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Comparing Probabilistic Economic Order Quantity and Periodic Order Quantity Model Performance Under Lumpy Demand Environment

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Abstract
Improper planning of inventory will affect the factory operating costs, building costs, the cost of loss, and the cost of product defects due to being stored for too long which will eventually become a loss. This research discusses the processing industry which is experiencing lumpy demand. In carrying out the production process, the company has never made plans for future demand, resulting in a waste of message costs due to repeated orders of raw materials ordered to suppliers. This paper contributes to overcoming this issue by simulating future demand by using the Material Requirement Planning (MRP) method with a probabilistic Economic Order Quantity (EOQ) and Periodic Order Quantity (POQ) model. The demand in the coming period is determined using the Autoregressive Integrated Moving Average (ARIMA) method, and an aggregate plan is carried out to determine the regular cost of raw material production and optimal subcontracting. The final analysis states that the calculation of MRP on the selected items using POQ produces the lowest cost for planning S45C-F, SGT-R, and SKD11-R, while SLD-R uses the probabilistic EOQ method.

Keywords
Lumpy demand, Material requirements planning, Probabilistic economic order quantity, Periodic order quantity, Aggregate plan.

Introduction

The results of the 2016 economic census stated that the processing industry provides the greatest value of remuneration. This impacts the next 2 years, in 2017 and 2018, the manufacturing sector contributes the largest growth in Gross Domestic Product and at present, the performance of the manufacturing sector is at an expansion level marked by the value of the Prompt Manufacturing Index (PMI) Bank Indonesia.

The processing of an item certainly aims to get profits and provide satisfaction to customers, but in a highly competitive industry competition, satisfying consumers is not a simple problem. Every company must maximize all its resources to be able to consistently produce high-quality products at competitive prices. A previous study discussed the quality control station allocation to minimize the number of product defects (Montororing & Nurprihatin, 2021). Any action the manufacturer take is always taken as an effort to meet or even exceed customer satisfaction (Gunawan et al., 2020; Tannady et al., 2018). A clear sign of a satisfied customer is the generated profit over time (Andry et al., 2020). When it comes to unsatisfied customers, a penalty may be given to the manufacturer (Andiyan et al., 2021). Determination of the selling price of an item is certainly influenced by the effectiveness and efficiency of the production process by the company. When it comes to finished goods inventory, some potential problems are outdated and inaccurate information, the excessive finished product which must be stored in a precarious way that can cause product deterioration (Marziali et al., 2021). Therefore, a company must be wise in determining the amount of inventory to be used because without proper planning, it will affect the factory operating costs, building costs, the cost of loss, and the cost of product defects due to being stored for too long which will eventually become a loss. This loss can be considered a waste and should be eliminated or reduced (Tannady, Gunawan, et al., 2019).

Previous research tried to tackle the effectiveness and efficiency issues using various techniques. A sys-

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tematic review of the transportation policy was developed to minimize the distance traveled (Nurprihatin & Tannady, 2018) and traveling costs (Nurprihatin & Lestari, 2020). Distance traveled as an integral part of the cost was also approximated by the time traveled, which is probabilistic, not deterministic (Nurprihatin, Elnathan, et al., 2019; Nurprihatin & Montororing, 2021). A study took the logistics cost given by third-party logistics into account (Nurprihatin, Regina, et al., 2021). Another study discussed the natural gas location-routing decision along with the feasibility study of the project (Nurprihatin, Octa, et al., 2019). A previous paper introduced the location-allocation model along with the routing for temporary health centers (Alinaghian & Goli, 2017). A study considered the feasibility study to obtain the selling price (Nurprihatin, Andry, et al., 2021). The Total Productive Maintenance (TPM) policy was developed to obtain the increasing effectiveness of the machine, which is marked by the increasing value of the Overall Equipment and Effectiveness (OEE) (Nurprihatin, Angely, et al., 2019). Furthermore, it was found that the work environment may affect effectiveness (Tannady, Erlyana, et al., 2019; Tannady et al., 2020).

