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FORECASTING PERIODIC SERIES TO REDUCE THE BULLWHIP EFFECT IN SUPPLY CHAIN SYSTEMS USING MOVING AVERAGE AND EXPONENTIAL SMOOTHING

Alivia Fazricha Muzamil Putri[1], Suryani Nurfadillah[2], Titik Ekowati[3]
[1),2),3)] Department of Agribusiness, Faculty of Animal and Agricultural Science,
University of Diponegoro, Semarang Central Java, Indonesia
email correspondence: aliviafazricha@gmail.com

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ABSTRACT

Demand forecasting is one of the key components in supply chain management particularly in the food and beverage industry, which has dynamic and fluctuating demand levels. This study aimed to analyze the occurrence of the bullwhip effect in the production of Parijoto (Medinilla speciosa) syrup of CV Seleksi Alam Muria. and to analyze the best forecasting method to minimize the bullwhip effect. The benefits of this research were to serve as a reference for development efforts aimed at reducing the bullwhip effect in production, thereby optimizing the supply chain in a company. The forecasting methods used were Moving Average and Exponential Smoothing. Minitab Software assisted the forecasting calculations in this study. The study results showed that the initial bullwhip effect value (1.043) was higher than the parameter value (1.005), indicating the occurrence of the bullwhip effect in the production of Parijoto syrup. Furthermore, this study also found that the Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) values for the Moving Average method were lower compared to the Exponential Smoothing method. The forecasting result using the Moving Average method shows that the bullwhip effect value is significantly lower if it follows the recommended values derived from this forecasting method. Applying the Moving Average method indirectly minimizes the risk of amplification or overproduction.

INTRODUCTION

Demand forecasting is one of the key components in supply chain management, particularly in the food and beverage industry, which has dynamic and fluctuating demand levels. Demand forecasting is the estimation of future to minimize errors based on historical data (Awaluddin et al. 2021). Demand forecasting is used as a reference in business decision-making (Asynari et al. 2020). The mismatch between production volume and market demand can lead to waste, supply shortages, and additional costs due to inventory accumulation or stockouts. One of the consequences of this inefficiency is the emergence of the bullwhip effect, a condition where small fluctuations in consumer demand cause larger fluctuations in demand at the producer and supplier levels (Latuny & Picauly, 2019). This condition becomes even more severe in industries that are highly sensitive to seasonal variations and consumer preferences, such as the fruit-based beverage sector.

Supply chain management is crucial as it involves multiple elements in the process of providing raw materials until the final product reaches consumers. The supply chain can also be defined as a management system encompassingtheflowofproducts,information, and financial transactions (Tubagus et al. 2016). The supply chain is a network of companies that create and deliver products to end consumers (Fadhlullah, 2018). Supply chain management is a series of approaches used to effectively integrate suppliers, manufacturers, warehouses, and retailers. Thus, the overall system costs can be minimized while maintaining a focus on meeting demands and improving services (Lukman, 2021).

The bullwhip effect often arises due to poor communication and information flow across supply chain tiers. When actual consumer demand is not properlyconveyed toproducers and suppliers, each level tends to make ordering decisions based on inaccurate or incomplete data. The bullwhip effect relates to the tendency for replenishment orders to become more variable as they move up the supply chain, which amplifies small fluctuations in demand (Darmawan et al. 2025). Understanding how such behavior impacts the bullwhip effect promises to enrich our comprehension of supply chains dynamics, especially in sector where synchronization between demand and supply is crucial (Jalali & Menezes, 2024).

To analyze the bullwhip effect, many studies discuss the method of measuring it, as quantifying the effect is essential for understanding its impact and designing mitigation strategies (Yin & Tang, 2025). The magnitude of the bullwhip effect is indicated by a numerical value, where a higher demand variability coefficient (>1) resulting from the measurement indicates a greater occurrence of the bullwhip effect (Winarno et al. 2023).

The literature on the bullwhip effect has been significantly advanced by numerous analytical and empirical studies, providing deeper insights into the causes, patterns, and consequences of demand amplification (Patil & Prabhu, 2024).

