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Integration models of demand forecasting and inventory control for coconut sugar using the ARIMA and EOQ modification methods

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ABSTRACT

Inventory control is critical because the inability to overcome inventory problems causes unpreparedness to meet consumer demand. MSMEs Bekawan Agro Coconut Sugar, independently around 35% -70%, cannot meet consumers' demand for coconut sugar, so an inventory control model is needed. Inventory control models must integrate with demand forecasting as an inventory control input. This study aims to integrate the demand forecasting model with the inventory control model. The method used for demand forecasting is ARIMA. The inventory control model uses a modified EOQ hybrid method because coconut sugar products have a shelf life; they also use coconut sap as raw material, which must be processed to prevent fermentation. The research results show that demand forecasting for one year ahead is a total of 10,310.82 Kilograms with an economic lot size of 120 Kilograms and a reorder point when the inventory position is 30 Kilograms. Daily production of 30 kilograms requires 210 litres of coconut sap/per day. The amount of sap needed requires 105 coconut trees / per day. Arrival time of coconut sugar at the storage warehouse every five days. The resulting model can be a solution for sustainable MSMEs.

1. INTRODUCTION

The primary element supporting the efficient operation of corporate activities is inventory control. Inventory control involves keeping items on hand for use or sale at a later time. Thus, it must be kept under control, be able to react promptly to customer demand, and offer top-notch services. This quality is mostly for products that are easily damaged, have a high demand for customer service, and have demand instability. Lack of readiness to meet market demand due to inventory control issues might result in the warehouse not having any inventory control when there is a spike in customer demand [1]. The primary goal of inventory control in the agroindustry is to maintain the proper quantity of each item to meet demand while preventing shortages and surplus stocks [2] and reducing costs [3].

Additionally, the retail and warehousing industries have faced significant difficulties maintaining acceptable quality and ideal inventory control levels due to changing customer behavior, fierce competition, rapid technological development, and globalization [4], [5]. From the research gap, it is necessary to integrate inventory control with demand forecasting [6]–[8]. Demand forecasting is the first step because it serves as an inventory control input, resulting in the optimization of inventory control [9]. Forecasting models are critical to optimizing and managing the number of products produced and stored in inventory [10]. Agroindustry with proper forecasting can avoid expensive over-supply or shortage of inventory control that hinders meeting consumer demand, and unreasonable demand can reduce the accuracy of inventory control [11].

Inventory applications in various industries, including the perishable and food industries [3], [12], the insecticide industry [13], and the retail industry [14]. In contrast, demand forecasting has been applied in various food industries [15], [16]. From several implementations of inventory and demand forecasting, there is still a tiny implementation of inventory integration with demand forecasting; besides that, according to Utama *et al.* [3], and Hrabec *et al.* [17], who have conducted a systematic review and meta-analysis that the application of inventory integration is still lacking, so this integration needs to do Demand forecasting and inventory control. One agroindustry that is challenging to integrate inventory control and demand forecasting is coconut sugar. The demand for coconut sugar in the future will increase because it has health benefits with a lower glycemic index value than Palm Sap Sugar with a coconut sugar glycemic index value (35–42) [18]. Indragiri Hilir Regency, Riau Province, Indonesia, produces most coconut sugar by developing micro, small, and medium-sized enterprises (MSMEs). MSMEs are essential because they create jobs and facilitate regional development and innovation, positively impacting the country's economic status [19]. In addition, coconut sugar has a significant economic impact on society [20], [21]. The Bekawan agro Mandiri MSMEs face new challenges in consumer demand with fluctuating requests. The existing inventory control is sometimes fulfilled and sometimes can-not meet consumer demand of around 35% to 70%.

