.382,03$

7. Determine Adjusted Values

After obtaining the raw value, the final step involves determining the adjusted values. The following example illustrates the calculation for the 37th period.

Average All :

$\hat{Y}(Adjusted) = 1.346,78 * 0,97$

$\hat{Y}(Adjusted) = 1.312$

Centered Moving Average :

$\hat{Y}(Adjusted) = 1.382,03 * 0,95$

$\hat{Y}(Adjusted) = 1.308$

Calculation of Forecasting Error

Example of calculating the forecasting error in the 36th period (December 2023).

1. Average All

   MAD = |1.038 – 1.200| = 162

   MSE = 162^2 = 29.123

   MAPE = 162 / 1.038 = 0,16

2. Centered Moving Average

   MAD = |1.038 – 1.140| = 102

   MSE = 102^2 = 10.445

   MAPE = 102 / 1.038 = 0,10

Calculations for forecasting error values using both the average and centered moving average methods can be performed cumulatively. This cumulative calculation is achieved by averaging all forecasting errors across each period.

1. *Average All*

$$\text{MAD} = \frac{(120+760+195+19+734+458+\ldots+298+162)}{36} = 809$$

$$\text{MSE} = \frac{(14.315+577.582+37.989+371+\ldots+26.218)}{36} = 1.243.590$$

$$\text{MAPE} = \frac{(0{,}04+0{,}42+0{,}04+0{,}01+0{,}31+0{,}16+\ldots+0{,}13+0{,}16)}{36} = 1{,}44$$

2. *Centered Moving Average*

$$\text{MAD} = \frac{(104+704+152+137+748+511+\ldots+157+102)}{36} = 825$$

$$\text{MSE} = \frac{(10.779+496.274+23.025+18.862+\ldots10.445)}{36} = 1.268.255$$

$$\text{MAPE} = \frac{(0{,}03+0{,}39+0{,}03+0{,}05+0{,}32+0{,}18+\ldots+0{,}07+0{,}10)}{36} = 1{,}40$$

Forecast calculations are carried out using demand data for 3 years starting from January 2021 to December 2023. For more details, forecasting calculations and forecasting errors can be seen in following table:

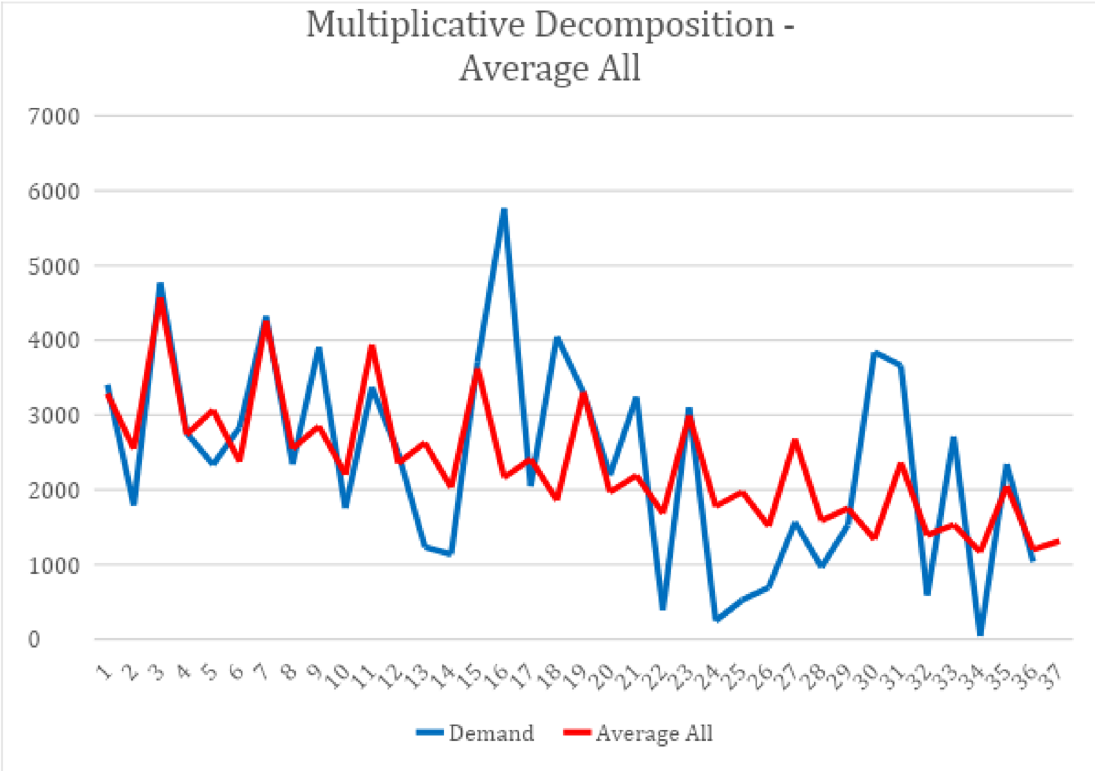
Table 3 The Result of Forecasting and Error Calculation Multiplicative Decomposition-Average All