Several factors contribute to the occurrence of the bullwhip effect, including rationing and shortage gaming, updating, forward buying, order batching, and demand forecasting (Perdana, 2015 in Darmawan et al. 2022). One way to mitigate the bullwhip effect is by conducting forecasting using time series analysis. Quantitative forecasting is a method that utilizes historical data and statistical techniques to predict future trends. Quantitative forecasting methods are classified into time series analysis and causal methods based on their applications. The time series forecasting method aims to identify patterns that can be categorized into four types (Arumsari & Dani, 2021): horizontal pattern (H),where data values fluctuate around a constant average; seasonal pattern (S),where a time series is influenced by seasonal factors; trend pattern (T), where there is a sustained increase or decrease over an extended period; and clyclical pattern (C), where long-term secular increases or decreases occur in the data.

In this context, various quantitative forecasting methods have been developed and applied to reduce demand uncertainty. Commonly used methods include Moving Average (MA), Exponential Smoothing (ES), and Minimum Mean Square Error (MMSE). The Moving Average method forecasts demand based on the average of previous period data and is suitable for relatively stable data patterns. Ithelpsinsmoothingout short-termfluctuations and highlighting longer-term trends or cycles. The Exponential Smoothing method weights the most recent data to forecast demand, making it more sensitive to changes in trends, which is especially useful in markets experiencing gradual demand shifts. MMSE, on the other hand, is an evaluative method used to select a model with the smallest forecasting error based on Mean Square Error, ensuring that the chosen model offers the highest predictive accuracy.

The fruit-based beverage industry is significantly influenced of raw material availability and fluctuating consumer preferences. During harvest seasons, raw materialsupplyisabundant, causingproduction to often exceed market demand. This leads to overproduction, which results in excess inventory, higher storage costs, and potential spoilage of perishable goods. Conversely, when raw material supply diminishes, companies face challenges in meeting market demand, resulting in missedsalesopportunities and customer dissatisfaction. Such conditions often exacerbate the bullwhip effect, suppliers may overreact to minor changes in order quantities, amplifying the variation in upstream supply chain stages. These amplified reactions can lead to unstable production schedules, inefficient resource utilization, and elevated logistics costs. In the agricultural supply chain, most of the work is found in the logistic of food supply, food safety, and imperfect information system (Alkahtani et al. 2020).

In this study, the bullwhip effect value is calculated by comparing the production coefficient (orders) and the sales coefficient (demand) of syrup. Demand represents actual customer requests, however, in bullwhip effect analysis, demand is approximated using sales data, as sales reflect actual consumer demand. The calculated bullwhip effect value from Januari 2021 to December 2024 is 1.043. Based on the calculation results, the obtained parameter value is 1.005. This result is derived from a total observation period of 48 months or 1,460 days. This parameter serves as a benchmark for identifying the occurrence of the bullwhip effect in the company. The comparison of bullwhip effect values indicates that the bullwhip effect value exceeds the bullwhip effect parameter value (1.043 > 1.005)

Several studies have indicated that the use of appropriate forecasting methods can reduce the bullwhip effect and improve supply chain efficiency. The application of time series models in the beverage industry has been shown to stabilize production planning (Singh et al. 2021). Accurate demand forecasting can be also reduce agricultural waste among small-scale farmers (Zhang et al. 2022). In addition, the exponential smoothing method has been successfully implemented to optimize inventory in the dairy industry. These studies indicate that forecasting methods can be effectively applied to agricultural product processing industries, particularly those facing supply and demand uncertainties.

The purpose of this study is to determine that best forecasting method to minimize the bullwhip effect in the supply chain system of fruit syrup production. The research will analyze two forecasting methods Moving Average and Exponential Smoothing on the supply chain system of a fruit syrup production company located in Kudus Regency, Central Java. The company operates in the agro-industrial sector, heavily reliant on local fruit harvest seasons. This study uses monthly sales and production data from 2021 to 2024 to determine the most accurate method and evaluate its impact on improving supply chain efficiency. The findings of this study are expected to provide practical recommendations for companies to develop more adaptive and efficient production strategies.

METHODS

This study was conducted from December 2024 to January 2025 at CV Seleksi Alam Muria, Colo, Dawe, Kudus. The data sources in this study consist of primary and secondary data. Primary data is source of information or documents provided or directly explained by individual or parties present at the time of the event, allowing them to serve as witnesses (Hardani et al., 2020). Primary data include respondent and company identity, production activities, factors influencing demand, future demand projections, and company strategies. Secondary data is a source of information provided by parties who did not directly experience or were not present at the time of the event (Hardani et al., 2020). Secondary data comprise time series data on sales and production over the past four years, as well as supporting literature. Data were collected through observation, interviews, and documentation. The interview method is applied by researchers to obtain from company executives, suppliers, distributors, retailers, and consumers (Saptaria, 2016).

