Impact of Reverse Supply Chain on Bullwhip Effects in Beef Supply

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***Abstract*— Efforts to reduce losses due to product returns and works to provide value to the products returned are topics that are widely discussed by researchers today. Many products returned by customers for various reasons have an impact on the company's stock, one of which causes inventory instability. Coupled with fluctuating beef demand patterns and are influenced by multiple factors and types of customers. For this reason, the purpose of this study is to minimize the risk of beef stock. The method used in this research is to analyze the reverse supply chain flow process and then look for the bullwhip effect in the beef industry. The next step is to analyze inventory patterns, and beef stock estimates, to get the most appropriate type of forecasting. From this study, we got a new model for the reverse beef supply chain. A new formulation for a simple stock policy by adding the return activity R_{t-n}, and completing the bullwhip effect using SARIMA, through this research, we can also see the impact of the reverse supply chain and product return on the bullwhip effect.**

***Keywords*—** *Reverse Supply Chain, Bullwhip Effect, ARIMA, Inventory, Beef.*

1. Introduction

Reverse supply chain arises because of product returns from customers for various reasons, which is an unavoidable event. Considering that there are still many problems regarding the deterioration of product quality, changing customer demand so that sales decline, shipping errors, and many factors that need to be appropriately controlled [1], [2]. With these conditions, the company must reduce losses due to product returns by making repairs, repackaging, and reselling it to consumers with the added value of the product still exists. Furthermore, the product still meets the following consumer quality standard.

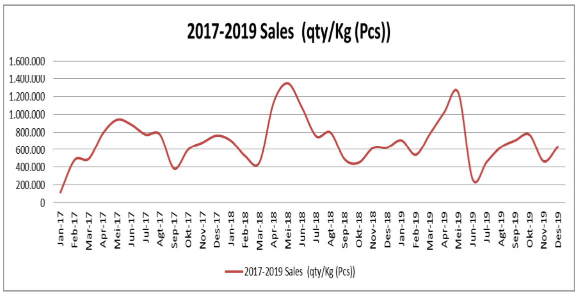

Figure 1. Record of fluctuating sales for the 2017-2019 period on a beef distributor in Cileungsi, West Java.

Figure 1 shows the pattern of sales that occur in PT Cianjur Artha Makmur as a beef distributor in Cileungsi, West Java, which is a distributor of beef that meets the demand for the Greater Jakarta area, Bandung, Surabaya, and Bali. The company has 250 customers [3]. The fluctuating and unpredictable demand conditions affect the level of beef supply in the company, wherefrom the supply side, some products are inadequate and excess quantities. Beef procurement patterns also influence supply conditions in this industry. When the company supplies meat through slaughtering cattle impact will produce results that are not needed by the customer at that time so that the excess stock and some products are lacking because of high demand. The same condition is also experienced if the company makes direct purchases of meat in the form of imported carcasses; in this condition, the company can indeed make purchases based on the items needed. However, there are also requirements to have to buy other products with a ratio of 70:30 between the products whose movements fast with products that move slowly. This condition influence by inaccurate information about the purchase plan from the customer.

Stock conditions also affect delivery patterns, because, for some products that are not available on-demand, they can only fulfill the next day or when meat products are available. Distribution patterns can see in the graph in Figure 2 below. From the chart, it

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can see that the number of shipments to customers is not always the same, and the conditions are very diverse.

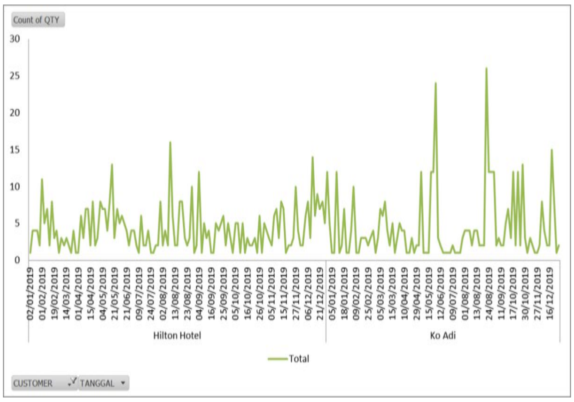

Figure 2. A pattern of customer shipments per day in one year in units of delivery intensity

Seeing from this condition, the writer tries to analyze the problem starting from the presence or absence of the bullwhip effect phenomenon in the company, then looking for the right inventory forecasting pattern to reduce the effect of the bullwhip effect.

