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Forecast of sugar demand in retail using SARIMA and decomposition models case study: a retail store in Indonesia

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Abstract
This study discusses forecasting demand in a retail store, focusing on sugar, which is a staple food in Indonesia, as the research object. Despite its importance and forecast challenge, there is no research has been done on sugar at the retail level. This study aims to find the most suitable forecast model that can capture data patterns well to give a good prediction of sugar sales in a retail store in Indonesia by comparing SARIMA and decomposition models. This study uses a stationary test and ACF pattern analyses to prepare the data, a residual test to avoid forecast bias, cross-validation to check the forecast model performance, and MAPE as the performance indicator. SARIMA (0,0,0)(0,1,1)8 and multiplicative decomposition with 3 periods of double-moving average models are chosen. Both models have similar patterns but different slopes because the decomposition model is more sensitive to data patterns, resulting in different MAPEs, which are 15.22% and 13.64%. Despite the popularity of SARIMA, decomposition can be an interesting alternative to use since it can capture trend data patterns better. However, the short forecast period is preferable for the decomposition model to avoid high trend slope prediction in the long run, leading to more frequent forecast activity and higher resources compared to SARIMA.

Keywords:
Decomposition;
Forecast;
Retail;
SARIMA;
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INTRODUCTION

Forecasting or demand prediction for retail has been receiving a lot of attention for a long time due to its difficulty because of the high variability of demand [1, 2, 3]. Ma and Fildes [4] and Veiga et al. [5] show that having a good forecast improves service level and demand satisfaction rate; it also reduces total cost operations in retail. This is because retail can anticipate the change in demand better. Thus, forecasting can serve as a tool for decision-making in operating retail [2] and be an important part of retail to ensure the sustainability of retail operations.

Despite much research conducted about forecasts, a recent study done by Kumar et al. [6] mentioned there is still a limitation of good forecasting in retail because the forecast methods fail to capture the pattern of the demand, such as the trend and seasonal pattern. To have a good prediction, the forecast model should be able to capture and accommodate the data patterns.

Based on this concern, this study aims to discuss forecasting in retail using SARIMA and decomposition models. Both models are used because both models are built to analyze and treat the pattern of the data before proceeding with the forecast [7]. Forcing forecast models cannot neglect the trend and seasonal data patterns. It is also worth noting that SARIMA is the extension of the ARIMA model for accommodating seasonal data patterns. If the data has a seasonal pattern, the forecast is automatically analyzed using SARIMA, instead of ARIMA.

The research object of this study is sugar demand or sugar sales in retail. Sugar is chosen in this study because every country consumes sugar, and it is part of the staple foods in Indonesia. The Indonesian government regards sugar as one of the staple foods, and this decision is written down in the Presidential Decree of the Republic of Indonesia No. 59 Year 2020 about the government arrangement and storage of staple goods [10]. This consideration is because a lot of household expenses are spent on sugar, and its availability impacts national inflation.

Indonesia's sugar consumption value is fluctuating; however, it keeps increasing, and to meet this demand, Indonesia has been importing sugar since 1967 [8]. This high consumption makes Indonesia the sixth country that has the highest sugar consumption in the world [9].

Sugar consumption is divided into two groups: sugar consumption for industry and households. The household can buy sugar directly from retail. Based on the Central Statistics Agency [11] Indonesian people consume around 31.5 grams of sugar per capita weekly for household consumption in 2023. It means that there is a certain demand for sugar in the retail. Facing this guaranteed demand, retail should provide sugar and maintain its stock efficiently so that it achieves customer satisfaction because of stock availability and avoids high inventory because of excessive stock. To achieve this, retail should have a good prediction for sugar demand by having a reliable forecast method.

Having a good forecast in retail not only benefits the retailer itself but also higher supply chain levels and the government [12]. Having a good forecast reduces the bullwhip effect for higher supply chain distribution levels since one of the major reasons for the bullwhip effect is the inaccurate forecast downstream [13][14]. Furthermore, having good predictions at the retail level for the long term can help the government understand the consumption rate of sugar for the household since retail is the nearest distributor for household consumption. This prediction can help the government make policies to stabilize the sugar supply and pricing.

Despite the importance of sugar demand prediction in retail, no study has discussed it. Table 1 shows the literature analysis regarding research in retail demand prediction as a general topic and research focusing on sugar prediction. Several customer goods, such as food, vegetables, and fashion, have been discussed widely at the retail level. However, sugar production has not been mentioned.

Table 1 indicates that research discussing sugar prediction has been done, however, it is not about sugar demand at the retail level; instead, some research studies about the prediction of sugarcane production [22][23], sugar price [27][28], and sugar consumption [26] outside Indonesia. Limited studies regarding sugar have also been done in Indonesia. Those studies even discuss the sugar demand prediction, but at the manufacturer [24], and national levels [25].

The forecast of sugar demand does not differ significantly from other demand forecast methods for other customer goods. Some of those studies use ARIMA, but many of the forecasts related to sugar uses regression and machine learning at the higher supply chain levels. However, many studies discuss product demand prediction at the retail level using ARIMA and SARIMA for demands that have seasonal patterns.

Almeida and Veiga [2] and Hyndman and Athanasopoulos [7] mentioned that ARIMA is often used because it can forecast demand well. Table 1 shows that ARIMA is often used at the retail level. Those studies prove that ARIMA and SARIMA perform well and can predict better compared to other methods [15, 16, 17, 23], even when compared to more recent forecast models, such as Facebook Prophet and LightGBM [17]. It can be concluded that SARIMA is believed to capture the demand data pattern well at the retail level.

The decomposition model is not as widely used as SARIMA. Based on the literature review analysis, the decomposition forecast model has not been used for demand prediction, especially at the retail level, and for sugar demand prediction. Despite the similar way of proceeding with the forecast of both models, there is still a lack of studies that compare both models to find the model that is more sensitive to the data pattern. Comparing both forecast methods might lead to an alternative forecast method that can predict product demand better than the popular forecast method at the retail level, which is SARIMA.

Based on the literature review analysis, only one study analyzed the comparison of SARIMA and decomposition forecast models; that was done by Guarnaccia et al. [29]. The result describes that both models perform well, but decomposition is better than SARIMA.