Months	**Periods**	**Demands**	**CTD MA**	**Ratio**	**Seasonal**	**Smoothed**	**Y-unadjusted**	**Y-adjusted**	**MAD**	**MSE**	**MAPE**
Jan-21	1	3.406	2.388	1,43	0,97	3.497	3.374	3.286	120	14.315	0,04
Feb-21	2	1.790	2.388	0,75	0,77	2.329	3.317	2.550	760	577.582	0,42
Mar-21	3	4.767	2.388	2,00	1,40	3.400	3.261	4.572	195	37.989	0,04
Apr-21	4	2.760	2.388	1,16	0,86	3.227	3.205	2.741	19	371	0,01
May-21	5	2.333	2.388	0,98	0,97	2.395	3.148	3.067	734	538.713	0,31
Jun-21	6	2.835	2.388	1,19	0,77	3.688	3.092	2.377	458	209.880	0,16
…	…	…	…	…	…	…	…	…	…	…	…
Jul-23	31	3.660	2.388	1,53	1,40	2.611	1.685	2.362	1.298	1.685.242	0,35
Aug-23	32	589	2.388	0,25	0,86	689	1.628	1.393	804	645.647	1,36
Sep-23	33	2.716	2.388	1,14	0,97	2.788	1.572	1.531	1.185	1.403.527	0,44
Oct-23	34	40	2.388	0,02	0,77	52	1.516	1.165	1.125	1.265.779	28,13
Nov-23	35	2.344	2.388	0,98	1,40	1.672	1.459	2.046	298	88.757	0,13
Dec-23	36	1.038	2.388	0,43	0,86	1.214	1.403	1.200	162	26.218	0,16
Jan-24	37				0,97		1.347	1.312			
Total	703	85.982				85.982			29.123	44.769.239	51,81
Average	18,5	2.388				2.388			809	1.243.590	1,44

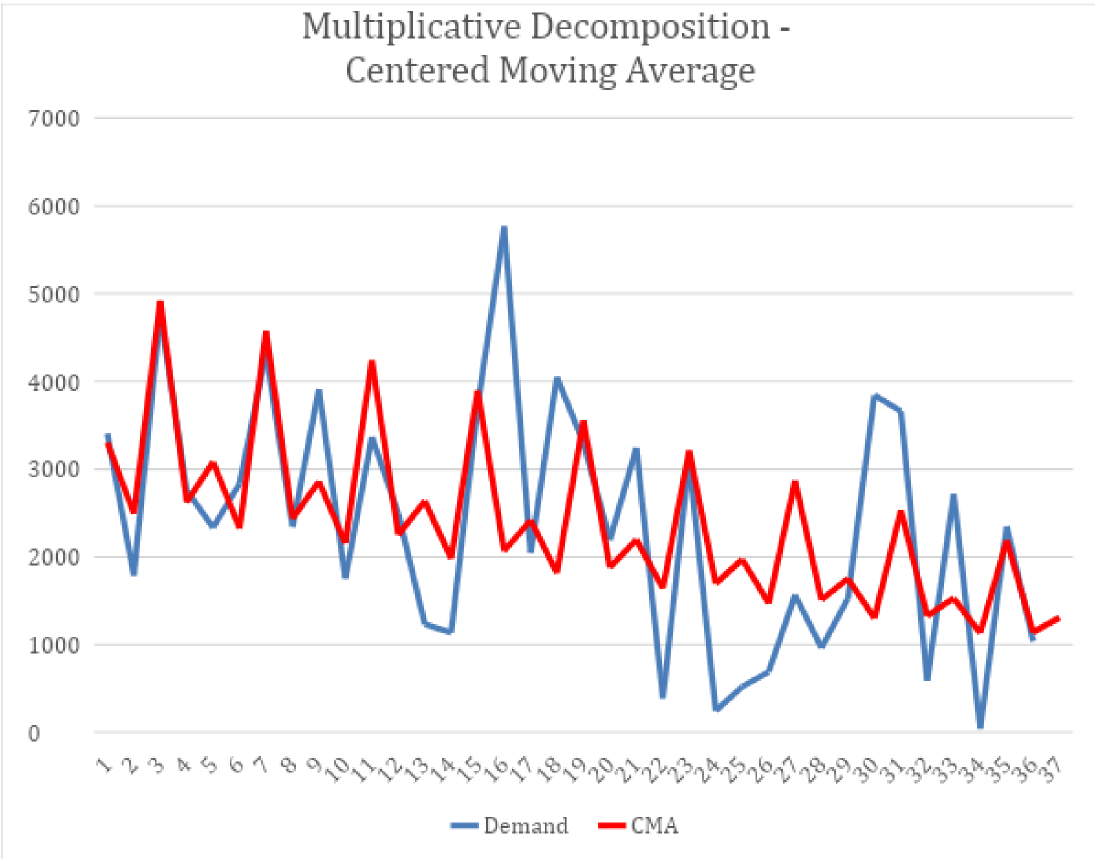
Table 4 The Result of Forecasting and Error Calculation Multiplicative Decomposition-Centered Moving Average