2. Literature Review

Beef demand forecasting is an important topic to discuss, considering beef is one of the typical agro-industrial products that is easily damaged and has a short shelf life in normal conditions without special treatment (Singh 2018). Considerable changes in demand are also a characteristic of meat products, given the high price of meat consumption will increase at certain times. The increase in beef consumption is affected by religious holidays, culture, the festive season, and the processed meat food industry. The cold chain is a solution carried out by industry to extend the life of meat during storage and distribution [4], [5]. The problem of differences in supply and demand will ultimately have an effect on reverse beef from customers returned to the company [6].

The obstacle that finds in distribution systems is the bullwhip effect phenomenon, namely the distortion between supply and demand [7]. The bullwhip effect is due to an incorrect interpretation of demand data in each distribution chain. The condition was found by The distribution company, where there are some errors in the distribution of its products. The situation is the bullwhip effect. The Bullwhip effect distorts the demand from the bottom chain (end customer) to the distribution chain above it. The error occurs caused by a different number of requests, that received by the distributor. It was compared with the amount needed by the market. The number of requests received by distributors from each retail differs from the amount required by the market or consumers, and this error is called the bullwhip effect [7]. [8] is doing a measurement of the bullwhip effect in the supply chain, with a first-order bivariate autoregression demand model. In this paper, the size of the bullwhip effect is determined through an analytical approach using the minimum average square error (MMSE) forecasting method. [9] measured the bullwhip effect concerning price and demand, where the bullwhip effect was measured using two simple stages using one supplier and one retailer who received dynamic demand.

Research on BWE has been done before, [10] in the study Look for the relationship between BWE and demand and forecast moving average (M.A) to stochastic lead times. Research using Autoregressive Model (AR 1) for Prediction of Lead Time Request and making forecast Prediction to got BWE, the BWE factor that analyzes is Demand and Lead Time forecasting. [11] Analyzing the main factors that influence BWE on the reverse supply chain. Research starting with examining the output order to know the forecasting type, Inventory conditions, and Shipping to finding the variance of the request. The BWE factor analyzed is stock, WIP, forecasting techniques, and variability of customer demand. [9] Measure BWE and its effect on price and demand sensitivity. The study analyzed the difference of request, Request lead time, and Difference in order amount for BWE factor, and this study focuses on Price and demand and the impact in BWE. [12] Conduct simulating, Forecasting, and customer requests to get their effects on BWE. The Analysis using SARIMA and comparing forecast to see the impact of predicting on BWE. Analysis in this study using SARIMA and then comparing the estimate to see the effect of Forecasting on BWE. The BWE factor in this study is the Accuracy of Forecasting, aggregate Forecasting, and responsive Forecasting. [13] Look for the causes of disruption of BWE Cash Flow in the centralized supply chain, the study indicates order policy, output, the impact of order size then get a Variant of BWE. Distribution of parameter information to all actors. Parameters of retailers and distributors. [7] Conduct BWE analysis for multi-products with public demand. In this study, the first step is to check the BWE level, then check BWE Impact, BWE Category, and conduct a Comparison of product level, category, and variant order. Order decisions based on the category level, order pooling.

Reverse logistics is the activity of returning products from customers to distributors or companies for various reasons, in reverse logistics activities returned products are given added value to avoid more losses due to disposal [9], [14]. Reverse logistics activities often occur due to excess stock, end of life (EOL) products, packaging returns, repairs for repairs, and due to consignment [15]. For this reason, prevention of reverse logistics needs to be done, one of which is to control distortions that occur due to the bullwhip effect, it is expected that the smaller the level of the bullwhip effect, the lower the reverse logistics will be carried out. Research on the relationship between reverse logistics effects has been done before [11] in his study found that the bullwhip effect will affect based on the percentage of the product returned.

In the paper [11] mentioned that only a few researchers who talk about the bullwhip effect in the reverse supply chain, most researchers discuss the bullwhip effect for the forward supply chain. The bullwhip effect research on this matter is about the importance of the bullwhip effect in the reverse supply chain, regarding the commercial policy of product returns and product refusal to be reused or recycled, the variance of inventory value, the combination of regular stock and the product of repairs. [16] conducted a literature review whose results showed that there was a common cause of the bullwhip effect in the closed-loop supply chain. However, most studies do not pay attention to the quality differences between new products and reverse products. The addition of additional variables causes higher variability, which in turn makes the bullwhip effect. The study for the bullwhip effect can see in table 1.

In his book [17] describes as the excessive attitude of the Supply Chain actors to changes in demand at the retail level, small changes at the retail level can cause significant changes at the supplier level, this can show in Figure 3 below.