The ARIMA model is a trusted tool for decision-making in the food industry's demand forecasting [22]. Arima is used widely by forecasting practitioners because of its interesting theoretical properties and empirical evidence that supports it. The ARIMA model has also been employed in numerous other studies for forecasting purposes, including studies that forecast total viral counts, yields, production, and productivity for various crops and perishables, as well as sugarcane production and cotton production on a broad scale and yields, output, and productivity for sugarcane and cotton [16], [23]–[27]. In order to adjust the estimated value obtained from the general ARIMA model, this research provided a technique for changing the conventional ARIMA model. It did this by employing information data calculated from the ARIMA model as actual data recorded in the past. An illustration would be the analysis and forecasting of COVID-19 event cases [28].

The Economic Order Quantity (EOQ) approach can be used for inventory control. The EOQ model is the accepted methodology for managing inventory [29], [30]. The ability to incorporate realistic features has allowed the EOQ model to advance significantly during the previous few decades. Additionally, EOQ includes a practical inventory control management framework to establish the level of inventory control necessary to meet customer needs while minimizing costs associated with maintaining inventory control [13], [31]. The development of inventory models always tries to involve relevant factors companies face. Some inventory models are EOQ models with product sales age constraints [30], [32]–[35], product warehouse capacity, and demand substitution [36].

According to Table 1, some of these studies have yet to consider the age of raw materials and the transportation capacity of the transportation of goods and raw materials. Thus, this research is creating techniques [33], [35], [36] because, based on field studies, the agroindustry of coconut sugar for inventory control model has several obstacles, including constraints on coconut sugar products that have a shelf life and raw materials that do not have a shelf life and transport capacity. This constraint requires modifications to the EOQ inventory control model. Two models are modified in this paper: (1) the coconut sugar product inventory model and (2) the raw material inventory model.

This study aims to close the knowledge gap and answer how the inventory control model using the EOQ hybrid technique and mass balancing may use the demand forecasting model with the ARIMA method as input. The study aims to identify and formulate the issue of improving

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Table 1. Overview of demand forecasting and inventory control

Reference	Method / Model	Application	Description of Weaknesses /Strengths
[7]	ARIMA/ Demand forecasting	Review	Demand forecasting and inventory management must be combined
[16]	ARIMA/ Demand forecasting	Perishable goods	Aggregate-level demand forecasts
[23]	ARIMA/ Demand forecasting	Pulse production	It helps in determining whether the demand will be fulfilled or not in the future.
[24]–[27]	ARIMA/ Demand forecasting	COVID-19	Able to produce fluctuating forecasts to be more linear and stationary.
[3], [12]	EOQ/Inventory Control	Perishable and food industries	Inventory control uses a single producer and multiple retailers method known as single vendor many buyers. However, inventory must still consider supply at the supplier and agroindustry levels.
[13]	EOQ/Inventory Control	The insecticide industry	Inventory control model on raw materials
[30], [32]–[35]	EOQ/Inventory Control	Product sales age constraints	Only focus on selling products and need to develop towards supplies for perishable products.
[33]	EOQ/Inventory Control	Perishables product	We need to consider other variables
[36]	EOQ/Inventory Control	Demand substitution	Formulation of the EOQ model for limited warehouse capacity
[37]	EOQ/Inventory Control	Printer remanufacturing	The EOQ for printer products is reverse, while for coconut sugar products, the possibility of reverse is minimal.
[38]	EOQ/Inventory Control	Impact of different payment schemes on retailer profitability	Models can expand from non-perishable goods to perishable goods.

demand forecasting and inventory control for SMEs, particularly Bekawan agro Mandiri SMEs. The research focuses on inventory management, from raw coconut sap to finished coconut sugar products. Because MSMEs have yet to adopt a discount system, it does not consider product discounts.

2. RESEARCH METHODS

2.1. Data collection

This research develops several data-based models for short-term forecasting. The demand forecasting model requires product demand data from January 2020 to January 2023. The MSMEs location in Bekawan Agro Mandiri Indragiri Hilir Regency, Riau, Indonesia. The output from the demand forecast becomes the input for the inventory control model. In addition, the inventory control model requires other data from MSMEs Bekawan Agro Mandiri, including ordering costs (Cp), storage costs (Cs), Order lead time (Lt), Shelf life (in), the amount of coconut sap needed for the production per kilogram of coconut sugar, the number of coconut trees per hectare.