Months	Periods	Demands	CTD MA	Ratio	Seasonal	Smoothed	Y-unadjusted	Y-adjusted	MAD	MSE	MAPE
Jan-21	1	3.406			0,95	3.599	3.489	3.302	104	10.779	0,03
Feb-21	2	1.790			0,73	2.462	3.431	2.494	704	496.274	0,39
Mar-21	3	4.767	3.047	1,56	1,46	3.268	3.372	4.919	152	23.025	0,03
Apr-21	4	2.760	3.043	0,91	0,79	3.487	3.314	2.623	137	18.862	0,05
May-21	5	2.333	3.118	0,75	0,95	2.465	3.255	3.081	748	558.909	0,32
Jun-21	6	2.835	3.010	0,94	0,73	3.899	3.196	2.324	511	260.884	0,18
…	…	…	…	…	…	…	…	…	…	…	…
Jul-23	31	3.660	2.553	1,43	1,46	2.509	1.733	2.528	1.132	1.281.002	0,31
Aug-23	32	589	2.226	0,26	0,79	744	1.675	1.326	737	542.443	1,25
Sep-23	33	2.716	1.587	1,71	0,95	2.870	1.616	1.530	1.186	1.407.650	0,44
Oct-23	34	40	1.478	0,03	0,73	55	1.558	1.133	1.093	1.193.733	27,31
Nov-23	35	2.344			1,46	1.607	1.499	2.187	157	24.750	0,07
Dec-23	36	1.038			0,79	1.311	1.441	1.140	102	10.445	0,10
Jan-24	37				0,95		1.382	1.308			
Total	703	85.982				88.734			29.683	45.657.165	50,54
Average	19	2.388				2.465			825	1.268.255	1,40

The calculation results above can also be graphed as follows. The graph illustrates a contrast between the actual demand and the forecasted values. The forecast graph appears to be relatively more consistent and resilient to fluctuations compared to the actual demand.



Graph 1 Graph of Method Forecasting Results Multiplicative Decomposition-Average All

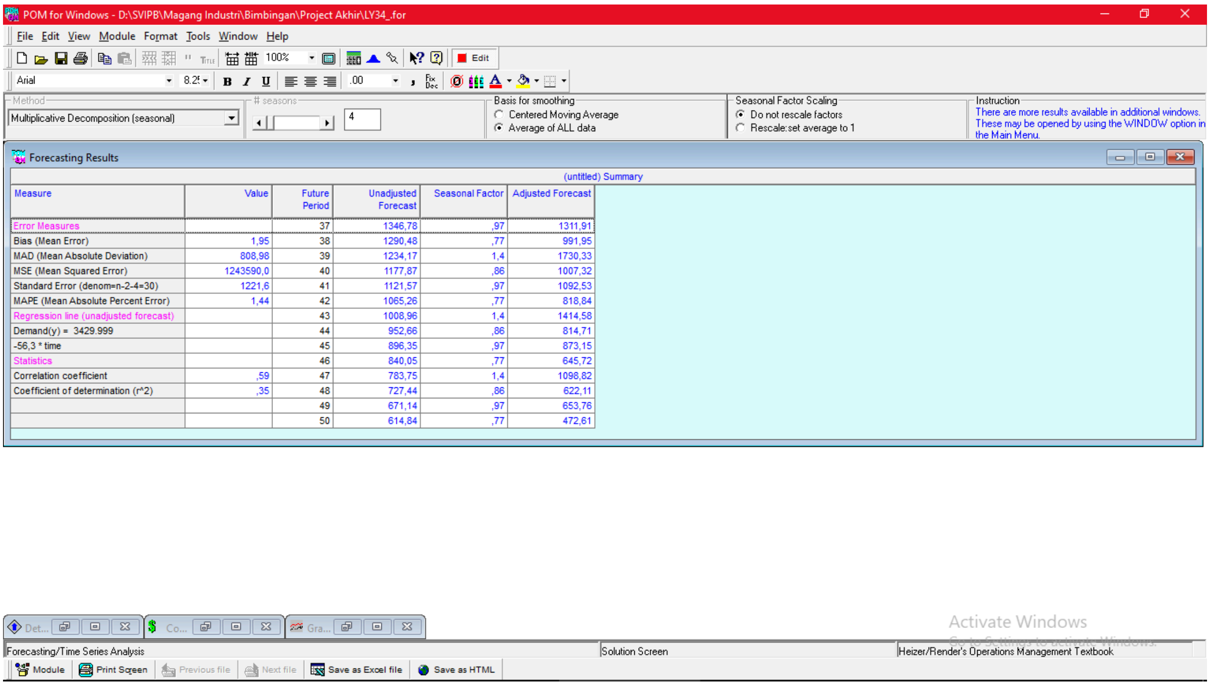


Graph 2 Graph of Method Forecasting Results Multiplicative Decomposition-Centered Moving Average