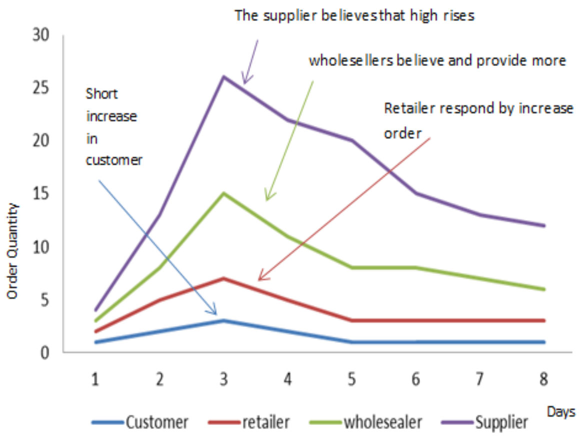

Figure 3. The illustrated impact of the Bullwhip Effect [17].

From Figure 3, it finds that fluctuations are more significant because orders were delivering to the supply chain from retailers. Bullwhip fluctuations lead to unstable production schedules. It also affects aspects of production, such as overtime, subcontracting, adding assets, re-ordering, adding new employees, and laying off workers and causing the raw material stock to expire [17].

The end of this study is to try a forecasting model that is suitable for the case of beef. Researchers have widely used several methods of Forecasting in many instances. [12] uses ARIMA because the data used tends to be used or requested to investigate the case of demand forecasting in the US car industry. [18] do time series forecasting to get passenger forecasting and aircraft type, this type of prediction uses because it can use because it can see about statistical changes. [19] use ARIMA for Deep Neural Network Based for case Demand Side Short Term Load Forecasting. This forecasting method is quite suitable to be applied in the case of beef given the type of sales demand that changes with the seasons. In this study, Seasonal ARIMA (SARIMA) will be used using R Studio.

To facilitate the research process, the methods used in this study is described as follows:

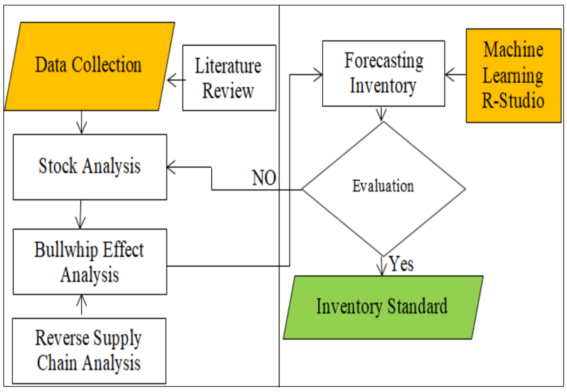

Figure 5. Research Flow Chart.

3. Model of Supply Chain and Bullwhip effect

In the case study of measuring the bullwhip effect in the beef industry according to field conditions, the effect will be discussed at two levels, namely distributors and retailers/retailers, as illustrated in Figure 4 below.

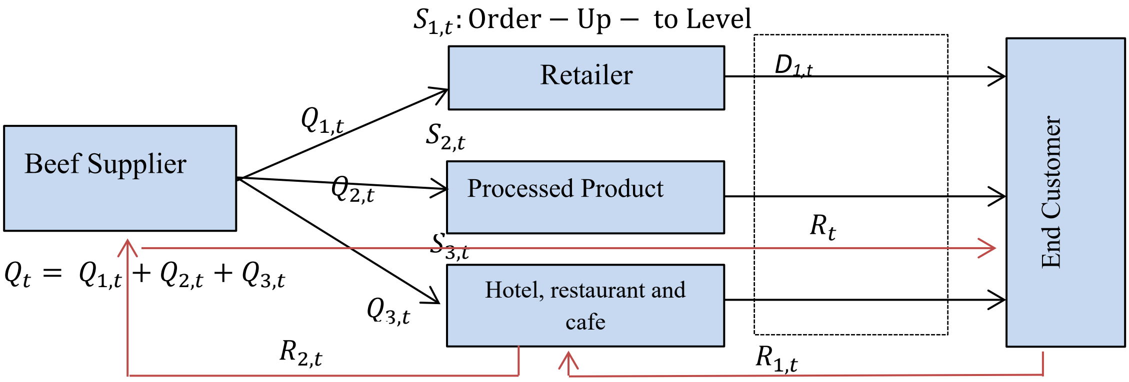

Figure 4. Supply chain models for stock movements and product returns.