2.2. Demand forecasting model development

When creating ARIMA models (p, d, q), the terms p, d, and q relate to the model's moving average, differentiation process, and auto regression order [39]. The model, in general, can be defined as in equation 1.

$$\Psi(B)(1-b)^d = \Theta(B)_{\mathrm{E}} \quad (1)$$

where yt and t represent the actual value of the daily emergency visits and the random error term on day t. Byt = yt-1 defines B. Ψ(B), and (B) is a definition as in equations 2 and 3.

$$\Psi(B) = 1 - \Psi_1 B - \Psi_2 B^2 - \Psi_3 B^2 - \cdots - \Psi_p B^p \quad (2)$$

$$\Theta(B) = 1 - \Theta_1 B - \Theta_2 B^2 - \Theta_3 B^2 - \ldots - \Theta_p B^p \quad (3)$$

The application of the ARIMA model has the following four steps:

1. Verify the monthly demand data's stationarity. To determine whether the time series is stationary, use the Box-Cox test. The differencing process is necessary when the time series data is not stationary.
2. Based on the order of differences determined in the previous step, determine the structure and estimate the parameters of the ARIMA model. Plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF) are crucial tools for locating ARIMA model sequences.
3. Use the residual normality test to validate the ARIMA model so it can be used for forecasting.
4. Forecasting future demand

2.3. Inventory control model development

Observation is needed to determine the inventory control model for coconut sugar products with material shelf life constraints to produce an optimal solution. Inventory control calculations use a formula that considers the product shelf life and coconut sap raw materials. Constraints on product shelf life and raw material shelf life will come with modifying the Economic Order Quantity (EOQ). EOQ modification can be a solution for planning the inventory control of coconut sugar products and raw materials that provide optimal inventory control levels by considering the shelf life. The following are the stages for developing the modified EOQ inventory control model:

1. Determine the order lot size (Q)
   Order lot size based on product requirements (D) in the planning period (T) begins with coconut sugar products (Qcs). Coconut sugar has a shelf life of one hundred and eighty days compared to sap raw materials with no shelf life. Coconut sap with no shelf life must be processed because it prevents fermentation and chemical preservatives. The shelf life of coconut sugar products is long when transported from the production site to the distribution warehouse. The transportation time is three hours using a canoe and a three-wheeled motorcycle, so a message fee (Cp) is required. Based on this, the optimal order lot size for coconut sugar is in Equation 4.

$$Qcs = \sqrt{\frac{2\,CpD}{CsT}} \quad (4)$$

2. Total quantity based on optimal order lots in order units with order size
3. The total quantity obtained on the order size (Os) of the type of transportation mode used so that the order quantity size (Qos) is obtained for the optimal order lot as in equation 5.

$$Qos = \frac{Qcs}{Os} \quad (5)$$

4. The total quantity of optimal order lots (Qcs*).
   The total number of optimal order lots (Qos*) is the multiplication of the size of the order quantity (Qos) with the total quantity based on the size of the order (Os), as shown in equation 6.

$$\mathrm{Qcs}* = Qos \times Os \quad (6)$$

5. Determine the length of the optimal order period (t*).
   The determination of the optimal order period length (t*) is the division between the total number of optimal order lots (Qcs*) and product requirements (D), as shown in equation 7.

$$\mathrm{t}* = \frac{\mathrm{Qcs}*}{D} \quad (7)$$

6. Calculate the number of orders (n) based on the ideal order amount.
   As stated in equation 8, the total number of optimal order lots (Qcs*) is divided by the product needs (D) to determine the number of orders (n) based on the optimal order quantity.