B. Calculations Using POM QM Software

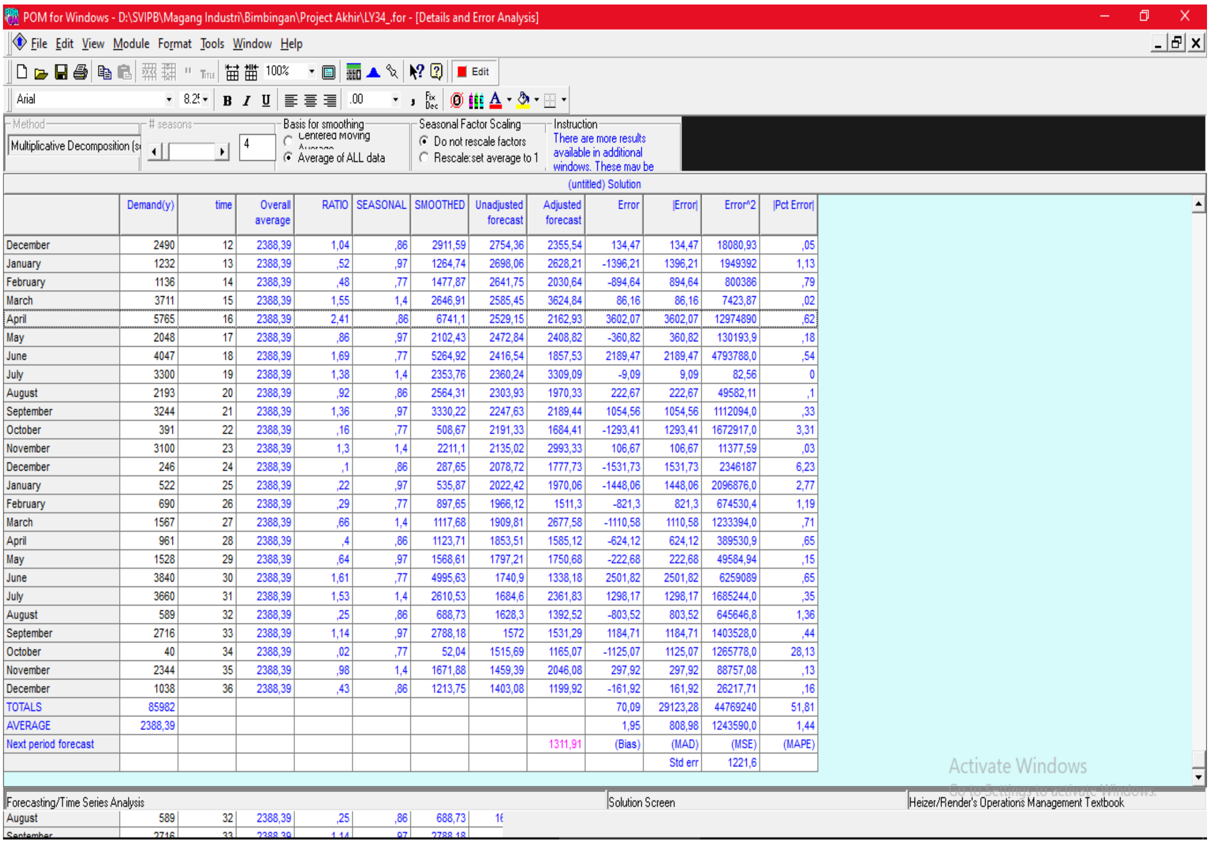
Subsequent to manual computations, researchers augmented their analysis utilizing the POM QM software for Windows version 3. Herein lies the outcome derived from the software-assisted calculations.

1. Multiplicative Decomposition – Average All



Measure	Value	Future Period	Unadjusted Forecast	Seasonal Factor	Adjusted Forecast
Error Measures		37	1346,78	,97	1311,91
Bias (Mean Error)	1,95	38	1290,48	,77	991,95
MAD (Mean Absolute Deviation)	808,98	39	1234,17	1,4	1730,33
MSE (Mean Squared Error)	1243590,0	40	1177,87	,86	1007,32
Standard Error (denom=n-2-4=30)	1221,6	41	1121,57	,97	1092,53
MAPE (Mean Absolute Percent Error)	1,44	42	1065,26	,77	818,84
Regression line (unadjusted forecast)		43	1008,96	1,4	1414,58
Demand(y) = 3429.999		44	952,66	,86	814,71
-56,3 * time		45	896,35	,97	873,15
Statistics		46	840,05	,77	645,72
Correlation coefficient	,59	47	783,75	1,4	1098,82
Coefficient of determination (r^2)	,35	48	727,44	,86	622,11
		49	671,14	,97	653,76
		50	614,84	,77	472,61

Figure 2 Multiplicative Decomposition Forecasting Method Results - Average All Using POM QM