From Figure 4, the Bullwhip effect measurement is calculated based on two supply chain levels, namely distributors and retailers, as in Figure 3. Where retailers use simple stock policies [20], [9], [12] [21], [22], namely minimizing storage costs and preventing the occurrence of stock shortages, where the policy of stock and product orders is defined as follows.

$$Q_t = S_t - S_{t-1} - D_{t-1} \qquad (1)$$

Where S_t is the message point limit or order-up-to (OUT),), S_{t-1} and D_{t-1} are the conditions of supply and demand received by retailers in the $t-1$ period, the assumption in this model is the order received at the beginning of the period t. In research[7]–[13], [16], [20], [23] the equation for finding the value of the bullwhip effect is defined as follows:

$$\text{BWE} = \frac{Var(O_t)}{Var(D_t)} \qquad (2)$$

Where $O_t = O_{1,t} + O_{2,t}$

and $D_t = D_{1,t} + D_{2,t}$

$$Var\ (O) = \frac{O_{order}}{\bar{X}_{order}}$$

$$Var\ (D) = \frac{O_{Demand}}{\bar{X}_{Demand}}$$

$$\sigma = \sqrt{\frac{\Sigma[x_1 - X]^2}{(N-1)}} \qquad (3)$$

If the value of BWE > 1 can be concluded that in the company's transactions, there is a bullwhip effect [17].

Forecasting demand can be analyzed with many forecasting methods are used by previous researchers [7], [10], [20], by using ARIMA (Autoregressive integrated moving average) to get the best inventory forecasting. ARIMA completely ignores independent variables, using past and present values of the dependent variable to produce accurate short-term Forecasting. ARIMA can use statistical relationships between variables to forecast the historical value of the variable to be predicted [24], [25]. The ARIMA formulation can be described as follows:

$$D_t^l = D_t + D_{t+1} + \cdots + D_{t+l-1} = \sum_{i=0}^{l-1} D_{t+1} \quad (4)$$

Where N is the number of periods used as an average parameter to estimate demand from retailers or retailers. To get the value of $\widehat{D}_t^l$, the formula for $\widehat{D}_t^l$ and $\hat{\sigma}_t^l$ must be determined beforehand, where $\widehat{D}_t^l$ is the accumulated value of the retailer's or customer's t demand from the t period to the period $t + L - 1$

In R studio, a seasonal ARIMA Model is an additional form of seasonal Forecasting in the ARIMA model. The model is defined as:

Arima $(p,\ d,\ q)\ (P,\ D,\ Q)_m$

Where (p,d,q) is a non-seasonal model part and (P, D, Q) is a Seasonal model part. With m is the number of observations in one year. For example in ARIMA $(0,0,0)\ (0,0,1)_{12}$ the model will show surges in lag 12 in auto correlation function (ACF) but no other significant surges and the exponential decay at the seasonal delay of Partial auto correlation function (PACF) (e.g., at slowness 12, 24, 36, ...).

4. Results and Discussion

This research begins by looking for the level of bullwhip effect that occurs in the beef industry. The analysis was conducted on several customers with the highest number of orders to the distributor. Based on Figure 3 above, a picture of the bullwhip effect condition that occurs within the company, the situation faced by the company is the shortage of meat inventory, which causes the repetitive delivery process. Efforts to meet the lack of inventory, by buying similar products to other distributors, with lower profits. Efforts to meet the shortage of inventory by making cuts to increase the risk of growing product stock in the slow-moving category.

Figure 4. List of customers based on shipping intensity

Based on Figure 4 above, the companies that will be calculated for bullwhip effects are PT Wahana, Lion Supermarket, and PT Aeon.

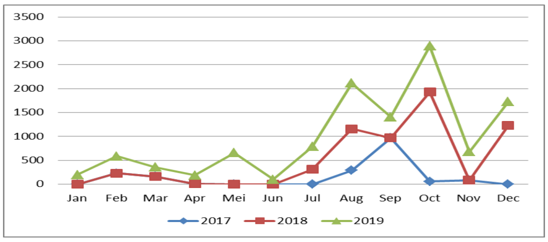

Figure 5. Customer Delivery trend in PT Wahana, a retailer company for the period 2017 until 2019.

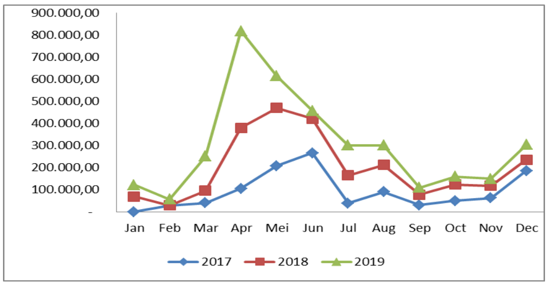

Figure 6. Customer Delivery trend in Lion Supermarket for the period 2017 until 2019.

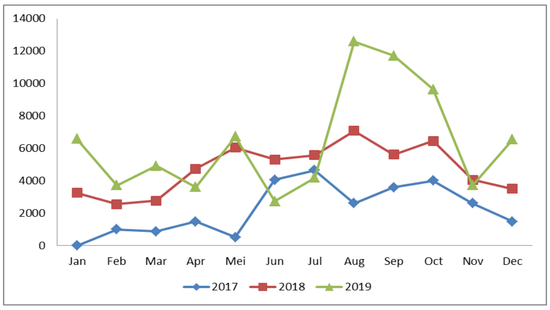

Figure 7. Customer delivery trend in Aeon hotel for the period 2017 until 2019.