$$n = \frac{D}{\mathrm{Qcs}*} \quad (8)$$

7. The next step is establishing the reorder point's (r) size.
   The number of periods in a year can calculate the reorder point (r) by checking for product needs during the lead time (Lt).

$$r = D \times Lt \quad (9)$$

8. Calculating the amount of the total cost of inventory control (TC) that MSMEs must spend.

$$TC = \frac{\mathrm{Qcs}{*}\mathrm{CsT}}{2} + Cp\frac{D}{\mathrm{Qcs}*} \quad (10)$$

9. Calculating the need for coconut sap raw material supplies
   The raw materials for the sap taken must be processed immediately. So, the sap needs to

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start with the daily product requirements (Qcs**) based on the lot size of the economic ordering of coconut sugar products, as shown in equation 11. The number of coconut trees needed to meet the needs of coconut sap per day (Dcs) is based on the fact that one kilogram is obtained with a requirement of 7 litres of sap. One coconut tree production is 2 litres/day, and 1 hectare has 144 coconut trees, so the number of trees needed to produce coconut sap depends on the economic lot size to process, as in equation 12.

$$Qcs ** = \frac{Qcs*}{t*} \quad (11)$$

$$Dcs = \frac{7Qcs**}{288}\ x\ 144 \quad (12)$$

3. RESULTS AND DISCUSSION

3.1. Numerical example

3.1.1. *Stationarity test in variance*

Demand prediction is the earliest stage that functions as input for the inventory control model. The model used for demand forecasting in this study is the coconut sugar demand model for the MSMEs Bekawan Agro Mandiri. The data used is data from January 2020 to January 2023. Fig. 1 explains that demand shows a trend but fluctuates and is often called a stochastic trend. This data pattern shows that the demand data is not stationary. Forecasting requires stationary data, so Box and Cox use transformations on data that is not yet constant [40], [41]. If a rounded value or lambda (λ) equals 1, the data has stationarity in variance.

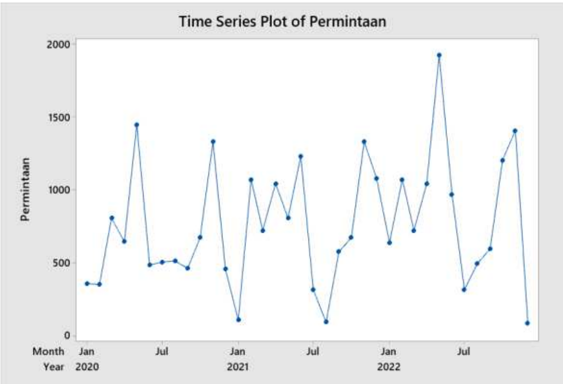

Fig. 1. Data plot of coconut sugar demand

However, if lambda (λ) is not equal to 1, then the data does not yet have stationarity in variance, so a transformation must occur until the rounded value on the Box-Cox is 1. Based on the research data, the rounded value (lambda) is 0.5, so it concludes that the data is not stationary in variance (Fig. 2). The lambda value does not equal 1, so it needs data transformation. The results of transformation 1 show that the rounded value is still 0.5 (Fig. 3), so the second transformation. Fig. 4 shows a rounded value of 1.00 that indicates that the request data already have stationarity in variance.