Table 1. Literature Analysis of Retail Demand Forecasting and Research Related Sugar

Author	Scope	Level	Research Object	Country	Forecast Method
Xu [15]	Demand prediction	Retail	Customer Goods	China	Multiple Regression and SARIMA
Falatouri, et al.[16]	Demand prediction	Retail	Fruits and vegetables	Austria	SARIMA and LSTM
Almeida & Veiga [2]	Demand prediction	Retail	Food products, drinks, and tobacco	Brazil	SARIMA and Wavelet Neural Network
Badorf & Hoberg [1]	Demand prediction	Retail	Customer Goods	German	Linear and non-linear models
Hasan, et al. [17]	Demand prediction	Retail	Customer Goods	United States	ARIMA, Prophet model, and LightGBM
Priyadarshi, et al. [18]	Demand prediction	Retail	Vegetables	Not specified	ARIMA, LSTM SVR, random forest regression, GBR, and extreme GBR
Giri & Chen [19]	Demand prediction	Retail	Fashion	European fashion retail company	Machine learning, clustering, and classification techniques
Petropoulos, F., et al. [20]	Demand prediction	Retail	Customer Goods	Various sources	Exponential smoothing and ARIMA
Ye et al. [21].	Demand prediction	Retail	Customer Goods	United States	Fourier time-varying grey model
Mishra, et al. [22]	Production prediction	Production	Sugarcane	India	ARIMA
Tyagi, et al. [23]	Production prediction	Production	Sugarcane	India	Naive, exponential smoothing, Holt's models, and ARIMA
Wardah, et al. [24]	Demand prediction	Manufacturer	Coconut sugar	Indonesia	ARIMA
Rosari, et al. [25]	Supply-demand prediction	National	Sugar	Indonesia	Deep learning with LSTM
Ekawati, et al. [13]	Demand prediction	Manufacturer	Sugar	Indonesia	Support Vector Regression (SVR)
Kantasa-ard, et al. [26]	Consumption rate prediction	National	sugar	Thailand	Regression and neural network models
Amrouk & Heckelei [27]	Sugar price prediction	Manufacturer	Sugar	International (worldwide)	Bayesian model averaging (BMA)

Several improvements can be made from previous studies. Guarnaccia et al. [29] use basic statistics to analyze the residual forecast to compare the performance of both models. However, a deeper analysis of residual testing can be implemented to improve the analysis and avoid bias. Both SARIMA and decomposition have residual assumptions that should be fulfilled, and part of the model characteristics [7][30], which were not discussed in depth in the previous study. Furthermore, the previous study does not state which decomposition model is used, whether an additive or a multiplicative model. There are two types of decomposition models those are additive and multiplicative decomposition models. The decision to choose between the two models is based on the data graph or residual testing [30].

Considering this condition, to improve the statistical analysis and reduce the bias of the result, this study does two residual analyses. First, check both residuals for SARIMA and decomposition models to avoid bias, through statistical residual assumption tests. Second, compare both residual models for the performance comparison to find the most suitable forecast model, through the MAPE comparison.

Based on literature review analysis, the study that focuses on sugar demand or sales in retail has not been widely discussed. Most of the studies about sugar focus on a higher supply chain level or national level. Considering this research gap and its importance, this study discusses the forecast of sugar demand for retail.

In conclusion, this study aims to find the most suitable forecast model that can capture data patterns well to give a good prediction of sugar sales in a retail store in Indonesia using SARIMA and decomposition models. This research takes a study case of a retail store in Yogyakarta Province, Indonesia. This study discussed the comparison of both models, through the forecast result and how the models treat the data, which has not been pointed out yet.

This study helps to fill the research gaps found by literature review analysis. First, about a lack of demand prediction study using the decomposition forecast model. Second about a lack of research that analyzes the comparison of SARIMA with the decomposition forecast model through comprehensive statistical analysis, which is mentioned to improve the analysis of previous study. This comparison is done to find the forecast model that can capture data patterns better. Third, about a lack of studies on sugar-related topics at the retail level in general, especially for the Indonesia case study.

There are two research questions in this study. First: "What is the most suitable forecast method between SARIMA and decomposition models to predict sugar sales at the retail level for a study case of a retail store in Indonesia?"; second: "Which is the forecast method that is more sensitive to data pattern between SARIMA and decomposition models?". The objectives of this study are to answer the research questions, which are to find the most suitable forecast model between SARIMA and decomposition models to predict sugar sales at the retail level for a study case of a retail store in Indonesia and to find the forecast method that can capture data pattern better between those two forecast methods.

In this study, data preparation is done by using a stationary test and pattern analysis. Later, residual testing for both models is analyzed to ensure there is no result bias, which was missing in the previous study. To ensure forecast performance, the cross-validation method is used by dividing the data into training and testing data sets. This study uses MAPE as a performance indicator to check and compare the forecast errors of both models.

METHOD

Methods

The retail store for this study is located in one of the strategic areas in Yogyakarta Province, Indonesia. The retail lying near universities and other stores leading the surrounding area to be highly populated. The data of one-kilogram-package white sugar sales is obtained from the sales record of the store, through interviewing the owner and checking the book record. There is a total of 72 monthly data of sugar sales from 2018 until 2023.

The numbers of data fulfill the minimum data requirement for ARIMA. The ARIMA forecast model needs quite a lot of data, around 40 to 50 observation data [31]. The SARIMA model might require a bit more data compared to ARIMA to capture the seasonality component. It might even require more data if the seasonal length is long. Considering the limited number of data sales collected and the high minimum number of data required to perform SARIMA, all of the collected data is used to make forecasts and proceed to the preprocessing step.

The preprocessing step of SARIMA and decomposition is the reason why this study uses both models to forecast. In this step, both models need to do basic statistical exploration and a stationary test to check whether the data is stationer or not. Stationer data means that its statistical properties such as mean, variance, etc. do not change or depend over time [31]. If the data is not stationer, it means that the data has a trend of seasonal patterns in the data. The Autocorrelation Function (ACF) is used to identify the data pattern further. After the identification is done, the data patterns need to be moved out, thus the data becomes stationer. The preprocessing data step is done only after the data is stationer and ready to be used for prediction.

This compulsory step, which does not happen in other forecast methods, makes both models identify the data pattern, without exception. This condition makes both forecast models sensitive to data patterns. Later, the steps to move out the data pattern to make the data stationer are taken into account to make the forecast model, leading the forecast models to capture and accommodate the data pattern directly.