From Figures 5, 6, and 7, it can be seen that the demand pattern of these two customers fluctuates quite high. However, peak demand experienced significant differences. Lion experienced peak sales in April, May, June, and July in connection with the month of Ramadan, Eid al-Fitr, and Eid al-Adha. While the Wahana PT has experienced peak sales in August and September. And to get the value of the bullwhip effect, the inventory and order are calculated.

4.1 Effect of the bullwhip effect and Reverse Supply Chain on Stock

Flow process reverse logistic in figure 5 is to find out the relationship between the reverse supply chain and bullwhip effect, it is necessary to describe the reverse process flow that occurs in the beef industry, based on a case study at beef distributor company [13], [26]. Reverse supply chain conditions can be illustrated in Figure 8 below.

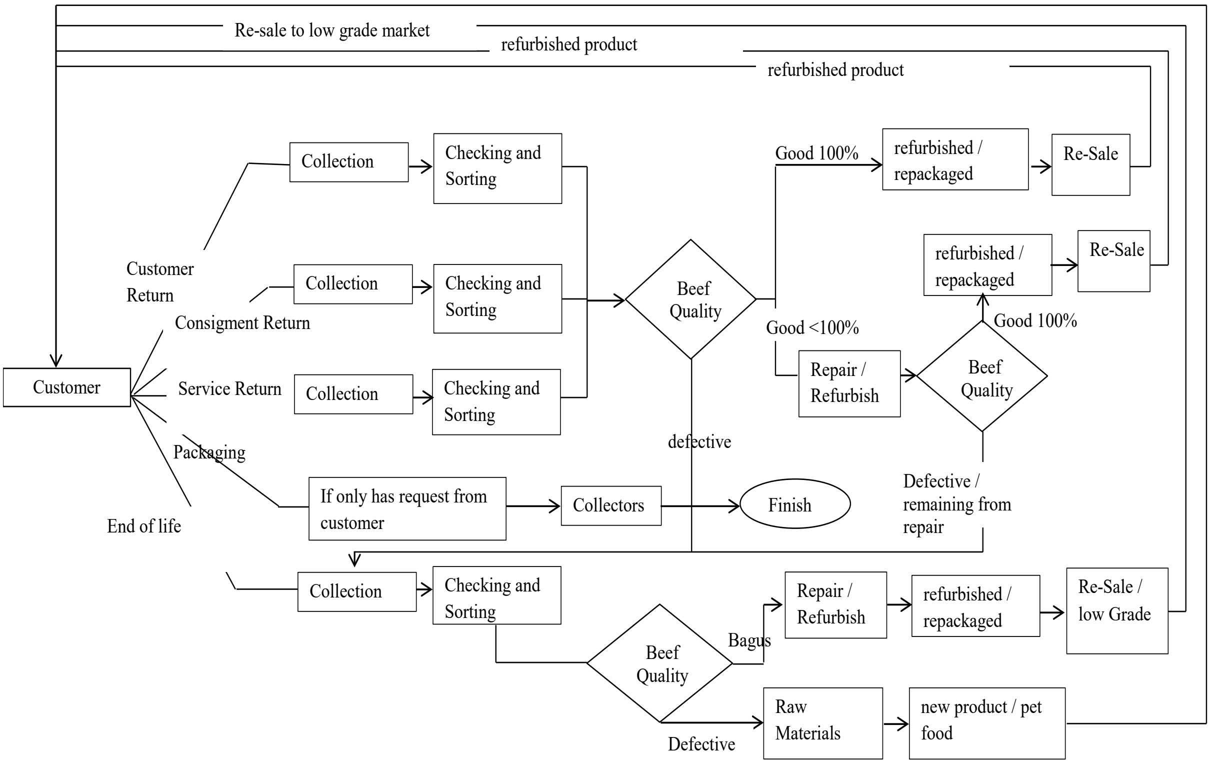

Figure 8. Reverse Supply Chain model in the Beef industry

Based on Figure 8, it can be concluded that the causes of Reverse in the beef industry are:

1. Product is expired
2. Defective products
3. Not suitable size
4. Does not match the quality
5. Not according to type
6. Over inventory

The model in Figure 8 was adopted from the model created by [27], while the cause of the bullwhip effect based on Figure 6 can be concluded as follows:

1. Empty stock so that it cannot meet customer demand.
2. Customers repeated requests due to increased demand at customers.
3. Incorrect forecasting information from customers can be impacted by the stock.

4. The impact of product return activities is the reduction in stock as a substitute item and the existence of products whose status cannot be used as inventory in functional categories until the quality investigation is completed.