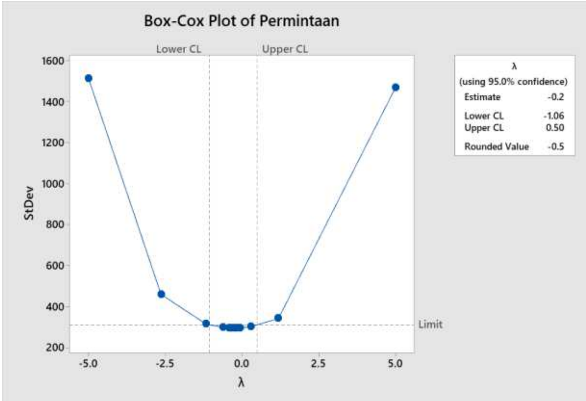

Fig. 2. Box-cox output of coconut sugar demand data

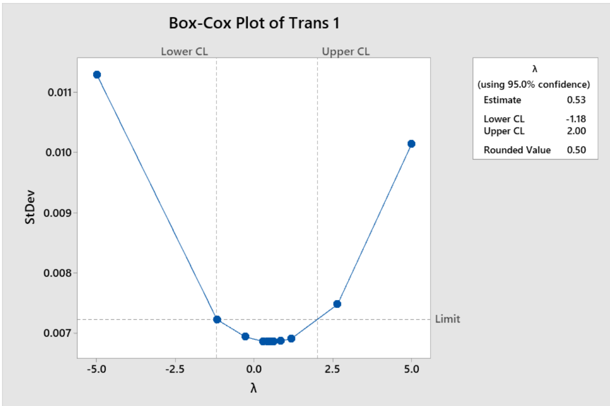

Fig. 3. Box-cox output of coconut sugar demand data at transformation 1

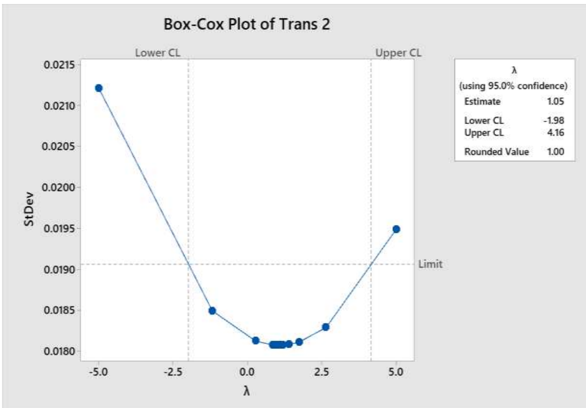

Fig. 4. Box-cox output of coconut sugar demand data in transformation 2

3.1.2. ***Test ACF and PACF***

Checking the mean's (average's) stationarity is the next step. Use time series charts, autocorrelation function (ACF) plots, or partial autocorrelation function (PACF) plots to test for stationarity in the mean. If there is no trend element in the time series plot, it can be concluded that the data has stationarity in the mean. Meanwhile, for inspection using the ACF plot, it can be seen from the lag in the ACF plot. If there is a rapid decrease to near zero after the second or third lag, then the data is stationary on average. Fig. 5 and Fig. 6 present that the graph is stationary because the blue line is within the limits of the red line, so it can be said that the data is stationary. If the data is stationary, then the ARIMA method calculation can be continued.

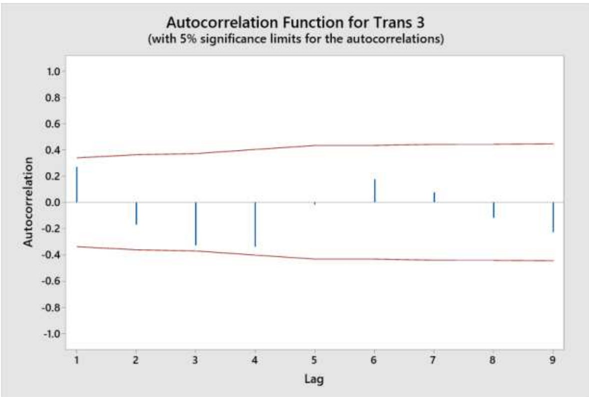

Fig. 5. Graph output of the autocorrelation function of coconut sugar demand data