The detailed research design of this study is depicted in Figure 1. Figure 1 describes that if the stationary test shows that the data is stationer, ARIMA can be used directly to predict sales. ARIMA also can be used for data that has a trend pattern, which can be known from ACF analysis. ARIMA is used after the trend pattern is moved out and the data becomes stationer. However, if the data has a seasonal pattern, SARIMA should be used to predict future sales after the seasonality of the data is moved out. The moving out data pattern is done using a different method.

There are usually several possible SARIMA models; however, not all of these possible models can be used to predict. A parameter estimate test is done to check the validity of the parameter used for model fitness, if the P-value of this test shows the parameter is less than 0,05, the tested parameter is valid [32]. To avoid bias, there are several assumptions that should be fulfilled. The models that pass all assumptions can be used to forecast future sales without bias. The best-fitted model is the one that has the smallest forecast error among the models that fulfill the assumptions.

Figure 1 also shows that there are two types of decomposition models; those are additive and multiplicative models. For non-stationary data, after ACF analysis is performed to find out the seasonality pattern, the data can be forecast directly using an additive or multiplicative decomposition model. The pattern of the data, such as the trend and seasonality should be moved out from the data. Later, the residual assumptions of additive and multiplicative are checked to choose the most suitable model among both of the models. After the model is chosen, a double-moving average model is used to predict the trend pattern in the data. Thus, the forecast model is a combination of decomposition and double moving average model.

The double moving average is decided by comparing the forecast error of several periods used in the forecast model. The model that has the smallest forecast error is chosen to represent decomposition with a double-moving average forecast model.

To check the performance of the forecast model, this study uses cross-validation by splitting the observed data into training and testing data sets. The training data set is used to make the forecast model, and the testing data set is used to see the performance of that built model by analyzing the forecast error. Because SARIMA needs a lot of data to build the model, this study only uses the last 10 data, or around 14% of data, as the testing data set.

This study uses Mean Absolute Percentage Error (MAPE) to see the forecast performance. The selection of the most fitted model among possible SARIMA models and the most fitted decomposition model among possible decompositions models, which fulfill the residual test, also uses MAPE comparison of testing data.

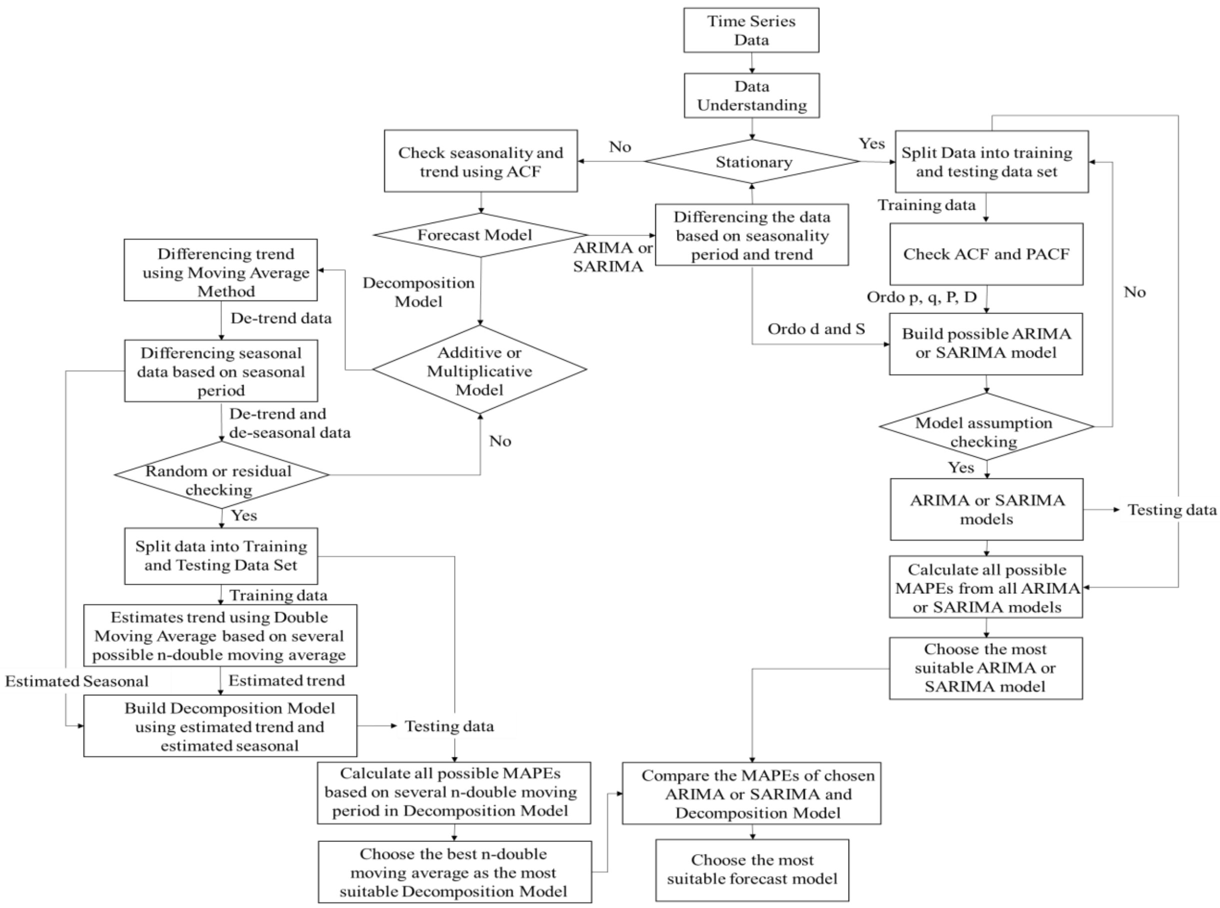


Figure 1. Research Design

Furthermore, the MAPE of testing data is also used to compare the best forecast performance between the chosen SARIMA and the chosen decomposition forecast models. A small MAPE value is better than a big MAPE value. MAPE formula is:

$$MAPE = 100x\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (1)$$

With n is the number of data, A_t is the actual or observed data of period t, and F_t is the forecast value of period t.

SARIMA Forecast Model

SARIMA (p, d, q)(P, D, Q)s model is the seasonal adjustment of the ARIMA (p,d,q) model. The (p, d, q) in SARIMA correspond with ARIMA (p, d, q) with p as the order of autoregressive (AR), d as the order of differencing (I) to take the trend out of the data for achieving stationary data, and q is the order of moving average (MA). The (P, D, Q)s in SARIMA correspond with seasonal adjustment, where P, D, and Q are the order of seasonal autoregressive, seasonal differencing, and seasonal moving averages, respectively, while s is the seasonal length.