	Demand(y)	time	Overall average	RATIO	SEASONAL	SMOOTHED	Unadjusted forecast	Adjusted forecast	Error	|Error|	Error^2	|Pct Error|
December	2490	12	2388,39	1,04	,86	2911,59	2754,36	2355,54	134,47	134,47	18080,93	,05
January	1232	13	2388,39	,52	,97	1264,74	2698,06	2628,21	-1396,21	1396,21	1949392	1,13
February	1136	14	2388,39	,48	,77	1477,87	2641,75	2030,64	-894,64	894,64	800386	,79
March	3711	15	2388,39	1,55	1,4	2646,91	2585,45	3624,84	86,16	86,16	7423,87	,02
April	5765	16	2388,39	2,41	,86	6741,1	2529,15	2162,93	3602,07	3602,07	12974890	,62
May	2048	17	2388,39	,86	,97	2102,43	2472,84	2408,82	-360,82	360,82	130193,9	,18
June	4047	18	2388,39	1,69	,77	5264,92	2416,54	1857,53	2189,47	2189,47	4793788,0	,54
July	3300	19	2388,39	1,38	1,4	2353,76	2360,24	3309,09	-9,09	9,09	82,56	0
August	2193	20	2388,39	,92	,86	2564,31	2303,93	1970,33	222,67	222,67	49582,11	,1
September	3244	21	2388,39	1,36	,97	3330,22	2247,63	2189,44	1054,56	1054,56	1112094,0	,33
October	391	22	2388,39	,16	,77	508,67	2191,33	1684,41	-1293,41	1293,41	1672917,0	3,31
November	3100	23	2388,39	1,3	1,4	2211,1	2135,02	2993,33	106,67	106,67	11377,59	,03
December	246	24	2388,39	,1	,86	287,65	2078,72	1777,73	-1531,73	1531,73	2346187	6,23
January	522	25	2388,39	,22	,97	535,87	2022,42	1970,06	-1448,06	1448,06	2096876,0	2,77
February	690	26	2388,39	,29	,77	897,65	1966,12	1511,3	-821,3	821,3	674530,4	1,19
March	1567	27	2388,39	,66	1,4	1117,68	1909,81	2677,58	-1110,58	1110,58	1233394,0	,71
April	961	28	2388,39	,4	,86	1123,71	1853,51	1585,12	-624,12	624,12	389530,9	,65
May	1528	29	2388,39	,64	,97	1568,61	1797,21	1750,68	-222,68	222,68	49584,94	,15
June	3840	30	2388,39	1,61	,77	4995,63	1740,9	1338,18	2501,82	2501,82	6259089	,65
July	3660	31	2388,39	1,53	1,4	2610,53	1684,6	2361,83	1298,17	1298,17	1685244,0	,35
August	589	32	2388,39	,25	,86	688,73	1628,3	1392,52	-803,52	803,52	645646,8	1,36
September	2716	33	2388,39	1,14	,97	2788,18	1572	1531,29	1184,71	1184,71	1403528,0	,44
October	40	34	2388,39	,02	,77	52,04	1515,69	1165,07	-1125,07	1125,07	1265778,0	28,13
November	2344	35	2388,39	,98	1,4	1671,88	1459,39	2046,08	297,92	297,92	88757,08	,13
December	1038	36	2388,39	,43	,86	1213,75	1403,08	1199,92	-161,92	161,92	26217,71	,16
TOTALS	85982								70,09	29123,28	44769240	51,81
AVERAGE	2388,39								1,95	808,98	1243590,0	1,44
Next period forecast								1311,91	(Bias)	(MAD)	(MSE)	(MAPE)
										Std err	1221,6	

Figure 3 Details of Multiplicative Decomposition Forecasting Method - Average All Using POM QM