After the data was collected, the next step was data processing, which involved calculating the bullwhip effect and forecasting demand using the Moving Average and Exponential Smoothing methods, with the forecasting calculations assisted by Minitab software. The formula for the bullwhip effect is:

$$BE = \frac{CV_Q}{CV_d} \quad (1)$$

$$BE = \frac{\frac{standard\ deviation\ of\ order}{averge\ of\ order}}{\frac{standard\ deviation\ of\ demand}{average\ of\ demand}} \quad (2)$$

The correct parameters are needed to assess whether the bullwhip effect of a company can be considered good or not. According to a study by Arifin (2018) in Darmawan et al., (2022), the formula that can be used to determine the bullwhip effect parameter is:

$$BE \geq 1 + \frac{2L}{P} + \frac{2L^2}{P^2} \quad (3)$$

The terms in the equation include L, which refers to the lead time from order to receipt of goods, and P, which represents the observation period.

In this study, data analysis begins by applying forecasting methods using time series techniques.

1. Moving Average method

This forecasting method involves calculation based on latest data, while older data values are excluded from the analysis (Hajjah & Marlim, 2021).

$$M_t = F_{t+1} \quad (4)$$

$$F_{t+1} = \frac{A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-n+1}}{n} \quad (5)$$

M_t represents the Moving Average value for period t, while F_{t+1} denotes the forecasted value for period t+1. Additionally, A_t refers to the actual value for period t, and n indicates the total number of data points used in the analysis.

2. Exponential Smoothing method

The Exponential Smoothing method involves data from all available periods. Each observation in this method contributes to determining the forecast value for future periods (Robial, 2018).

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \quad (6)$$

F_t represents the forecast for period t, while F_{t-1} indicates the forecast for the previous period. The smoothing constant, denoted by α(0≤α≤1), serves as the weighting factor. Additionally, A_{t-1} refers to the actual value for the previous period. The value of á ranges from 0.1 to 0.9, with a value closer to 1 indicating that more weight is given to the most recent data.

Obtaining more accurate forecasting data requires several calculations to assess the alignment between actual data and forecasted data.

1. Mean Absolute Deviation (MAD)

Mean Absolute Deviation (MAD) measures forecasting accuracy by calculating the average absolute value of forecasting errors.

$$MAD = \frac{\sum \left|Actual\ \ t - Forecast\ \ t\right|}{n} \quad (7)$$

Mean Absolute Deviation (MAD) represents the average absolute error in forecasting. The variable n indicates the number of forecasting periods involved, while "Actual t" refers to the actual value, and "Forecast t" denotes the forecasted value.

2. Mean Squared Error (MSE)

Mean Squared Error (MSE) calculates the averageofthesquareddifferencesbetweenthe forecasted values and actual observed values.

$$MSE = \frac{\sum \left|Actual\ \ t - Forecast\ \ t\right|^2}{n} \quad (8)$$

Mean Squared Error (MSE) represents the averagesquareddifferencebetweenforecasted and actual values. The variable n refers to the number of forecasting periods involved, while "Actual t" denotes the actual value, and "Forecast t" represents the forecasted value.

3. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a percentage calculated by diving the absolute error in each period by actual data value, followed by averaging these errors.

$$\text{MAPE} = \frac{\sum \frac{\left|Actual\ \ t - Forecast\ \ t\right|}{Actual\ \ t} x\ 100}{n} \quad (9)$$

The variable n refers to the number of forecasting periods involved, while "Actual t" denotes the actual value, and "Forecast t" represents the forecasted value.

RESULTS AND DISCUSSIONS

Sales Fluctuation and Forecasting Results

Forecasting is the process of estimating future values or events based on the analysis of historical data and identified patterns. The forecasting in this study refers to estimating the number of products to be ordered or demanded in the upcoming period, based on previous product sales data. The forecasting methods used in this research are the Moving Average method and the Exponential Smoothing method. This forecasting process utilizes time series sales data over a period of 48 months (4 years) and is conducted with the assistance of Minitab software.

