

Optimization of Delivery Cost on Reverse Logistic for Product Claim in the Two-Wheel Vehicle Industry

Paduloh Paduloh^{1a♦}, Tiswy Mayana^{1b}

Abstract. Product returns are one of the obstacles faced by two-wheeled motor vehicle industry companies in Indonesia, where the company's head office is based in Japan. The obstacle faced is the excess cost of shipping product claims compared to the planned cost budget. These products are replacement parts for CBU (completely built-up) units for two-wheeled motor vehicles exported to Japan. This case will be solved using reverse logistics, where the initial analysis is carried out by finding the value of the bullwhip effect on the company's orders and requests. The next stage is forecasting for the next period using the ARIMA method using Rstudio. The results showed the occurrence of a bullwhip effect, and then the best result was the ARIMA model (0,1,3) (2,1,0). The value of the bullwhip effect managed to decrease by applying the forecasting model. Then optimizing the shipping cost of claim products processed by LINGO results in a 5% reduction in shipping costs from the budget.

Keywords: Reverse Logistic, Linear Programming Optimization, Forecasting, Bullwhip Effect, two-wheel vehicle.

I. INTRODUCTION

Reverse Logistics is the process of planning, executing, and controlling efficient two-way flows to recover the value or proper disposal of secondary products (Kaviani et al. 2020). In sending CBU units in this company, the goods will be sent using sea transportation. On the way to the customer, this CBU unit often has damage, and it becomes a claimed product. Then the product that replaces the claim will be sent back by the company to the customer using air transportation due to the urgent nature of the goods to meet production capacity at the customer. Almost all cases of damaged goods/claims from customers are not returned for repair to reduce the cost of return shipping and repairs that are greater than sending back with new goods. This study focuses on the reverse logistics process between the customer in Japan and this company in Indonesia to deliver product claims from the CBU unit. There is also a gap

between plan orders and actual orders in 2020, with 87%. The plan order received is 12,470 units during the actual order of 10,687 units.

Then the percentage of claimed products compared to units sent is 15%, with total units sent / actual orders throughout 2020 as many as 10,687 units and units claimed as many as 1,630 units. The cost of shipping claim products is 32% above the budgeted cost because the actual costs incurred are Rp. 659,379,178, - while the shipping cost budget is Rp. 499,130,338,-. As shown in Figure 1, Delivery uncertainty indicates an imbalance between demand and supply, so a strategy is needed to control this condition.



Figure 1. Graphic of plan order and actual order

Based on these conditions, it is necessary to analyze the delivery and withdrawal of the product. Optimization is carried out to reduce claim costs to a minimum. Many previous studies for this condition have been carried out (Trochu, Chaabane, and Ouhimmou 2018) using reverse logistics networks to redesign for wood waste CRD industry under uncertainty. (Paduloh, Djatna,

¹ Industrial Engineering Program Study, University of Bhayangkara Jakarta Raya, Bekasi, Indonesia

^a email: paduloh@dsn.ubharajaya.ac.id

^b email: tiswymayana@yahoo.co.id

♦ corresponding author

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Sukardi, et al. 2020) in this review, the most method used in the reverse supply chain is Mixed Integer Linear Programing to control uncertainty. (Kurilova and Zelinskaya 2021) redesign new mathematical model for reverse supply chain in social sustainability. (Özçelik, Faruk Yılmaz, and Betül Yeni 2020) The researcher makes the performance of reverse supply chain using the ripple effect on the system and makes a robust model reduce uncertainty. Due to these problems, a solution is needed to overcome them. Things that need to be improved are the forecasting of plan orders to overcome the bullwhip effect, forecasting of shipping costs, and the last thing that requires proper modeling to optimize the minimization of shipping costs for these claim products.

In this study, to solve problems and answer goals, an analysis will be carried out using the reverse logistics concept; the initial stage will be an analysis of the suitability between demand and supply, forecasting using ARIMA, and checking the condition of the bullwhip effect, then the withdrawal process and product claims will be controlled using mathematical modeling.