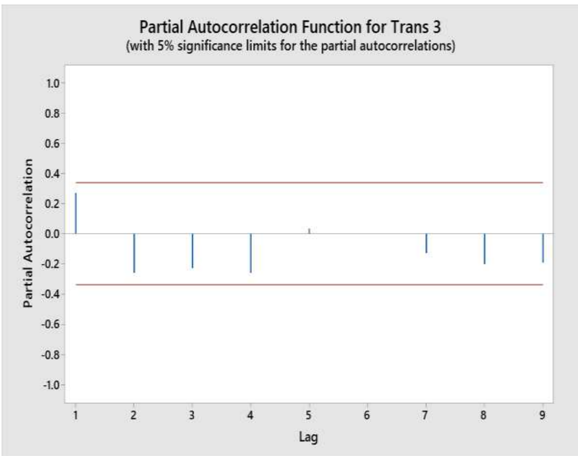

Fig. 6. Output graph of partial autocorrelation function for coconut sugar demand data

3.1.3. ***ARIMA model estimation and forecasting future demand***

After the data is said to be stationary, the next step is to estimate the ARIMA pattern, which produces a P value that has a value of 0 so that it can be said that the test results have a significant effect. These estimates will be tested individually, and the error rate will be selected. The estimation step is to obtain the estimated coefficient of the selected model. The results in Table 2 use MINITAB 19 software to fill in the forward forecast, and the error value of each ARIMA model can be known. The selection of the ARIMA model was taken based on the value of the significance test results. ARIMA forecasting with order (1,0,1) is the chosen model. The calculation results show that the ARIMA equation is Y = 1430-0.668 y-1 - (-0.9713 e-1). The Y value is the request value, while the e value is the residual value obtained from MINITAB. Fig. 7 is the final result of forecasting coconut sugar for the following year that shows the next twelve months with a total demand of 10310.82 kilograms. Future predictions tend to fall due to causal factors such as research conducted by Mishra *et al.* [23] and Siddiqui *et al.* [42]. In this study, demand forecasting has decreased due to the post-fasting month and Eid al-Fitr and Eid al-Adha. In addition, the forecasting results are not too volatile as in the initial data (Fig. 1), and this also happened in previous research conducted by Alzahrani *et al.* [43], Sahai *et al.* [44], Sarkodie [45], and Mishra *et al.* [23].

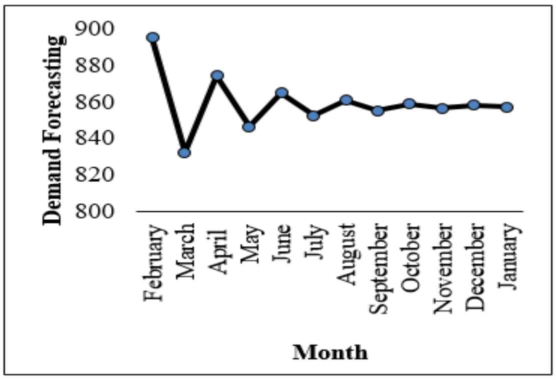

Fig 7. Forecasting results of coconut sugar demand for the next year period

3.1.4. ***The residual normality test***

The residual normality test is a requirement that is met to prove that the forecasting results are valid and can be used [46]. The residual value is the difference between the forecasted data minus the actual historical data. With a significant level of 5%, the residual test results are shown in Fig. 8.

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Table 2. ARIMA model estimation of coconut sugar demand data

No	Model Estimation	Parameter	P. Value	Significance Test Results
1	1,0,0	AR(1)	0.305	Not significant
		LAG (0)	0.000	
		MA (0)	0.000	
2	0,0,1	AR(0)	0.000	Not significant
		LAG (0)	0.000	
		MA (1)	0.108	
3	1,0,1	AR(1)	0.000	Significant
		LAG (0)	0.000	
		MA (1)	0.000	
4	2,0,0	AR(2)	0.217	Not significant
			0.112	
		LAG (0)	0.000	
		MA (1)	0.000	
5	0,0,2	AR(0)	0.000	Not significant
		LAG (0)	0.000	
		MA (2)	0.783	
			0.004	
6	1,0,2	AR(1)	0.035	Not significant
		LAG (0)	0.000	
		MA (0)	0.068	
			0.009	
7	2,0,1	AR(1)	0.002	Not significant
			0.098	
		LAG (0)	0.000	
		MA (0)	0.308	
8	2,0,2	AR(1)	0.101	Not significant
			0.615	
		LAG (0)	0.000	
		MA (0)	0.136	
			0.536	