The data pattern in this study plays a crucial role in identifying trends within a dataset. Before applying forecasting methods, the initial step required is plotting the data to recognize existing patterns. Based on the plot results, a clear depiction of the dynamics and changes in sales data throughout the observation period is obtained. Sales data patterns can be seen in Figure 1. stationary data tends to remain stable or fluctuate around a certain value, whereas non-stationary data shows a pattern of significant increases or decreases over time. The lowest sales volume occurred in the 44th month, specifically in August 2024, with a total of 170 liters, while the highest sales volume was recorded in October 2022, reaching 420 liters. Illustration 1 also depicts

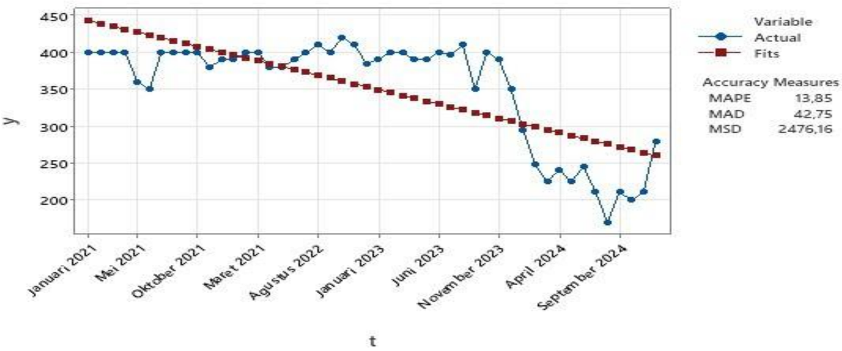

Figure 1. Sales Data Patters Syrop Production

Based on Figure 1, it can be observed that the sales data pattern fluctuates throughout the period used in this study. The data represents the actual sales of syrup from January 2021 to December 2024. In the context of forecasting, data stationarity is often associated with the stability of the mean and variance over a specific period. Similarly, in the syrup sales data pattern, there are periods where the data remains stable or does not exhibit extreme fluctuations continuously. Therefore, the data can still be considered approximately stationary in the short term, eliminating the need for differentiation. The aligns with the statement by Armeina & Alam (2019), who argue that that, despite sales fluctuations, the data exhibits a downward trend over time. This is consistent with the statement by Arumsari & Dani (2021), who explain that a trend pattern occurs when there is an increase or decrease in a time series over an extended period. Given this downward trend pattern, the Moving Averageand Exponential Smoothing methods can be applied for forecasting. According to Restyana et al., (2021) in Anitya et al., (2023), besides the Moving Average method, the Exponential Smoothing method is also considered suitable for time series forecastingwith stationary patterns, especially when there is no seasonal component or significant trend. The downward trend in this sales data is not extreme in every period, as there are still stable points. Thus, both Moving Average and Exponential Smoothing methods remain applicable for forecasting.

Next, the forecasting process is carried out using the Moving Average and Exponential Smoothing methods. In the Moving Average method, the initial step is to determine the averaging period used. The selection of the averaging period in this study was conducted through a trial-and-error approach using the Minitab application. The comparison of error values can be seen in Table 1.

Based on Table 1, among the four averaging periods used, the one with the smallest MAD, MSE, and MAPE values or the closest to zero is 3-period Moving Average. This indicates that in the Moving Average calculation, each forecast is based on the average of the three most recent data points. Forecasting is a conducted to determine the projected demand for the next 12 months. The demand forecast for months 49 to 60, using the Moving Average method with a 3-period average, is illustrated in the graph shown in Illustration 2.

The graph in Figure 2 presents the forecasting results using the Moving Average method with a 3-period average. In the graph, the blue line represents the actual data, the red line indicates the forecast for the same period based on the existing data, and the

Table 1. The Comparison of Error Values

Averaging period	MAD	MSE	MAPE
2	14.179	415.860	4.776
3	13.167	363.273	4.436
4	14.039	422.751	4.708
5	14.400	435.783	4.828

Source: Primary Data, 2025.