Orders p and P are attained from the analyses of the number of significant spikes of the Partial Autocorrelation Function (PACF), while orders q and Q are attained from the analyses of the number of significant spikes of the Autocorrelation Function (ACF). The significant spikes are the values that are out of the control line of the PACF or ACF graph. The formulas for ARIMA and SARIMA are [33]:

ARIMA:

$$\emptyset_p(B)(1-B)^d Y_t = \theta_0 + \theta_q(B)e_t \quad (2)$$

SARIMA:

$$\emptyset_p(B)\Phi_p(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_0 + \theta_q(B)\Theta_Q(B^s)e_t \quad (3)$$

With Y_t as the real or observed data value, $\emptyset_p(B)$ s the order of p, $(1-B)$ is a differencing operator for non-seasonal patterns, d as the number of differencing, t as the period at t, θ_0 the constant term, $\theta_q(B)$ as the order of q, and e_t as the error at time t. These symbols are used both in ARIMA and SARIMA. For SARIMA there are more symbols in the formula. With $\Phi_p(B^s)$ is the order of P, $(1-B)^d$ in order of Q, s as the seasonal period length, D as the seasonal differencing, $(1-B^s)$ as a seasonal differencing operator.

There are several residual requirements for both ARIMA and SARIMA, so that the model can be considered valid or not biased. Those are the residuals of the model should be independent, or not have autocorrelation, be homoscedasticity, and have a normal distribution [34]. The autocorrelation and homoscedasticity can be checked by ACF and PACF graphs [2, 31, 34]. If no value surpasses the control line on those graphs, these assumptions are satisfied [31]. In addition, the Ljung-Box Statistics Test can also be used to check the autocorrelation [2].

Decomposition Forecast Model

The concept of the decomposition model is to break down the data composition to understand the data and to help the forecast. For non-stationary data. The data can consist of trend, seasonal, and residual or error data.

There are two types of decomposition models those are additive and multiplicative decomposition models. An additive decomposition is used if there is a considerably constant variability in the data over time and the other one for the opposite condition [30]. However, if it is difficult to decide which decomposition model is used, both models can be analyzed, and the error assumption for both models. Later, the model that satisfies this assumption is chosen. The formulas for decomposition models are [30]:

Additive Decomposition Model:

$$Y_t = T_t + S_t + e_t \quad (4)$$

With the sum of seasonal component values is 0 or $\sum_{j=0}^{s} S_j = 0$ and e_t or error or residual component has Gaussian N(0, σ^2).

Multiplicative Decomposition Model:

$$Y_t = T_t \; x \; S_t \; x \; e_t \quad (5)$$

With the sum of seasonal component values is the total of the seasonal length or $\sum_{j=0}^{s} S_j = s$ and e_t has Gaussian N(1, σ^2).

Where Y_t is the real data, T_t is the trend component value at period t, S_t is the seasonal component value at period t, e_t is the error or residual or random component value at period t and j is the duration of the seasonal period.

It is worth noting that S_t is constant for the same t for each seasonal period. Thus, after choosing the decomposition model, the estimate of seasonal data can be known. For the trend data, the other estimation is still needed. In this study, the double moving average method is

used. A double moving average forecast model can help to predict trend patterns in the data [35]. The double moving average model is [36]:
Single Moving Average (S') of period t:

$$S'_t = \frac{Y_t + Y_{t-1} + Y_{t-2} + \cdots + Y_{t-n+1}}{n} \tag{6}$$

Double Moving Average (S'') of period t:

$$S''_t = \frac{S'_t + S'_{t-1} + S''_{t-2} + \cdots + S'_{t-n+1}}{n} \tag{7}$$

The value of the constant or intercept of period t:

$$a_t = 2S'_t - S''_t \tag{8}$$

The value of the trend of period t:

$$b_t = \frac{2}{n-1}(S'_t - S''_t) \tag{9}$$

The forecast value of period t+m:

$$F_{t+m} = a_t + b_t m \tag{10}$$

Where Y_t is the input data, and n is the number of periods chosen to make the average period.

To decide the best n period to fit the forecasting model, several n periods are run to predict trend composition data, and this trend prediction is combined with the seasonal decomposition to get the final decomposition forecast. The best-fitted n period is chosen based on the smallest MAPE of the testing data set.

RESULTS AND DISCUSSION

Data Exploration and Understanding

To understand the data, there is a need to know the basic statistics of the data, pattern analysis, and the data graph. Table 2 and Figure 2 show the basic statistics and pattern analysis, while Figure 7 shows the sales graph in the observed data part.

Table 2 explains that the retail sells more than 100 packages of sugar every month. There is high variability of the sales shown by the coefficient of variability (CV). The CV is used to understand how volatile the data is [3]. The CV is the standard deviation divided by the mean [3][37]. The CV is 27,44% and it is higher than the variability severity threshold, which is 15% [37].

The stationarity test is done by using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [3][7][38] in R Software. KPSS test value of sales is 0.44, which is higher than the critical value of 10% significance level, which is 0.34. Thus, the data is not stationary.

Table 2. Basic Statistics of Data

Basic Statistics	Value
Total Data	72
Mean	185.46
Median	179.5
Variance	2589.6
Standard Deviation	50.89
Coefficient of Variance	27.44%
Maximal	389
Minimal	103
P-value of Kolmogorov-Smirnov Test	>0.15 (normal distribution)
Kwiatkowski-Phillips-Schmidt-Shin (KPSS) value	0.4419 (non-stationer)

The seasonality and trend patterns are checked using ACF. Figure 2 shows the ACF Graph from the analysis done in Minitab Software. The data is considered to have a seasonality pattern if there is a repetition of a high number or spikes of the ACF value in the same multiple periods [39]. A trend pattern is considered if the ACF scores decrease over time gradually.

Figure 2 indicates that there are spikes in periods 1, 8, and 16 months. It means that the sales have seasonal data with a seasonal length of 8 months. The seasonality of sugar sales is quite long, thus it requires a lot of data to analyze so that it can capture the seasonality pattern. Hence, this study uses the SARIMA model instead of the ARIMA model because the data has seasonality. It also shows that based on ACF, there might be no significant trend pattern.

Figure 7 explains that the sugar sales look very fluctuating. It is in line with the analysis in Table 2 which indicates the high variability of sales. The high variability can lead to the difficulty of sales prediction.