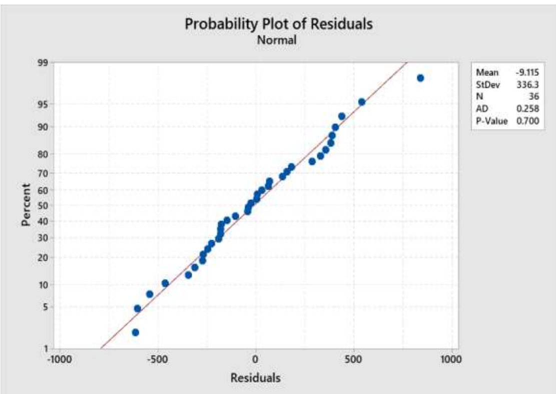

Fig. 8. Output from the probability plot of the residual test

Data hypothesis test with H0: data is usually distributed, H1: data is not normally distributed, if p-value < α, then reject Ho; if p-value> α, then accept With a significant level of 5%, or 0.05, it can see that the p-value is 0.700 > 0.05 (α value), so accept Ho, which means that the data is a normal distribution. A value that proves that the residual value in the demand forecasting model is a normal distribution. Fig. 8 shows that the residual values are normally distributed because it shows the p-value is 0.700 > 0.05 (α value) so that the forecasting results can be used.

3.2. Inventory control model of coconut sugar

After obtaining the demand forecasting model, the next stage is modelling the inventory control of economic coconut sugar products by the shelf life of coconut sugar products and coconut sap raw materials. Product demand using demand

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forecasting over one year is 10,310.82 Kilograms/Year. The inventory control model for coconut sugar products show that the shelf life of coconut sugar is longer than the ideal ordering window. Fig. 9 shows orders from the production site to the distribution warehouse when the position reaches 30 Kilograms. Coconut sugar from the production site will come every five days. With the Arrival of coconut sugar products, the inventory control in the storage warehouse will be complete again by 120 Kilograms. Thus, on the inventory control cycle until planning for one year.

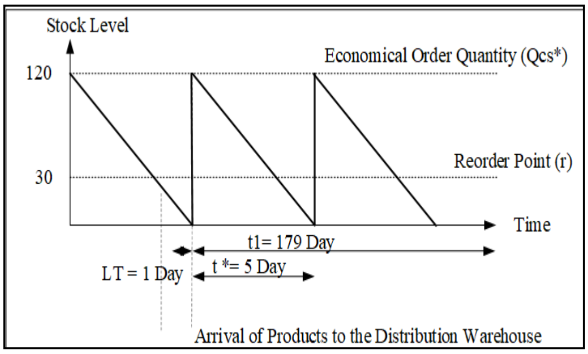

Fig. 9. Generated inventory control cycle model

Fig. 10 produces an inventory control schedule that shows it will return to the storage warehouse five days after the coconut sugar's Arrival. After five days, 120 kilograms of coconut sugar will come. The total inventory control cost is IDR 175,924. The next stage is to calculate the need for raw material inventory control daily based on the inventory control model in the storage warehouse. Raw material preparation will be done daily because the product is produced without chemical preservatives, so the sap taken must be processed so that fermentation does not occur, reducing the quality of coconut sugar. The economic lot size is 120 Kilograms, so 30 Kilograms of coconut sugar must be produced daily with a sap requirement of 210 Liters/day obtained from 105 coconut trees/day.