Its to illustrate inventory patterns with additional conditions due to returns to reverse supply chains at the distributor level, formulation 6 completes inventory patterns if there are returns from customers who have received in the previous period.

$$Q_t = S_t - S_{t-1} - D_{t-1} - R_{t-n} \qquad (5)$$

Thus S_t is a message or order-up-to (OUT) limit, S_{t-1}, and D_{t-1} are the conditions of supply and demand received by retailers in the period $t-1$, R_{t-n} is the stock reduction to replace product returns p from the customer for reverse purposes of products sent in the previous period. The assumption in this model is that orders are received at the beginning of the period t. Mathematically, the stock movements using new formulation (5) can show in Table 2.

Table 2. Compare stock movement with the old model (1) and the new model (5)

	Old Formulation (1)				New Formulation (5)				
Product Name	$\boldsymbol{Q_t}$	S_t	S_{t-1}	D_{t-1}	$\boldsymbol{Q_t}$	S_t	S_{t-1}	D_{t-1}	$\boldsymbol{R_{t-n}}$
Shortrib (Kg)	**70**	100	10	20	**70**	100	10	10	10
Knuckle (Kg)	**40**	100	20	40	**40**	100	20	20	20

From Table 2, it can be seen that when a product is returned, the reverse supply chain procedure will apply, as shown in Figure 7, the distributor automatically sends a replacement product under the amount recovered. Automatically, the return status of the product recording becomes dependent because it is defective as the work goes out of the customer to be returned. At the same time, the distributor cannot record it as stock because the product has not been received or is on its way. If the stock reaches the central warehouse or branch warehouse, the output does not necessarily be included in the capital. Because it has to undergo various tests to find out whether the product is still feasible or not and is included in the Good stock category, it may be sent back to the customer or bad stock that must be destroyed.

The bullwhip effect conditions in Table 1 that used a new formulation. In case of recording a substitute product coming out of the warehouse to replace the returned product, the server will write it as a product going out to the customer, resulting in average shipping being seen rising, even though it shouldn't be. It happens a lot in the actual conditions of recording that have not been able to distinguish outgoing products for replacement with products for sale, according to Sales Orders.

[11] in a paper that analyzes the main factors that affect the bullwhip effect in the reverse supply chain using the same formulation as the formulation in equation 5. According to the paper, the influencing factors are stock factors, products work in process (WIP), and Forecasting. Lion and Wahana are the two customers who have the most significant order. Thus the effect of reducing stock to replace the returned product will significantly affect inventory. So companies need to make additional cuts or speed up the arrival of products from suppliers to keep maintaining product stock to meet customer demand [28]–[30].

Table 3. Average products with poor categories due to returns over three months

Type /Grade	Qty (Kg)	Beg. (Kg)	In (Kg)	Out (Kg)	End (Kg)	%
Chill Impor	1.014	103.743	207.421	208.604	102.560	10.2
Frozen	2.152	698.040	821.037	720.318	798.759	79.4
Chill Lokal	368	112.703	680.512	732.908	60.307	6%
A	854	31.727	23.276	16.523	38.480	3.8
B	761	5.884	4.930	4.873	5941	0.6
R	175	181	601	561	221	0.02
Total	5.324	952.278	1.737.778	1.683.787	1.006.269	100

Based on the condition of the returned product as the return data in Table 3 above, the actual bullwhip effect is as shown in Figure 9, where the bullwhip effect occurs for the three customers who are an example. In Figure 9, the score of a bullwhip is more significant than 1, based on [17] if the BWE value is more than one, a bullwhip effect occurs.

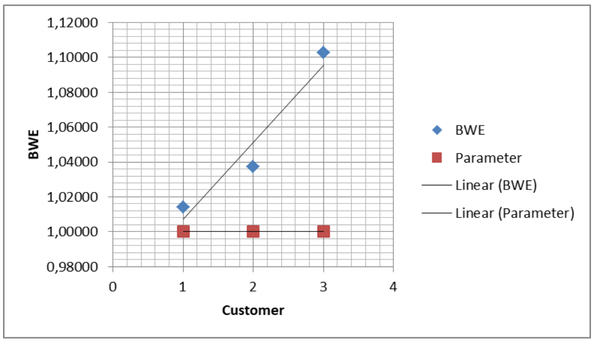

Figure 9. Bullwhip effect of Wahana, Aeon, and Lion

4.2 *Inventory Forecasting*

After analyzing the bullwhip effect phenomenon, the next step in this paper is to make the best forecasting pattern based on the data movement of the company. The meat distribution company used as a model is a company that obtains raw materials from two sources, namely cattle fattening cattle and direct carcass meat import. The company's sales data that are used for analysis are the data at the time the company starts operating, i.e., from January 2017, research and prediction of Forecasting are made using R Studio (Hyndman & Athanasopoulos 2018; Wickham & Grolemund 2016). The purpose of making inventory forecasting is so that the level of losses due to shortages and excess stocks can be minimized.