SARIMA (p, d, q)(P, D, Q)s Forecast

Since the sales are not stationary, the data should be transformed first. This transformation is done in the training data set by taking out the seasonal pattern by seasonal differencing. This differencing is done by subtracting the data on each same seasonal period from its previous seasonal observation data, or it can be written as [7]:

$$X_t = Y_t + T_{t-m} \tag{11}$$

While Y_t is the input data, m is the number of periods in the seasonal pattern, and X_t is the new data after the differencing process.

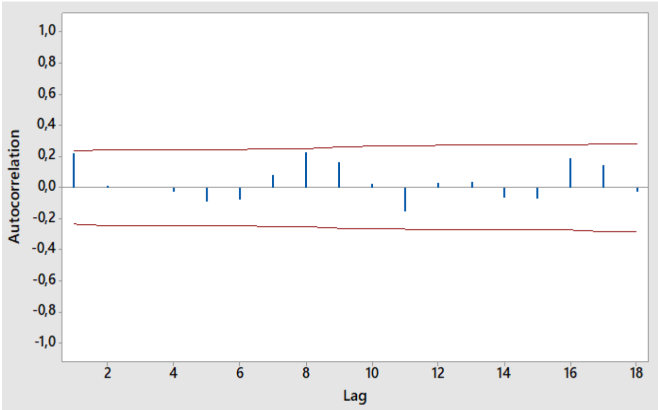


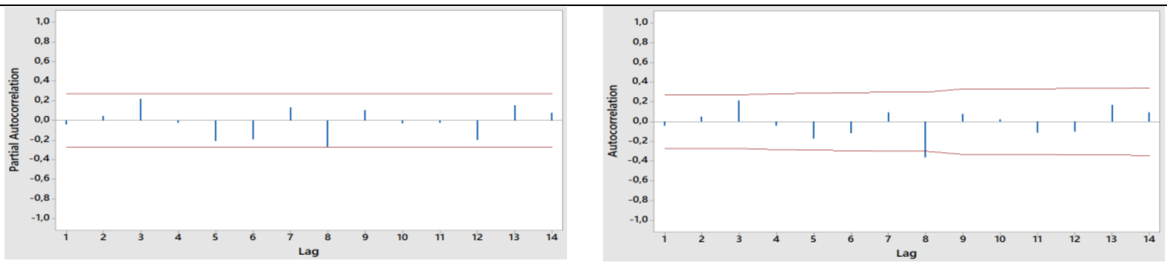
Figure 2. ACF Graph of Sugar Sales

The KPSS test shows that this transformed data has a value of 0.12. This value indicates that the transformed data is stationer since the KPSS value is under the critical value of 10% significance level, which is 0.34. This result explains that there is no need to differentiate the trend pattern.

This new data is ready to be analyzed to find the SARIMA order. Since there is no need to do trend differences, the trend order in (p,d,q) is (0,0,0). The seasonal length is 8, s is 8, and there is one-time seasonal difference, therefore, D is 1. The PACF and ACF graphs are analyzed. The number of PACF and ACF values that exceed the control line are considered the maximum number of order P and Q possibilities, respectively. These spikes happen in the corresponding number of lag values that same to the seasonal period length or its multiple length [7].

Figure 3 (a) describes the PACF, and Figure 3 (b) explains the ACF graphs of the stationer data. There is a spike in lag 8 for each graph so that P=1 and Q=1. Thus, there are three possible SARIMA models those are SARIMA (0,0,0)(0,1,1)8, SARIMA (0,0,0)(1,1,0)8, and SARIMA (0,0,0)(1,1,1)8.

Those three models are run on the training data to see whether the SARIMA assumptions are satisfied. If more than one model can satisfy the parameter estimate test and residual requirements, this study compares the performance of those forecast models by choosing the smallest MAPE from the testing data.



(a) (b)

Figure 3. Graph of Transformed Training Data After Seasonal Differencing (a) PACF and (b) ACF

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
SAR 8	-0,653	0,212	-3,08	0,003
SMA 8	-0,082	0,264	-0,31	0,756
Constant	-9,17	7,6	-1,21	0,233

(a)

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
SAR 8	-0,594	0,123	-4,84	0
Constant	-8,97	6,9	-1,3	0,2

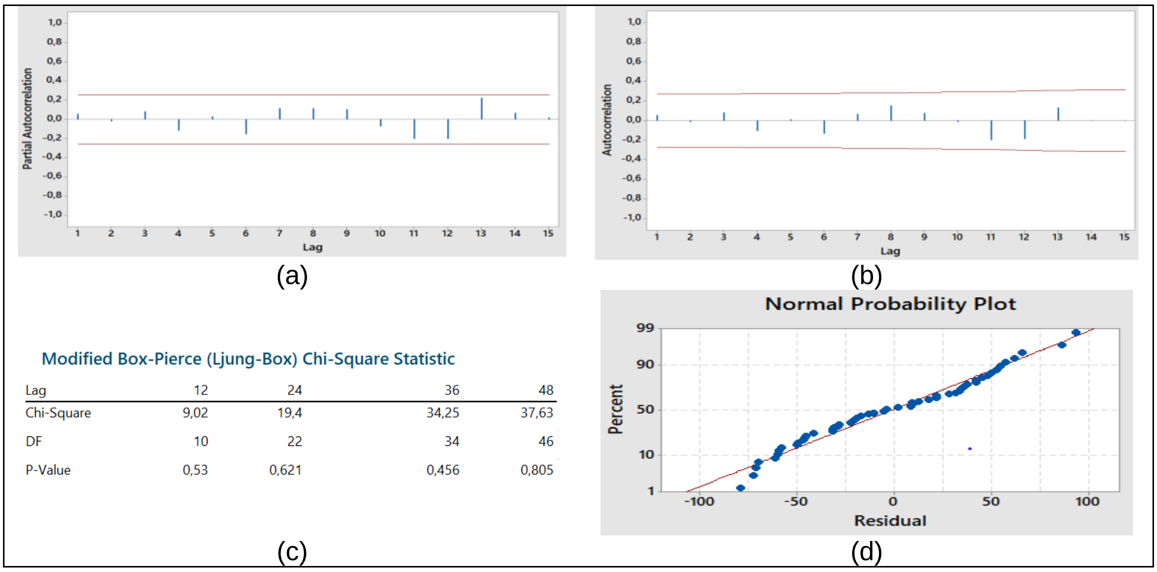
(b)

Final Estimates of Parameters

Type	Coef	SE Coef	T-Value	P-Value
SMA 8	0,781	0,104	7,48	0
Constant	-5,64	2,01	-2,81	0,007