II. RESEARCH METHOD

Reverse supply chain management is a set of approaches utilized to integrate suppliers efficiently, manufacturers, warehouses, and stores so that merchandise is produced and distributed in the right quantities, to the suitable locations, and at the right time, to minimize system-wide costs while satisfying service level requirements (de Oliveira, Mônica, and Campos 2019) (Paduloh and Djatna 2021). The bullwhip effect is an inventory term that defines how demand moves in the supply chain (Nguyen, Adulyasak, and Landry 2021), (Michna, Disney, and Nielsen 2019). Forecasting is needed to provide accurate forecasts of the future (Boone et al. 2019; J. Li et al. 2021; Ntakaris et al. 2018; Patria and Sudarto 2020). Forecasting plays an important role in the success of a business or business. Forecasting is a way to predict predictive information in determining the future by using historical data as the basis of reference (Michna, Disney, and

Nielsen 2019; Petropoulos, Wang, and Disney 2019; Sagheer and Kotb 2019). In addition, it also means that forecasting is a method of estimating future numbers using existing data from the past; lamp data are systematically combined and processed to predict a value in the future (Alasali et al. 2021; S. Li et al. 2019).

The linear programming method is a way to solve the problem of allocating limited resources among several competing activities in the best possible way (Nasseri and Bavandi 2019; Sembiring et al. 2018; Wu, Chang, and Hsu 2018). This division problem will arise when it comes to choosing a level for certain activities that compete on the issue of resource use of scarce resources needed to perform these activities. Then linear programming can be used to obtain an optimal result, namely: the result that obtains the best goal compared to other alternatives (Indrawati et al. 2018; Yıldız and Soylu 2019).

To achieve the research objectives, the procedures carried out in this study were firstly data processing, and data analysis carried out after successfully collecting all the data to solve the problems discussed in this study. The first step is summarizing the raw data in the form of the number of daily shipments and shipping costs into processed data for the 2020 period from January 2020 to December 2020 and analyzing the summarized data to examine the elements of the bullwhip effect. Perform calculations of the bullwhip effect with the formula described on a theoretical basis for the number of shipments and shipping costs. Analyze the results of bullwhip effect calculations and look for cause-and-effect relationships. Perform calculations for forecasting the number of shipments using the ARIMA method using Rstudio software. Perform forecasting calculations for shipping costs using the ARIMA method using Rstudio software (Paduloh, Djatna, Muslich, et al. 2020). Analyze the results of forecasting from the amount and shipping costs for 2021. The forecasting results will be used as a solution for more precise forecasting in 2021. Perform shipping cost optimization calculations using the linear programming method with Lingo software. This

optimization is to minimize shipping costs in 2021 with the proper modeling.

III. RESULT AND DISCUSSION

To conduct this research, the following are the steps the researcher takes to obtain the results of modeling and optimization of shipping costs.

Bullwhip Effect

To calculate the value of the bullwhip effect, a formula is used where the value of the bullwhip effect is equal to the order coefficient divided by the value of the coefficient of demand. This stage aims to prove the bullwhip effect phenomenon in this case. The following is the result of calculating the value of the bullwhip effect.

$$BE = \frac{CV_o}{CV_d} = \frac{0.490}{0.380} = 1,280 \tag{1}$$

Forecasting

This stage aims to predict the number of unit production needs for the future. For the foreseeable timeframe for the next one year. Reference data to be used as forecasting material is actual order unit data from 2015 to 2020. To see the complete data, you can check the attachment. Forecasting is done using the autoregressive integrated moving average (ARIMA) method, and also for the calculation is done with the Rstudio software tool. The following is a plot of demand data from Japanese customers for 2015 to 2020.

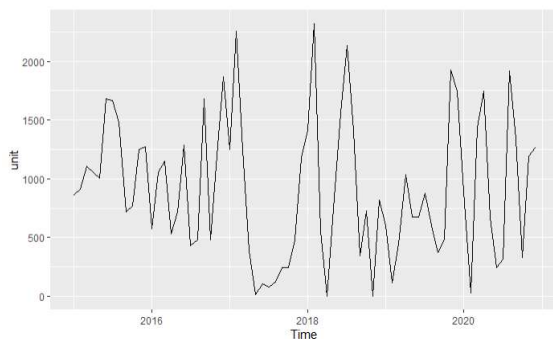


Figure 2. Plot Time Series Actual Order

After that, the residuals were checked using the ARIMA fit method to get the best forecasting value, and the best model results were (0,1,3) (2,1,0).