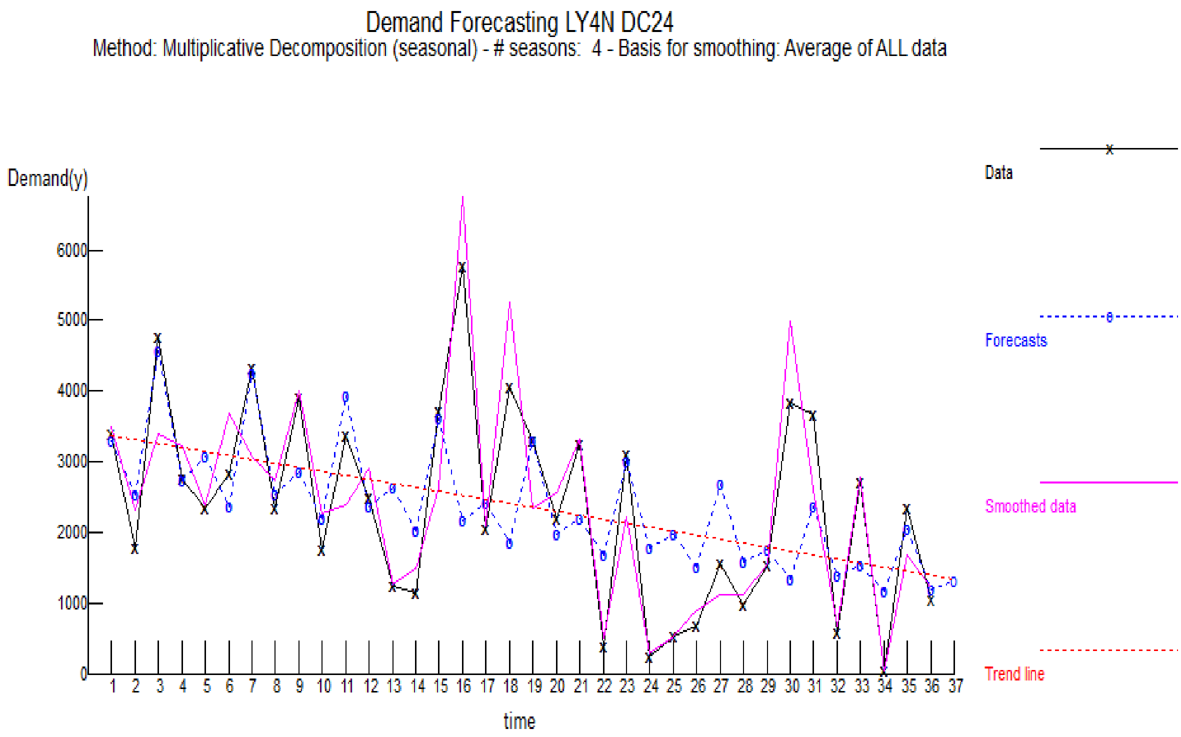
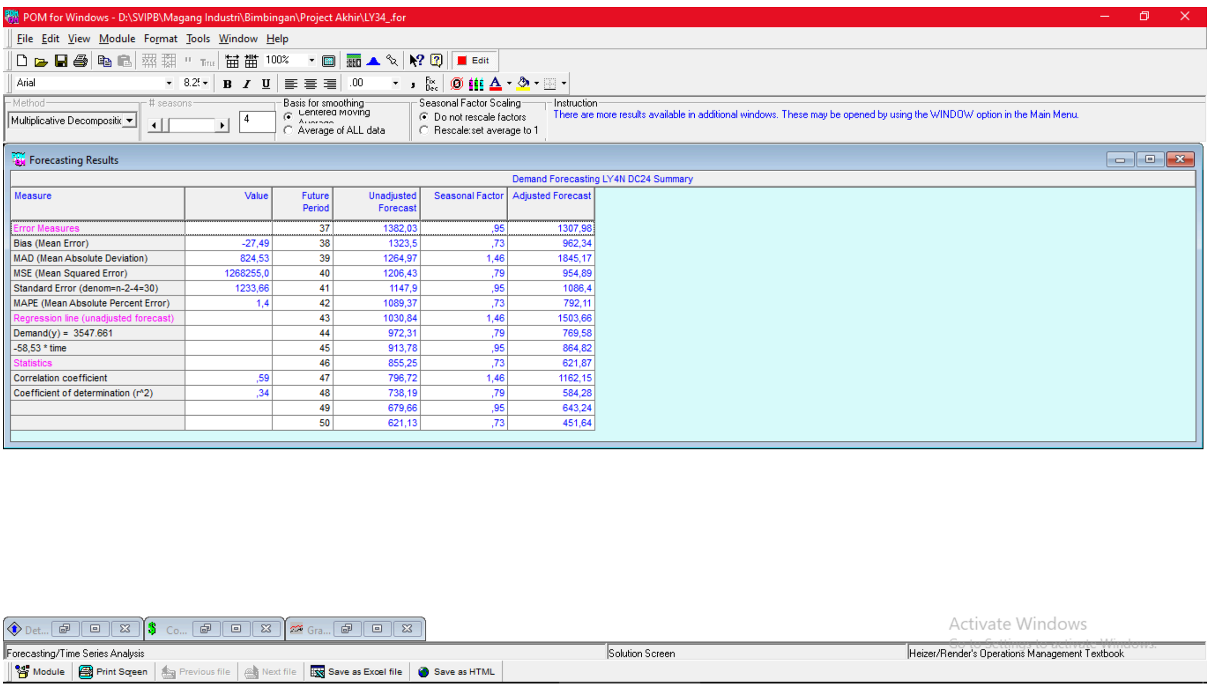