(c)

Figure 4. Parameter Estimate Test (a) SARIMA(0,0,0)(1,1,1)8, (b) SARIMA(0,0,0)(1,1,0)8, (c) SARIMA(0,0,0)(0,1,1)8



Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag	12	24	36	48
Chi-Square	9,02	19,4	34,25	37,63
DF	10	22	34	46
P-Value	0,53	0,621	0,456	0,805

Figure 5. Residual Testing of SARIMA(0,0,0)(0,1,1)8 Model (a) PACF, (b) PACF, (c) Normal Probability Plot, (d) Ljung-Box Test

Figure 4 shows that there is only one model that satisfies the parameter estimate test, that is SARIMA (0,0,0)(0,1,1)8. The parameter estimate test is done in Minitab Software. If all the P-values of the test are less than 0,05, the parameter is significant or fit to be used [32]. The residual of SARIMA (0,0,0)(0,1,1)8 the forecast should be independent, homoscedasticity, and have a normal distribution to avoid a biased forecast. These assumptions can be checked using ACF, PACF, Ljung-Box test, and normal distribution tests [2, 31, 32, 34].

Figure 5 shows these residual tests of SARIMA (0,0,0)(0,1,1)8. Figures 5 (a) and (b) indicate that there is no value of each PACF and ACF graph that is out of the control line, concluding that the residuals are independent or have no autocorrelation [32]. These figures also indicate that the residuals are homoscedastic. Strengthening this analysis, Figure 5(c) also explains that the P-value of the Ljung-Box test is above 0.05, indicating that the residuals are independent, if there is no autocorrelation [32]. Figure 5(d) shows that the residual also has a normal distribution.

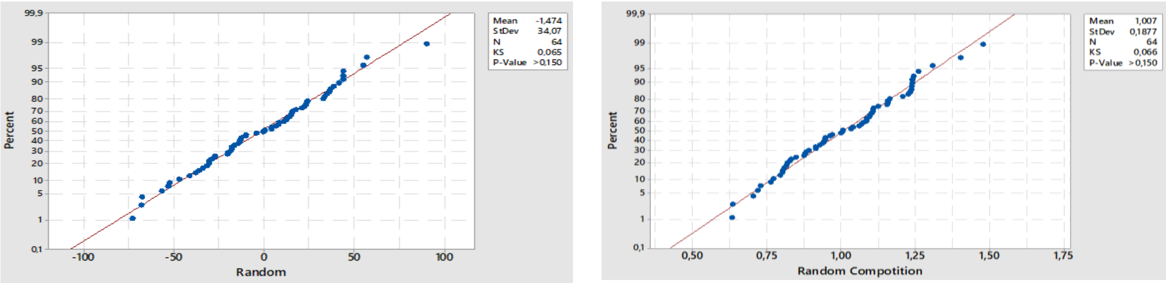
After the forecast model is found, this study needs to see the performance of this model by calculating MAPE. Based on the testing data, the MAPE of this forecast model is around 15.22%. It means that SARIMA (0,0,0)(0,1,1)8 has a good forecast result because its MAPE is around 10%-20% [16]. This good forecast result also strengthens the popular belief that SARIMA performs well [2][7] and is suitable to be used as a forecast model in retail as has been concluded based on the literature review study analysis.

Decomposition Forecast

After running additive and multiplicative decomposition models based on (4) and (5), and later checking the residual or random assumptions for both models, only the multiplicative model meets this assumption. Figures 6a and 6b give information about the test of both decomposition models using the Kolmogorov-Smirnov Test. Figure 6b shows that the distribution of residual in the multiplicative model is normal and its mean is nearly 1, which fulfills the residual assumption for the multiplicative decomposition model [30]. Figure 6a shows that the residual test for additive decomposition cannot meet its residual assumption. Although the residual distribution is normal, its mean is around -1.47, which is far from 0 [30]. The residual assumption of the additive model is not satisfied. Hence, this study only uses multiplicative to forecast.

This residual testing to justify the decision to choose the decomposition model is conducted to improve the comparison study between SARIMA and the decomposition model that was done by Guarnaccia et al. [29]. This test is important to avoid bias. Figure 7 shows the result of multiplicative decomposition in sugar sales. This figure has not shown the forecast value yet, but it shows each decomposition pattern of the data clearly.

The decomposition cannot only be used to help forecast but also can be used to explore and understand the data pattern in the preprocessing step [7, 40, 41]. Decomposition can be used to explore the data since by using decomposition, all trend, seasonal, and random patterns of data can be known and visualized.



(a) (b)

Figure 6. Decomposition Residual Test (a) Additive Model (b) Multiplicative Model

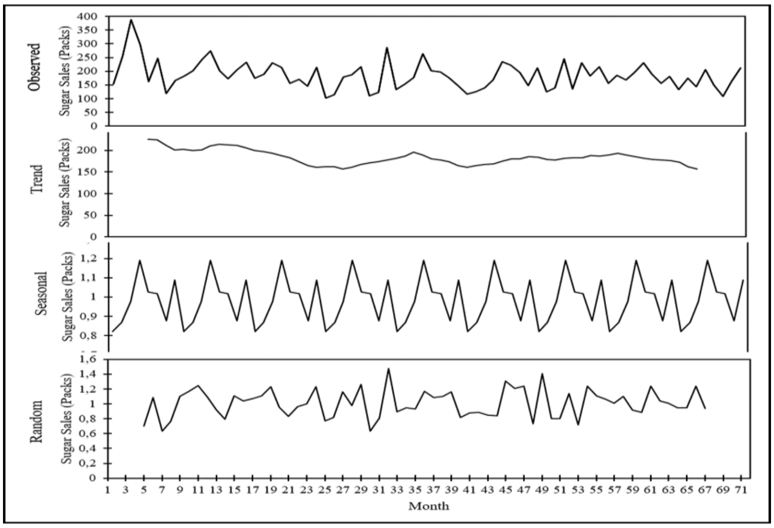


Figure 7. Multiplicative Decomposition of Sugar Sales

Figure 7 explains that there is a declining trend in sales of sugar but this trend is only little and almost not noticeable. This slight downward trend might be the reason for SARIMA does not consider it in the model. However, if the decomposition is used, this slight trend is still considered and it will be taken into account in the forecast model. This condition also indicates that decomposition is more sensitive to trend data patterns than SARIMA.