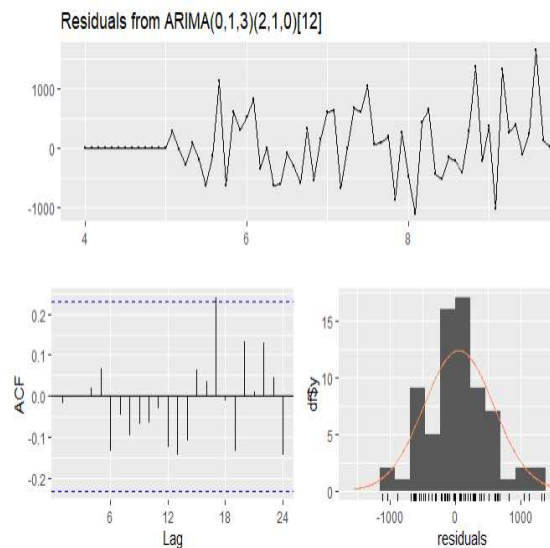


Figure 3. Residual ARIMA (0,1,3) (2,1,0)

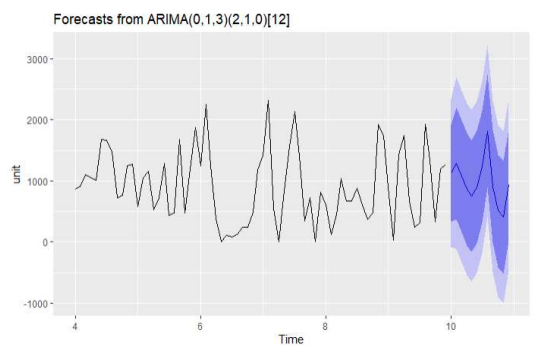


Figure 4. Result of ARIMA (0,1,3) (2,1,0)

Table 1. ARIMA Forecasting Result of 2021

Month	Forecasting result (unit)
Jan 21	1,124
Feb 21	1,287
Mar 21	1,074
Apr 21	863
May 21	750
Jun 21	898
Jul 21	1,232
Aug 21	1,812
Sep 21	910
Oct 21	511
Nov 21	406
Dec 21	934
Total	11,801

Furthermore, the best forecasting results with the ARIMA model (0,1,3) (2,1,0) are shown in the following graph.

Cost Optimization with Linear Programming

In this study, finding the best mathematical model was also carried out to obtain a claim product delivery model by optimizing shipping costs. Therefore, the formulation model is obtained as follows.

Index:

- i : claim product i = 1,2,...p
- j : shipping method j = 1,2,...c
- t : time t = 1,2,..q

Parameter details obtained are as follows:

- C_j = shipping cost per shipping method "j"
- P_i = claim product shipping weight (Kg)
- q = number of periods
- F = claim quantity limit defined as product claim level control
- H = maximum weight in the truck

Decision variables :

- X_t = frequency of product claims with air cargo at time "t"
- Y_t = frequency of product claims with the courier at time "t"

Explanatory Variables:

- A_t = total cost of using air cargo
- B_t = total cost of using the courier
- D_t = total shipping cost of claim products

Objective Function:

The objective function is to minimize the cost of shipping claim products, namely from the sum of the total operational costs of shipping using air cargo and courier, which consists of shipping costs multiplied by the quantity of delivery and then multiplied by the frequency of delivery of claim products. Optimization of the shipping cost of this claim product on two shipping methods and a 12 month time pattern; here is the formulation,

$$\min Z = \sum_{t=1}^q (C_1 * P_1 * X_t) + \sum_{t=1}^q (C_2 * P_2 * Y_t) \tag{2}$$

Constraints :

The following are the conditions or constraints to support the predetermined objective function,

- 1) As the maximum limit for the capacity of the claim product delivery cost for each transportation method.

$$\begin{aligned} C_1 * P_1 * X_t &\leq A_t \\ C_2 * P_2 * Y_t &\leq B_t \end{aligned} \tag{3}$$

- 2) As a maximum limit of the total capacity of the claim product shipping cost on all transportation methods.

$$A_t + B_t \leq D_t \tag{4}$$

- 3) To control product claims, the ratio of claimed products to overall sales must be smaller than the specified ratio.

$$X_t + Y_t \leq F_t \tag{5}$$

- 4) Maximum truck capacity for air cargo delivery.

$$P_1 * X_t \leq H \tag{6}$$

- 5) Non-negative constraint.

$$X_t \geq 0, Y_t \geq 0 \tag{7}$$

Then at the data analysis stage, several variables are prepared to be used as data in the optimization model for the cost of shipping claims using the LINGO application. There is also a limit on the claim ratio, which is less than 15% for the standard reduction in the number of product claims from the previous year.