Based on sales and order delivery data from 2017 to 2019 as a database to find sales Forecasting numbers that are most close to the available data. In the initial stage, a preliminary analysis is carried out on existing data. A preliminary report can be seen in Figure 10.

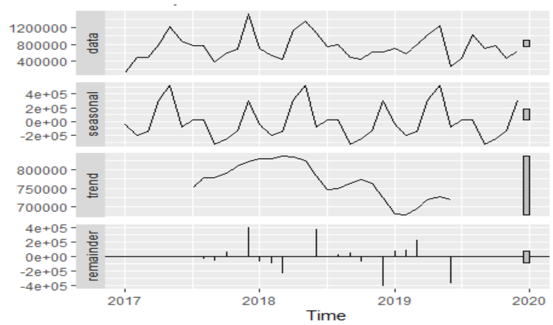

Figure 10. Decomposition of additive time series on sales data for 2017 - 2019.

From the data in the figure above, we get an interpretation in terms of trends, the seasonal, remainder (error), when compared with the original processed data. From the graph, there is a trend pattern that is still up and down, and this condition indicates that there are always seasonal trends that have not been obtained or other possibilities is that in the sales pattern, there are more than one or multiseasonal seasonal. For this reason, it is illustrated in the seasonal plot in Figure 11.

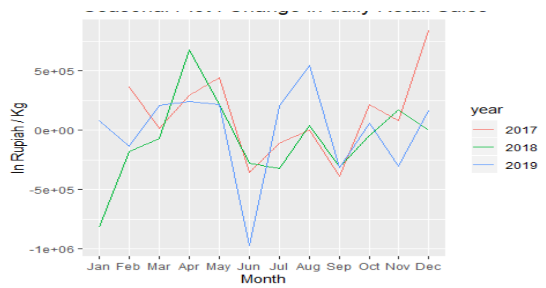

Figure 11. Seasonal Plot: Change in daily retail sales.

From Figure 11, we get a comparison of sales patterns between 2017, 2018, and 2019. It can be seen that there are multi-seasonal sales patterns because the customers of this distributor company are diverse, ranging from hotels, restaurants, cafes, supermarkets, catering, processed food industries, and the middle market and traditional.

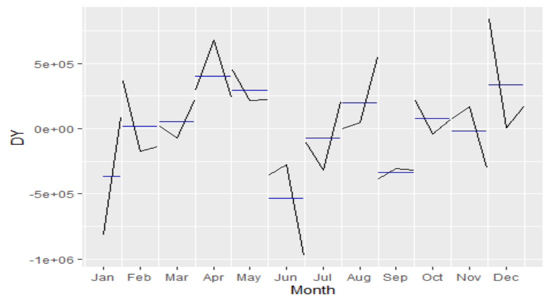

Figure 12. GG Subseries Plot (DY) towards sales patterns.

To obtain sales forecasting, the Forecast method used is the Seasonal naive method via the snaive library (DY). After that, the fit is made to all sales transactions and a summary of all transactions. The results obtained residual value sd: 408917.7823. Residuals are useful for checking whether a model has captured enough information in the data. The residuals were carried out in 3 stages, namely seasonal naive Bayes, A, N, N, and finally, the seasonal model obtained after ARIMA fit. A good forecasting method will produce residuals with uncorrelated residual properties. If there is a correlation between residuals, then there is information left in residuals that must be used in calculating estimates. Remaining has zero average. If the residual has an average other than zero, then the forecast is biased.

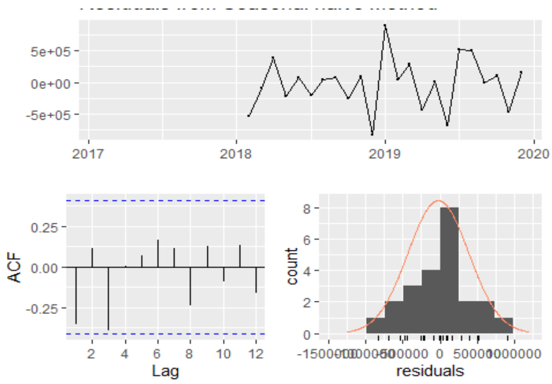

Figure 13. Residual from the seasonal naive method

From Figure 13 Ljung-Box test data Residuals from Seasonal naive method obtained is Q* = 9.6834, df = 7, p-value = 0.2072 with model df: 0 dan total lags used 7.