The resulting inventory control model needs to be analysed for sensitivity. Sensitivity analysis is performed to validate the model against the effect of changing different parameters, making the results optimal for decision-making [31], [32], [47], [48]. Sensitivity analysis is needed to ensure that the optimal order lot size has the nominal inventory control cost. Sensitivity analysis changes the order lot size to determine the total inventory control cost (TC) generated. The order lot size changes include 100 Kilograms, 140 Kilograms, 160 Kilograms, 180 Kilograms, and 200 Kilograms. Fig. 11 shows that the order lot size of 120 Kilograms is an economic order lot size with a production of 30 kilograms/day. In addition, based on field conditions, the production of coconut sugar is 9 Kilograms/Day, so with future demand predictions, there will be a profit loss of 70% of the total demand.

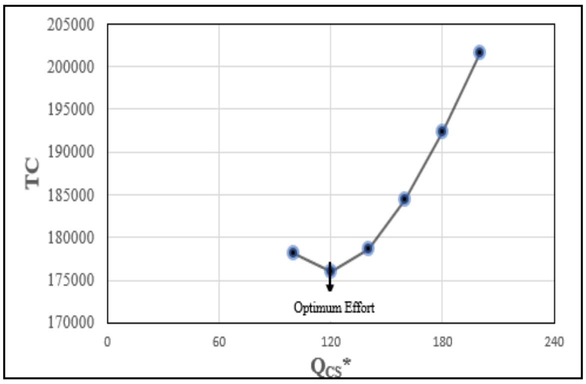

Fig. 11. Graph of sensitivity analysis for inventory control model

Month	Date																														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
February	Qcs*			r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*	
March				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*	
April			r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*		
May			r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*		
June		r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*			
July		r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*			
August	r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r
September	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	
October	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*
November	r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				
December	r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r
January	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*				r	Qcs*

Fig. 10. Inventory control scheduling

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3.3. Managerial implications

This research is an integrated demand forecasting and inventory control model that can help resolve the significant issues in MSMEs, particularly Bekawan Agro Mandiri. The main problem is the need for more fluctuating stock of around 35-70%. They are solving problems directly, starting with a demand forecasting model and continuing with an inventory control model so that there is no doubt for MSMEs to increase production. Technically, this model can assist MSMEs in determining the demand for coconut sugar, EOQ and reorder points so that they can provide coconut sugar according to consumer demand. In addition, to validate that this model can provide technical implications, operational validation has been carried out to determine the readiness of this model to be implemented in Bekawan Agro Mandiri SMEs. This model is a knowledge base that MSMEs Bekawan Agro Mandiri can use, which is directly interested in improving MSME performance in meeting consumer demand. This research also contributes to science, namely an integrated model of demand forecasting and inventory control by modifying the method based on coconut sugar's shelf life and raw materials' shelf life. Different from several previous studies only considered the product's shelf life without considering the shelf life of raw materials. Apart from that, this modelling also models the supply of raw materials that do not have a shelf life of raw materials because MSMEs do not use chemical preservatives.

4. CONCLUSION

In this study, we succeeded in developing an integration model. The model is a demand forecasting model and an inventory control model for Bekawan Agro Mandiri MSMEs. This model uses the ARIMA method for the demand forecasting model and the modified EOQ method based on shelf life for the inventory control model. The results of the demand forecasting research show that the total demand one year ahead is 10310.82 Kilograms. The economic lot size for sending coconut sugar to the distribution warehouse is 120 Kilograms with a raw material requirement of 210 Liters/day obtained from 105 coconut trees with a total inventory control cost of IDR 175,924. The resulting ARIMA model has been validated with a residual normality test, while the inventory control model is valid with a sensitivity analysis. The resulting model expects to overcome demand forecasting and inventory control problems in MSMEs, especially Bekawan Agro Mandiri MSMEs, so that they can be sustainable.

Further research needs to develop a decision support system. This development expects to facilitate MSMEs in making inventory control decisions based on forecasting future demand to produce more precise and faster decisions. In addition, this study has limitations on the demand forecasting model because it only considers the month and the number of requests. Furthermore, the inventory control model has not considered the discount criteria. Based on this, adding multiple criteria yet to be considered in this model is necessary.

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