At every level of operations management, inventory control strategies such as replenishment actions must be taken to minimize costs (Boute et al., 2022). Besides, the purpose of the inventory management is to maximize the service level while reducing the waste of resources (Saha & Ray, 2019). From an inventory management point of view, the decisions include the carrying costs of inventory, asset management, inventory forecasting, inventory valuation, inventory visibility, future inventory price forecasting, physical inventory, available physical space, quality management, replenishment, returns of defective goods, and demand forecasting (Singh & Verma, 2018). Those strategies are utilized to excel in the competition while minimizing valuable resources (Christian et al., 2021). This research discusses the manufacturing industry that produces goods with the main raw material for metals. The order fulfillment system uses a pull system where production will only occur if there is a demand from the customer. The demand that companies receive is always different and rarely repeats orders for the same type of goods. When it comes to dairy products, the demand behavior is very complex which makes forecasting future demand very important (Goli et al., 2021). Whenever there is a demand, the company always buys raw materials from suppliers who offer the lowest price with an estimated amount sufficient to meet demand. This is indeed beneficial because the company gets a cheap price, but only estimates the number of purchases that are sufficient to fulfill the order, which often makes the company have to re-order if it turns out the amount ordered is not enough to meet the existing demand. Therefore, raw material inventory planning needs to be done to minimize the production costs incurred.

The previous study discussed the use of ABC analysis and the critical index of an item (Mahagaonkar & Kelkar, 2017). ABC analysis is useful to classify the most influential items in the inventory. This research determines the raw materials that are often used and calculates the total costs incurred if processing raw materials are normally or subcontracted. In the end, this research also calculates the optimum number of orders for each raw material so that minimum ordering and storage costs are incurred.

A previous study utilized several forecasting methods for certain and uncertain demands (Nurprihatin et al., 2020). A fuzzy number was used to determine the number of demands, especially when it comes to the high level of uncertainty (Goli & Malmir, 2020). The uncertainty of the data was overcome by probabilistic graphical methods in forecasting demand (Bounou et al., 2021). A hybrid multi-layer perceptron (MLP) and RRA algorithm were proposed to predict the future demand for each product (Goli et al., 2019). Another study utilized only the Holt's-Winter method due to the demand pattern, which is perfect for the seasonal data (Nurprihatin, Gotami, et al., 2021). A two-stage stochastic programming model was proposed to solve the problem under a seasonal demand (Mahmoud et al., 2020). These actions were taken to make sure that the best forecasting method was taken to further calculation.

This research is limited to certain conditions, such as the direct raw materials namely metals by considering the weight of raw materials without including their size. This study does not consider parts that were purchased and subcontracted by the company and did not count the number of raw materials stored at the beginning of the period. This research also does not determine the cost of subcontract raw materials other than S45C-F, because subcontracts only occur in this type. This study also did not calculate the waiting time for processing raw material into finished goods, so the waiting time was assumed to be for 1 period.

Literature review

Inventory classification

Inventory plays an important role in business operations because inventory is the wealth the company has. A previous study considered the scheduling strategy to obtain a better inventory decision (Nurprihatin, Elvina, et al., 2021). When it comes to job scheduling, the jobs are grouped into several categories based on similarities (Goli & Keshavarz, 2022). In this study, goods are categorized based on ranking values such as from highest to lowest value can be done by the ABC method, where this method divides 3 groups of quantities called groups "A", "B", and "C". The three groups in the ABC classification have meaning, where "A" means very important, while "B" means important enough, and "C" means least important. Item "A" generally accounts for about 10 to 20 percent of the total number of items in inventory and accounts for around 60 to 70 percent of the annual value of the goods stored. On the other hand, item "C" amounts to around 50 to 60 percent of the total number of items, but only about 10 to 15 percent of the value of goods stored (Stevenson, 2018).

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a development of the AR, MA, and ARMA models. This model is used if a time series is not stationary, where the data is said to be not stationary if all the moment data (middle value, variance, and covariance) are not constant over a certain period. Non-stationary time series data can be converted to a stationary time series by differencing (d). That is, the original time series was replaced by a series of differencing. The ARIMA model can be denoted ARIMA (p, d, q), where p denotes the order of the autoregressive part (AR), d denotes the number of differences, and q denotes the order of moving average parts (MA). If the initial time series is stationary with no differencing ($d = 0$), then the model that occurs is not ARIMA but ARMA.