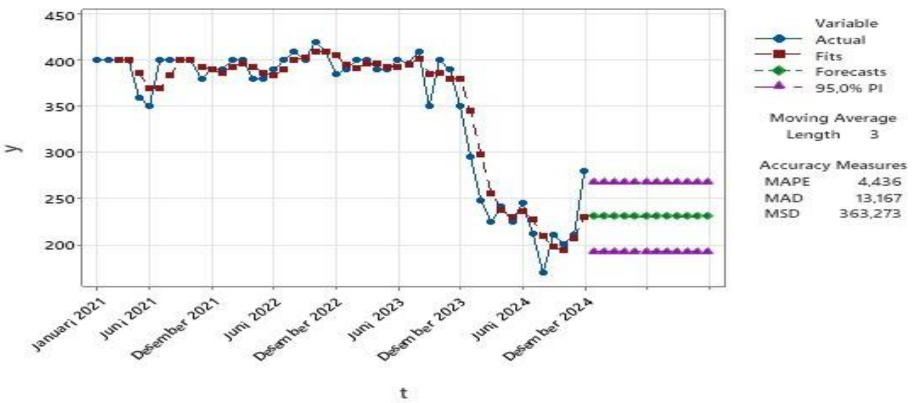

Figure 2. Moving Average Forecast Graph

green line illustrates the forecast for the next 12 months. The graph pattern shows that the forecast closely follows the fluctuations of the actual data, particularly in the relatively stable trend observed from the beginning until around June 2023. After that period, a significant decline in demand is evident, which is also reflected in the forecast line, albeit in a smoother pattern. The forecast resultsformonths 49 to 60 in thegraphindicate a consistent value of 230.333 liters. This is because historical data exhibits a relatively stable pattern without extreme fluctuations over a specific period, indicating a near stationary characteristic. Field observations suggest that this stability in demand may be due to the market's tendency to remain consistent within certain periods. As a result, stationary data tends to produce more stable forecast, as it is not influenced by seasonal patterns. According to Armeina & Alam (2019), a time series dataset is considered stationary if its mean and variance remain constant over time orare statistically balanced.

Thenextmethodusedis ExponentialSmoothing, the Exponential Smoothing method involves data from all available periods. Each observed data point in this method contributes to determining the forecasted value for future periods. The Exponential Smoothing method utilizes a smoothing coefficient, referred to as the á coefficient. The determination of á in this method also employs a trial-and-error technique using the Minitab application to identify the á value that yields the smallest MAD, MSE, and MAPE values or those closest to zero. The determination of the smallest á value can be seen in Table 2.

Based on Table 2, it can be observed that the á value used is 0.9. This selection is based on the fact that it has the smallest MAD,

Table 2. Determination of The Smallest α Value

Alpha	MAD	MSE	MAPE
0.1	34.31	2918.97	13.66
0.2	27.07	1653.29	10.19
0.3	22.71	1172.75	8.15
0.4	20.381	946.893	7.087
0.5	19.423	823.356	6.655
0.6	18.734	749.316	6.349
0.7	18.263	703.037	6.157
0.8	18.086	674.668	6.088
0.9	18.032	659.566	6.062

Source: Primary Data, 2025.

MSE, MAPE values compared to other α values, with a MAD = 18.032, MSE = 659.566, MAPE = 6.062. The forecasting results with an α value of 0.9 can be illustrated through the graph in Figure 3.

result, stationary data tend to produce more consistent predictions, as they are not influenced by seasonal patterns. According to Armeina & Alam (2019), a time series dataset is considered stationary if its mean

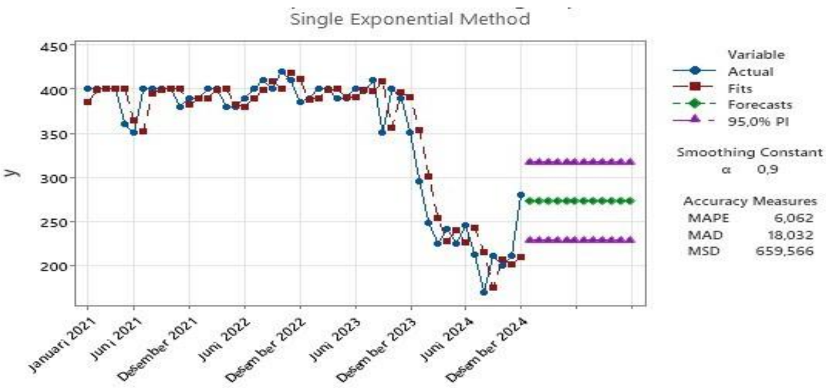

Figure 3. Exponential Smoothing Forecast Graph

Based on Illustration 3, the graph presents the forecasting results using the Exponential Smoothing method with an alpha parameter of 0.9. The blue line represents the actual data, the red line indicates the forecast for the same period as the actual data, while the green line shows the forecasted results for the next 12 months. The graph demonstrates that the forecast closely follows the trend pattern of the actual data, with significant fluctuations in demand during certain months. The forecasting results for months 49 to 60 show a consistent value of 272.997 liters. This condition occurs because the historical data exhibits a relatively stable pattern without significant fluctuations over specific periods, indicating a tendency toward stationarity. Based on field observations, this stability may be due to relatively constant market demand over certain periods. As a

and variance remain unchanged over time or are in a statistically balanced state.