SARIMA(0,0,0)(0,1,1)8 only has a seasonality pattern recognized and forecasted. Because the orders of trend pattern or p, d, and q in SARIMA(p,d,q)(P,D,Q)s model are all 0.

The decomposition forecast model is classified as a hybrid forecast model [42]. It means that the decomposition splits the data into several data patterns, forecasts each data pattern, and combines it as a final forecast result.

Sugar sales can be split into seasonal, trend, and error patterns. For the seasonal data, after the decomposition of splitting data is done, the estimation of seasonal data can be known, and the values are fixed for each of the same t periods in different seasonal times.

This research estimates the trend data by using a double-moving average. To find the period in a double-moving average that has the minimum MAPE of testing data, the simulation using several periods in a double-moving average with a multiplicative decomposition forecast model is done.

Figure 8 informs the MAPE comparison of several possible periods. The MAPE has a U-shape graph. The MAPE values of the multiplicative decomposition model with double moving average trend prediction have smaller MAPE values than SARIMA (0,0,0)(0,1,1)8 at periods three and four of the double moving average. Those MAPEs are 13.64% and 14.01% respectively. These MAPE values keep increasing and become higher when the period of double moving average gets longer. The MAPE value increases above 20% when the period of double moving average reaches nine periods. Therefore, multiplicative decomposition with 3 periods of double moving average forecast model is used based on the smallest MAPE.

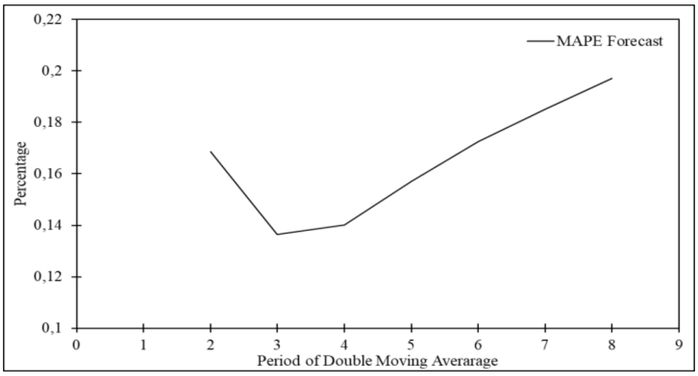


Figure 8. MAPE Comparison of n Period from Double Moving Average for Multiplicative Decomposition Model

Based on this result, similar to SARIMA (0,0,0)(0,1,1)8, the decomposition model has a good forecast result because its MAPE can be around 10%-20% [16].

Discussion

This study aims to answer two research questions. First, to find the most suitable forecast model between SARIMA and decomposition models to predict sugar sales at the retail level for a case study of a retail store in Indonesia. Second, to find the forecast method that can capture data patterns better between those two forecast methods.

Based on pattern analysis and residual testing, SARIMA(0,0,0)(0,1,1)8 is the only possible model from the SARIMA model. Considering the graph of sales pattern and residual test, the multiplicative decomposition model is chosen to be analyzed further. Based on the MAPE comparison of several periods of double moving average, the multiplicative decomposition with three periods of double moving average forecast model is chosen to represent the decomposition model.

Table 3 shows the MAPEs of SARIMA and multiplicative decomposition models of the testing data set. Both models have good prediction abilities since their MAPEs are under 20% [15][16]. However, the multiplicative forecasting model performed better by 1.58%.

Although neither model has a MAPE under 10% to get an excellent prediction ability standard [15][16]. This result can be considered good since the sales of sugar have high variability based on the coefficient of variation (CV) that is above the accepted standard. The CV of these sales is 27.44%, while the CV standard is 15%. This high volatility in retail is similar to what has been mentioned in previous studies by Badorf and Hoberg [1] and Almeida and Veiga [2].

Table 3. MAPE Comparison of Forecast Models

Possible Forecast Models	MAPE (%)
SARIMA (0,0,0)(0,1,1)8	15.22
Multiplicative Decomposition Using Double Moving Average	13.64

This result also fulfills the first aim of this study, which is to find the most fitted forecast model between SARIMA and decomposition models to predict sugar sales at the retail level for a case study of a retail store in Indonesia. The answer to this objective is the multiplicative decomposition model.

The result of this study is in line with Guarnaccia et al. [29] research. As mentioned previously, in the study of Guarnaccia et al. [29]There is no clear explanation of which decomposition type is used and no residual test of decomposition. If the residual test for the decomposition model is not performed, there will be a possibility of bias in the result. This results in a problem for future forecasts, in which the data is not analyzed in the study. This is because the forecast model is rigid or very sensitive only to the training data.

This problem is tackled in this study by analyzing the residual testing for the decomposition model, which was missing in the previous study. However, unexpectedly, the results of both studies are the same, which shows that the decomposition model performs better than SARIMA. This condition might be because the decomposition model is more sensitive and can accommodate the data pattern better.

There is a significant difference in how both models treat the data pattern. The crucial difference for both models is that SARIMA depends on the stationary test every time the differencing is done to treat the data pattern, either seasonal or trend differencing. Further, differencing is needed if the stationary test shows the data has not been stationary yet. Different from SARIMA, the decomposition model only depends on the stationary test for initial data checking. If the stationary test shows that the data is not stationary and shows there is seasonal data in the ACF, both the seasonal and trend difference will always be performed, without checking the seasonality test again. Thus, no matter how small the trend pattern is, the decomposition will always treat it as a significant pattern to be considered. Making the decomposition model more sensitive to trend patterns.

This conclusion satisfies the second objective of this study, which is to find the forecast method that can capture data patterns better between SARIMA and decomposition forecast models. In terms of trend pattern, the decomposition forecast model is more sensitive compared to SARIMA, however, both models show similar sensitivity for seasonal patterns.

Based on many previous studies, ARIMA or SARIMA is a forecast model that is widely known and used for prediction [2, 7, 17, 22, 23]. However, based on this analysis, the decomposition model can be a good alternative to be used for prediction at the retail level because it can capture and accommodate data patterns better than SARIMA.

Figure 9 shows the forecast result of the SARIMA and decomposition models for the next 10 periods in the future. The pattern of the forecast is quite similar, but there is a difference in the level or number of sales forecasted. Both models show a similar seasonality pattern but a different trend pattern. This similarity is because those forecast methods use the same approach to predict, which moves out the considered significant data pattern by using differencing, before performing a forecast.