This shipping cost optimization modeling is carried out on the claim product delivery process in one of the two-wheeled motor vehicle automotive industry companies. The goal is to minimize shipping costs, namely reducing the cost of shipping claim products by finding the optimum model of the frequency of delivery of claim products allowed by the company. Claim products are sent in two shipping methods in the shipping process, namely using air cargo and courier. The air cargo delivery method is a shipping method using airships / commercial aircraft with flight reservations through the services of a freight forwarder. In contrast, the courier delivery method is shipping using privately-owned airships/aircraft from the shipping service company used, and generally, shipping costs are more expensive than using a courier.

The cost of shipping a claimed product is determined by the shipping cost of each shipping

method used, the quantity of the goods, and the frequency of deliveries made. The research uses 12 months for the same delivery destination in this case study, namely Japanese customers. The cost of sending using air cargo is Rp. 10.234.00/kg, and for the courier, it is Rp. 23,386.00/kg. In the model to be made, it has been determined that the permissible weight capacity of the claimed product is 45 kg for air cargo in each shipment and 20 kg for the courier in each shipment.

As a control of the level of claim products that will arise, the terms of the allowable claim product ratio are also determined, which is less than 15% of the 2021 forecast number to the total claim product sent. If the product claims that are sent are decreased, the shipping costs will also definitely go down. Based on these conditions, the index and model parameters are as follows,

Index :

i : claim product i = 1,2,...p

j : shipping method j = 1,2,...c

t : time t = 1,2,..q

Parameter :

C_j = shipping cost j,

C₁ = Rp. 10.234,00-/kg ,

C₂ = Rp. 23.386,00-/kg

P_i = claim product shipping weight,

P₁ = 45 kg,

P₂ = 20 kg

q = number of time periods, q = 12

F = claim quantity limit defined as product claim level control is 15% from the total forecast 2021

H = maximum weight in the truck, H = 5.000 kg

The optimization modeling of claim product delivery costs was carried out using the LINGO 19.0 software. For the Lingo syntax, see the Appendix. From the processing results on Lingo, the solution obtained is in the form of a minimum shipping frequency that is allowed to get a reduction in shipping costs. The solution obtained is a linear programming class model, and the results are already minimally optimal. The initial shipping costs are based on the claim figures in 2020, and in this Lingo formulation, the estimated

claim delivery data is entered with a ratio of 15%, the same number as last year. The following are the results obtained from this modeling.

The frequency/number of shipments from each shipping method obtained is as follows. The average percentage for delivering the air cargo method (Xt) is 66%, and the courier method (Yt) is 34%. According to the quantity of shipments that occur each month, there are variations in the percentage of shipments for each method in each

Table 2. Number of Shipments on each Shipping Method

Period	Frequency of Air Cargo (Xt)	Percentage of Air Cargo	Frequency of Courier (Yt)	Percentage of Courier	Total Frequency of Product Claim
1	104	63%	60	37%	164
2	19	63%	9	32%	28
3	15	71%	6	29%	21
4	66	68%	31	32%	97
5	50	64%	28	36%	78
6	103	65%	55	35%	158
7	23	70%	10	30%	33
8	107	63%	62	37%	169
9	62	65%	34	35%	96
10	10	71%	4	29%	14
11	19	70%	8	30%	27
12	111	69%	50	31%	161
Total	689	66%	357	34%	1,046