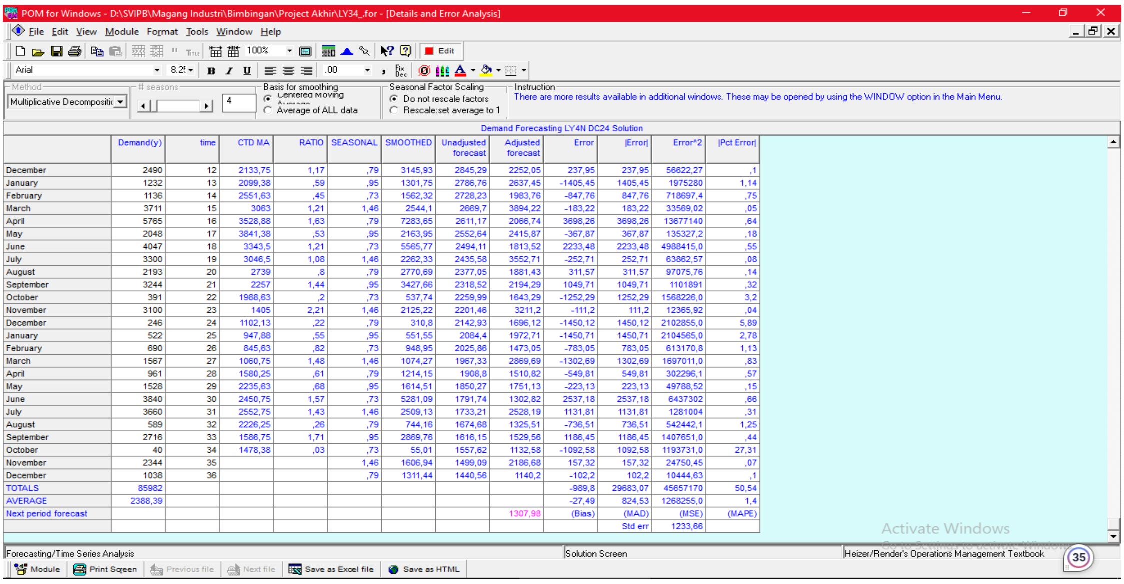
Figure 4 Multiplicative Decomposition Forecasting Graph Results - Average All Using POM QM

2. Multiplicative Decomposition – Centered Moving Average



Measure	Value	Future Period	Unadjusted Forecast	Seasonal Factor	Adjusted Forecast
Error Measures		37	1382,03	,95	1307,98
Bias (Mean Error)	-27,49	38	1323,5	,73	962,34
MAD (Mean Absolute Deviation)	824,53	39	1264,97	1,46	1845,17
MSE (Mean Squared Error)	1268255,0	40	1206,43	,79	954,89
Standard Error (denom=n-2-4=30)	1233,66	41	1147,9	,95	1086,4
MAPE (Mean Absolute Percent Error)	1,4	42	1089,37	,73	792,11
Regression line (unadjusted forecast)		43	1030,84	1,46	1503,66
Demand(y) = 3547.661		44	972,31	,79	769,58
-58,53 * time		45	913,78	,95	864,82
Statistics		46	855,25	,73	621,87
Correlation coefficient	,59	47	796,72	1,46	1162,15
Coefficient of determination (r^2)	,34	48	738,19	,79	584,28
		49	679,66	,95	643,24
		50	621,13	,73	451,64

Figure 5 Multiplicative Decomposition Forecasting Method Results - Centered Moving Average Using POM QM



	Demand(y)	time	CTD MA	RATIO	SEASONAL	SMOOTHED	Unadjusted forecast	Adjusted forecast	Error	|Error|	Error^2	|Pct Error|
December	2490	12	2133,75	1,17	,79	3145,93	2845,29	2252,05	237,95	237,95	56622,27	,1
January	1232	13	2099,38	,59	,95	1301,75	2786,76	2637,45	-1405,45	1405,45	1975280	1,14
February	1136	14	2551,63	,45	,73	1562,32	2728,23	1983,76	-847,76	847,76	718697,4	,75
March	3711	15	3063	1,21	1,46	2544,1	2669,7	3894,22	-183,22	183,22	33569,02	,05
April	5765	16	3528,88	1,63	,79	7283,65	2611,17	2066,74	3698,26	3698,26	13677140	,64
May	2048	17	3841,38	,53	,95	2163,95	2552,64	2415,87	-367,87	367,87	135327,2	,18
June	4047	18	3343,5	1,21	,73	5565,77	2494,11	1813,52	2233,48	2233,48	4988415,0	,55
July	3300	19	3046,5	1,08	1,46	2262,33	2435,58	3552,71	-252,71	252,71	63862,57	,08
August	2193	20	2739	,8	,79	2770,69	2377,05	1881,43	311,57	311,57	97075,76	,14
September	3244	21	2257	1,44	,95	3427,66	2318,52	2194,29	1049,71	1049,71	1101891	,32
October	391	22	1988,63	,2	,73	537,74	2259,99	1643,29	-1252,29	1252,29	1568226,0	3,2
November	3100	23	1405	2,21	1,46	2125,22	2201,46	3211,2	-111,2	111,2	12365,92	,04
December	246	24	1102,13	,22	,79	310,8	2142,93	1696,12	-1450,12	1450,12	2102855,0	5,89
January	522	25	947,88	,55	,95	551,55	2084,4	1972,71	-1450,71	1450,71	2104565,0	2,78
February	690	26	845,63	,82	,73	948,95	2025,86	1473,05	-783,05	783,05	613170,8	1,13
March	1567	27	1060,75	1,48	1,46	1074,27	1967,33	2869,69	-1302,69	1302,69	1697011,0	,83
April	961	28	1580,25	,61	,79	1214,15	1908,8	1510,82	-549,81	549,81	302296,1	,57
May	1528	29	2235,63	,68	,95	1614,51	1850,27	1751,13	-223,13	223,13	49788,52	,15
June	3840	30	2450,75	1,57	,73	5281,09	1791,74	1302,82	2537,18	2537,18	6437302	,66
July	3660	31	2552,75	1,43	1,46	2509,13	1733,21	2528,19	1131,81	1131,81	1281004	,31
August	589	32	2226,25	,26	,79	744,16	1674,68	1325,51	-736,51	736,51	542442,1	1,25
September	2716	33	1586,75	1,71	,95	2869,76	1616,15	1529,56	1186,45	1186,45	1407651,0	,44
October	40	34	1478,38	,03	,73	55,01	1557,62	1132,58	-1092,58	1092,58	1193731,0	27,31
November	2344	35			1,46	1606,94	1499,09	2186,68	157,32	157,32	24750,45	,07
December	1038	36			,79	1311,44	1440,56	1140,2	-102,2	102,2	10444,63	,1
TOTALS	85982								-989,8	29683,07	45657170	50,54
AVERAGE	2388,39								-27,49	824,53	1268255,0	1,4
Next period forecast								1307,98	(Bias)	(MAD)	(MSE)	(MAPE)
										Std err	1233,66	