If the only consideration in choosing the forecast model is the smallest MAPE, multiplicative decomposition using the double-moving average forecast model is chosen for this case. However, there is a need to understand that the longer the forecast is used, the lower the number of forecast results is. This is because the slightly inclined trend from the observed sales is considered in the decomposition model. For the SARIMA forecast, this condition does not occur. The forecast for a long period will fluctuate at the same level because SARIMA does not consider the trend. To avoid a deep slope for the long forecast in the decomposition model, it is better to not forecast for a long period and try to observe new data to adjust the forecast model. Moreover, since the double moving average period is only three, the forecast result is highly affected by the recent sales; thus, making the long period forecast is not preferable.

Based on this conclusion, retail should consider the forecast period carefully. If the retailer prefers a more precise forecast, the retailer can use a multiplicative decomposition forecast model with a short forecast period, leading to more frequent forecast activity. If the retailer prefers a longer forecast period and less frequent forecast activity, the retailer can use the SARIMA forecast model.

The sugar sales data also shows that the sugar demand is very volatile. The volatile demand is considered a threat to the supply chain since it decreases supply chain performance, increases supply chain transportation costs [3] and increases the risk of the bullwhip effect [13]. Considering the result that the precise forecast at the retail level needs a short forecast period and frequent forecast activity, which might lead to some resources for doing forecasts, the actors at higher supply chain levels might consider collaborating with retailers to forecast and share inventory information, to reduce the bullwhip effect.

The reason why the decomposition forecast model captures data patterns better than SARIMA is based on the fundamental step of treating the data. The result of this study can give an insight into the fact that there is another alternative forecast model for retail that is sensitive to data patterns other than SARIMA. Logically, because this fundamental step of treating the data in the decomposition model will always be repeated when the decomposition forecast model is used, the result of this study can be applied to other forecasts of different products and different locations. However, further research must be conducted because there is still a limited study focusing on decomposition forecasts for retail. Moreover, the performance of the forecast model depends on the data itself.

Wu, et al. [41] also mentioned that decomposition is often used only for preprocessing steps in time series data analysis and its potential has been unnoticed and has not been explored thoughtfully for forecast. This condition might be the reason for limited studies discussing decomposition for forecasting, not only in retail cases but in general. Thus, the forecast uses decomposition should be studied more, moreover discussing how to improve the forecast performance of long-term forecast using decomposition, because this study shows that decomposition can outperform SARIMA when it is used for short-term forecast.

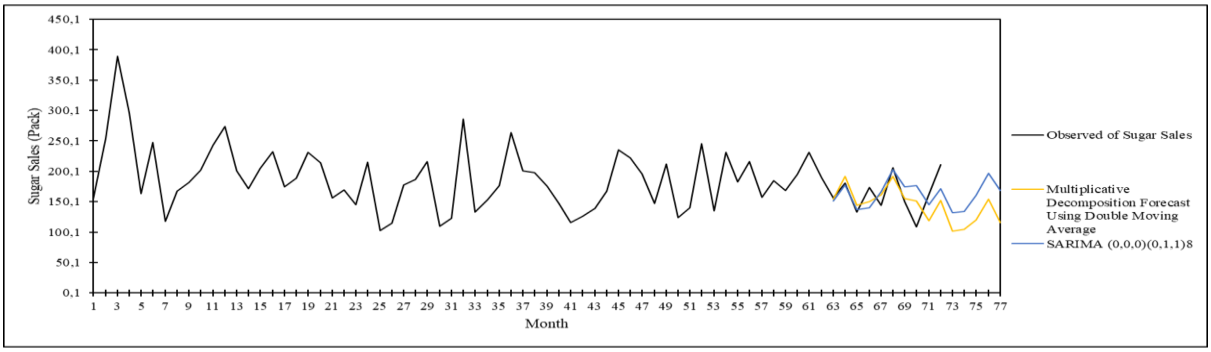


Figure 9. Comparison of Forecast Results

The method for predicting the trend pattern contributes to the quality of the decomposition forecast result. Hence, different methods to predict the trend, such as linear regression and others, can lead to different MAPEs. It can be an interesting topic to find the most suitable method to predict the trend in the decomposition model for future research.

It is worth noting that it is impossible to use both forecast models in Software R with the available packages in this study. Software R mentioned that there was a need to have more data input. This might be because of the long period of seasonal data patterns. Therefore, the calculation forecast in this study mainly used Minitab and MS Excel. This condition also indicates that there is a limitation of this study regarding data, which shows the necessity to have more data.

CONCLUSION

This study focuses on finding the most suitable forecast model that can capture data patterns well to give a good prediction of sugar sales in a retail store using SARIMA and decomposition models and also finding the forecast method that can capture data patterns better between those two forecasts methods. This research takes a case study of a retail store in Yogyakarta Province, Indonesia.

Sugar sales in this retail store have high volatility, which is shown by the coefficient of variability (CV). The CV of these sales is 27.44%, which is almost twice as high as the maximum standard of accepted CVs. Therefore, it is quite difficult to get good forecast results.

Despite this challenge, both SARIMA and multiplicative decomposition with double moving average forecast models achieve considerably good forecast results, which is indicated by small MAPE. The MAPEs of both models are 15.22% and 13.64% respectively. Thus the decomposition model performs better than SARIMA. This condition is because decomposition is more sensitive to trend data patterns compared to SARIMA. The decomposition model is forced to consider the trend pattern as a significant pattern to be treated, no matter how small the trend pattern is, but this is not the case for the SARIMA model.

This study chooses multiplicative decomposition with 3 periods of double moving average as the most suitable forecast model for this case. This short period of double moving average means the forecast can not be done for a long period because the forecast is heavily affected by recent sales. Hence, to have the most precise decomposition forecast result, the retailer needs a short forecast period and more frequent forecast updates, leading to higher resources to forecast compared to those of SARIMA.

This study uses a double-moving average to predict the trend. However, different trend prediction models can lead to different MAPEs. Therefore, it might be interesting to find other models to predict trend patterns that are more suitable to be combined with the decomposition model and can be used for longer forecast periods.

Having good sugar forecasts is important because sugar is one of the staple foods in Indonesia, the sugar sales in retail are the representation of the household sugar consumption in Indonesia, and there is a high volatility of sugar sales in retail. The precise forecast of sugar helps to control inventory and maintain consumer satisfaction. Furthermore, it can reduce the bullwhip effect for the higher supply chain level. Reducing the bullwhip effect can also help the government to understand the demand pattern well and help to maintain the sugar supply and price.

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