Table 3. Optimization Results Minimize Shipping Costs

Shipping Methods	Period	Actual Cost (Rp)	Minimize Cost Result (Rp)	Reduce Cost (Rp)
Air Cargo	1	63,677,485	47,895,120	-15,782,365
	2	8,959,420	8,750,070	-209,350
	3	12,418,881	6,447,420	-5,971,461
	4	35,398,489	30,394,980	-5,003,509
	5	38,024,056	23,026,500	-14,997,556
	6	63,871,728	44,671,410	-19,200,318
	7	12,477,865	10,592,190	-1,885,675
	8	95,849,669	47,895,120	-47,954,549
	9	35,333,535	28,092,330	-7,241,205
	10	11,647,056	4,605,300	-7,041,756
	11	20,095,459	7,829,010	-12,266,449
	12	50,624,200	47,895,120	-2,729,080
Total		448,377,841	308,094,570	-140,283,271
Courier	1	29,965,875	28,063,200	-1,902,675
	2	4,216,197	4,209,480	-6,717
	3	5,844,179	2,806,320	-3,037,859
	4	16,658,112	14,499,320	-2,158,792
	5	17,893,673	13,096,160	-4,797,513
	6	30,057,284	25,724,600	-4,332,684
	7	5,871,936	4,677,200	-1,194,736
	8	45,105,726	28,998,640	-16,107,086
	9	16,627,546	15,902,480	-725,066
	10	5,480,968	1,870,880	-3,610,088
	11	9,456,686	3,741,760	-5,714,926
	12	23,823,153	23,386,000	-437,153
Total		211,001,337	166,976,040	-44,025,297
Grand Total		659,379,178	475,070,610	-184,308,568

month. After optimization, the total product claims are 1,046 units compared to 1,630 units in 2020.

In the results shown in Table 3, the modeling carried out resulted in a decrease in shipping costs for each shipping method. For shipping using air cargo, the total reduction in shipping costs for 12 months is Rp. 140,283,271.00. Then for shipping using a courier, the total reduction in shipping costs for 12 months is Rp. 44,025,297.00. Then the total reduction in shipping costs in 12 months is Rp. 184,308,568.00. If you look at the changes in shipping costs in detail each month of delivery, there is a decrease in each month of shipping costs.

Sensitivity Analysis

In this study, sensitivity analysis was also carried out on the variables of changes in optimal results from minimizing the cost of shipping claims for products. This analysis was conducted to determine the effect of changes in the parameters that have been determined in the optimal modeling. The first parameter change is by testing the values of the X_t and Y_t variables. With this test, the delivery frequency is changed every period.

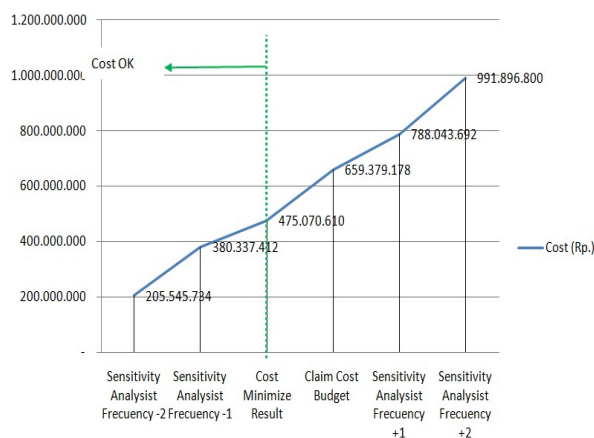


Figure 4. Graph of Sensitivity Analysis of the Model

With the addition of 1 delivery in each period, the shipping cost is not optimal but above the initial shipping cost. There is a change from the optimal value of Rp for the air cargo method. 308.094.570.00 to 552.167.080.00 and courier method from Rp. 166,976,040.00 to Rp. 235.876612.00. In both results, the overall cost

also exceeds the initial delivery cost and the optimal cost in the optimal modeling.

If the analysis continues by reducing and adding more shipping frequencies, then the total cost of shipping the claimed product can be seen in Figure 6. This graph shows that in the model that has been obtained if the shipping frequency is added only once, the cost of delivery will exceed the cost limit of the product claim that has been determined. So the modeling change that is allowed is to reduce the number of times the claimed product is sent.

IV. CONCLUSION

Uncertainty in the returned product claim based on the analysis results, it is found that the bullwhip effect is known that the value of the bullwhip effect that occurs is 1,280, above the bullwhip effect parameter of 1,005, it can be said that the bullwhip effect occurred on orders and requests in 2020 at this company with Japanese customers. The forecasting results using the ARIMA method were successfully carried out for 2021, and from the forecasting results, an analysis of the bullwhip effect was carried out again. The result obtained is 0.992, so there is a decrease in the number of bullwhip effects. Then the ARIMA forecasting results are used to model the optimization of claim delivery costs to minimize costs.

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