Figure 6 Details of Multiplicative Decomposition Forecasting Method - Centered Moving Average Using POM QM

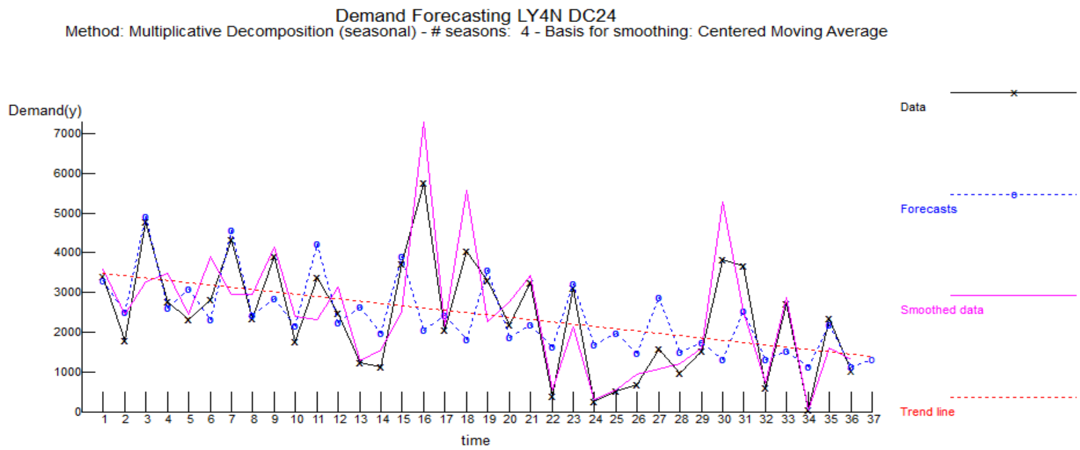


Figure 7 Multiplicative Decomposition Forecasting Graph Results - Centered Moving Average Using POM QM

C. The Calculation Results

Based on analysis of calculations carried out both manually and using POM QM software, both produce the same value. This shows that manual calculations have been verified consistently with systematic forecasting methods. The following are the results of forecasting calculations which has been done.

Table 5 Forecasting Calculation Results

<table>
<tr><th rowspan="2">Metode Multiplicative Decomposition</th><th colspan="2">Hasil Forecast</th><th colspan="2">MAD</th><th colspan="2">MSE</th><th colspan="2">MAPE</th></tr>
<tr><th>Manual</th><th>POM QM</th><th>Manual</th><th>POM QM</th><th>Manual</th><th>POM QM</th><th>Manual</th><th>POM QM</th></tr>
</table>

Average All	1.312	1.312	809	809	1.243.590	1.243.590	1,44	1,44
Centered Moving Average	1.308	1.308	825	825	1.268.255	1.268.255	1,40	1,40

CONCLUSION

From the research results in the previous chapter, The results of forecasting using this method are known Multiplicative Decomposition (Seasonal) Centered Moving Average produces a lower forecasting error value than Average All with a MAD value of 825, MSE 1,268,255 and MAPE 1.40 or 140% which is an error MAPE is classified as very high because it is above 50%, which means weak forecasting power, so this method is expected Multiplicative Decomposition (Seasonal) can be iterated first to get a lower MAPE percentage used as a method to do estimate demand for LY4N DC24 products at PT Omron Manufacturing Indonesia more accurately. Evaluation of the model's performance in real business situations and identification of factors influencing its accuracy will be important steps in future research. This allows us to understand how the application of the multiplicative decomposition method in sales forecasting and stock management can provide added value in daily practice.

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