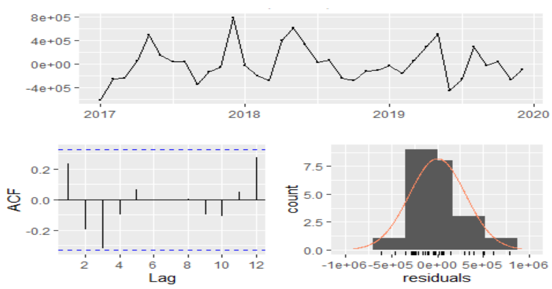

Figure 14. Residual from ETS (A, N, N)

From Figure 14 Ljung-Box test data residuals from ETS(A,N,N) obtained is Q* = 8.4884, df = 5, p-value = 0.1313 with Model df: 2. Total lags used: 7. The next step is to find the best forecast value by performing an ARIMA fit so that the best ARIMA model is obtained (0,1,1) (0,1,0) [12].

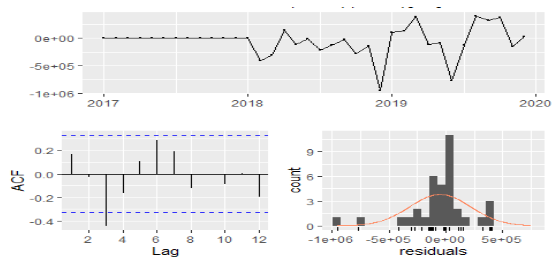

Figure 15. Residual from ARIMA (0,1,1) (0,1,0) [12]

From the Ljung-Box test in Figure 15 for Residual from ARIMA (0,1,1) (0,1,0) [12] we get Q * = 16,166, df = 6, p-value = 0.01289 and the df: 1 Model. Total lags used: 7. From best model (0,1,1)(0,1,0)[12} is obtained coefficient:

	ma1
	-0.8365
s.e.	0.2030

With log-likelihood = -325.98, AIC = 655.97, AICc = 656.57 dan BIC = 658.24. for error measurement for ME is -52905.77, RMSE 269435.5, MAE 159816.1, MPE -15.66592, MAPE 29.13241, MASE 0.7410097 dan ACF1 0.1628138. Akaike's Information Criterion (AIC) is useful in selecting predictors for regression. It is also useful for determining the order of ARIMA models [31]. Like only the AIC, the minimum BIC value is also obtained [32]. Where the AIC value is 655.97, and BIC is 658.24—thus forecasting with the best ARIMA model (0,1,1) (0,1,0) [12] can be visualized in graphical form, the results in Figure 17 below.

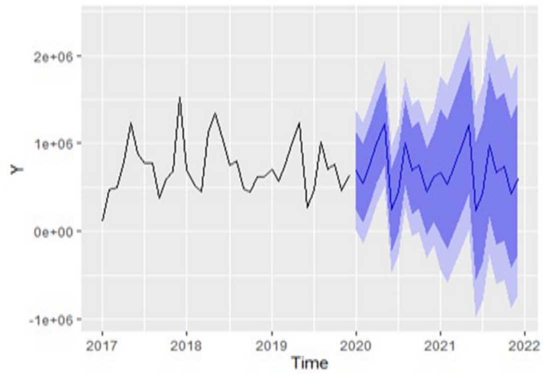

Figure 17. Forecasting using SARIMA in Rstudio with the best solution model (0,1,1) (0,1,0) [12].

From Figure 17, the results of Forecasting for 2020 to 2021, using ARIMA obtained sales tend similar to the previous period. So companies can use this forecasting pattern while evaluating Forecasting and actual.

5. Conclusion

The study found a new reverse supply chain model for beef. Where the pattern of product movement from product information is returned, withdrawn, then inspected the product. Then the product can be immediately resold, repaired, and then resold to a lower market or added value to a new product. From the reverse supply chain model, it was found that the reverse supply chain activities and product returns affect the bullwhip effect. Formulations for simple stock calculations should be added R_{t-n}, so those product return activities instead of products returned are not counted as sales, so the formulation becomes $Q_t = S_t - S_{t-1} - D_{t-1} - R_{t-n}$ so that each activity will be recorded more clearly. After knowing the bullwhip effect, an analysis is also conducted on the most appropriate type of Forecasting. In this case, the researchers used Seasonal ARIMA with three stages of residual Seasonal Naive Bayes, A, N, N. Finally, the seasonal model obtained after ARIMA fit so that the best forecasting results received ARIMA (0,1,1) (0,1, 0) [12]. From the results of Fit ARIMA, we get a sales prediction pattern that is similar to sales from the actual three years before for the next two years. This study provides an opportunity for further research, namely optimization of the cost of repair and quality control of reverse supply chain activities and the provision of added value to reduce distributor losses.

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