Next is the determination of the best forecasting method, which aims to obtain the most accurate forecasting result that align with the observed data patterns. This study indicates that each method produces variation in MAD, MSE, and MAPE values, where the values closest to zero are considered to have the highest accuracy. These parameters are used to determine the most optimal method among the two analytical methods applied. A comparison of error parameter values between the Moving Average and Exponential Smoothing methods is presented in Table 3.

Based on Table 3, the comparison result indicate that the error value from the analysis output using the Moving Average method is lower than the error value from the analysis

Table 3. Determination of The Best Forecasting Method

Method	MAD	MSE	MAPE
Moving Average	13.167	363.273	4.436
Exponential Smoothing	18.032	659.566	6.062

Source: Primary Data, 2025.

output using the Exponential Smoothing method. This means that the Moving Average method with a 3-period average is the best method and can be used for forecasting the demand for syrup production. The 3-period average refers to the calculation in the Moving Average method, where each prediction is based on the average of the last three data points. The forecasting results show that the demand for syrup from January to December 2025 is predicted to be 230.333 liters per month. Based on obtained data, the actual sales in January 2025 reached 255 liters, indicating that the actual sales are not significantly different from the forecasted results, with a deviation of 24.667 liters or only 9.76% of the actual sales. Additionally, the forecasting method used has a MAPE value of 4.436, which indicates a very high level of accuracy. The MAPE criteria guidelines can be seen in Table 4. This also demonstrates that the Moving Average method with a 3-period average can provide a fairly accurate estimate. According to Assauri (1984) in Wardah & Iskandar (2016), a good forecasting method is one that produces predictions that are not significantly different from actual conditions. This prediction indicates a stable market potential, whichcan assistmanagement in planning production and product availability more effectively.

Bullwhip Effect Value Change

Changes in bullwhip effect values are analyzed todeterminetheimpact of demandforecasting on the bullwhip effect within the syrup supply chain system at CV Seleksi Alam Muria, Kudus, assuming that production planning aligns with the forecasting output. When syrup production planning follows the forecasted results, the bullwhip effect value obtained is 0.809, which is significantly lower than the bullwhip effect threshold of 1.005.

Table 4. The MAPE Criteria

MAPE	Criteria
<10	Very good
10 – 20	Good
– 50	Fair
>50	Poor

Source: Darmawan et al.2022.

this indicates that aligning production planning with forecasting values prevents demand amplification in syrup production. The changes in bullwhip effect values are presented in Table 5.

Table 5. Changes in Bullwhip Effect Values

Description	Average	Sd	CV	Bullwhip Effect
Order	384.270	83.609	0.217	0.809
Demand	311.646	83.771	0.268	

Source: Primary Data, 2025.

values for the Moving Average method are lower than those for the Exponential Smoothing method.

Based on the results in Table 5, it can be concluded that the implementation of forecasting methods, particularly the Moving Average method, is essential to minimize and prevent overproduction or the bullwhip effect in demand fluctuations. Additionally, demand forecasting plays a crucial role in optimizing costs and improving the efficiency of syrup production activities.

The findings of this study are specific to the production characteristics of the observed fruit syrup company. Therefore, the applicability of the Moving Average method as the most accurate forecasting technique may vary in other industries with different production systems and demand behaviors.

CONCLUSION

Based on the research findings on time series forecasting to reduce the bullwhip the following conclusions were drawn:

1. Forecasting results using the Moving Average and Exponential Smoothing methods reveal that the MAD, MSE, MAPE values for the Moving Average method are lower than those for the Exponential Smoothing method.
2. Forecasting result using the Moving Average method show that the bullwhip effect value is significantly lower if follows the recommended values derived from this forecasting method. Applying the Moving Average method indirectly minimizes the risk of amplification or overproduction.

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