The formation of the ARIMA model (p, d, q) based on the Autocorrelations Function (ACF) and Partial Autocorrelations Function (PACF) charts (Table 1).

Table 1
Coefficient autocorrelation and partial autocorrelation for the ARIMA model.

Model	Autocorrelations	Partial autocorrelations
MA(q)	Cut off after the order q of the process	Die out
AR(p)	Die out	Cut off after the order q of the process
ARMA(p, q)	Die out	Die out

The MA (q) model will be formed if a cut-off occurs on the lag of q of the ACF while the PACF moves slowly towards 0 (die out), the model AR (p) will be formed if the ACF chart pattern moves slowly towards 0 (die out) while a cut-off occurs in the lag of q of the ACF, and ARMA pattern (p, q) will be formed if ACF and PACF move slowly towards 0 (die out).

Aggregate planning

Aggregate production planning is a medium-term production decision in a manufacturing company that determines the level of production, the level of inventory, the number of subcontracts, and the level of labor in each period to overcome existing constraints (Chen & Sarker, 2015). The linear programming model is a mixed aggregate planning method used to obtain optimal solutions to problems that involve the allocation of resources in terms of minimizing costs and maximizing profits. This model is formulated as a transportation model to obtain an aggregate plan that can match capacity with demand requirements and minimize costs (Stevenson, 2018).

Fig. 1 shows the appearance of Solver software that can be used to determine the minimum aggregate planning costs, and where to get the minimum costs. The solver will combine regular and subcontract production costs with limits on the level of regular and subcontract compliance according to existing production capacities and amounts produced must be following the number of demands.

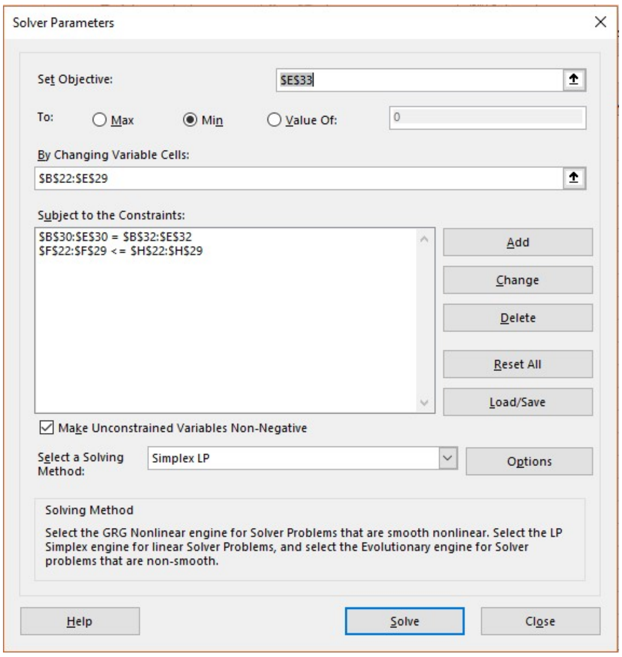

Fig. 1. Solver for aggregate planning

Master Production Schedule

The Master Production Schedule (MPS) or can be called the master production schedule states what final items should be produced, when needed, and in what quantities (Heizer et al., 2020). MPS is made to plan demand that is far enough into the future, so the company has some general ideas about possible future demand (Stevenson, 2018).

Probabilistic Economic Order Quantity Model

The EOQ model is a very popular and successful model for managing the supply chain (Yıldız & Yaman, 2018). This article presents a model that is different from the deterministic model, where the probabilistic EOQ model calculates demand behavior, and the lead time is uncertain or cannot be determined with certainty. The other difference between deterministic EOQ and probabilistic EOQ is that the probabilistic EOQ model can calculate the percentage of order fulfillment if it is known that the cost of inventory shortages (stock out cost). Following are the steps to calculate inventory capacity based on a probabilistic EOQ model (Ballou, 2004):

1. Calculate the determination of the optimum number of orders using the basic formula as presented in Eq. (1).

$$Q_0 = EOQ = \sqrt{\frac{2DS}{IC}} \tag{1}$$

2. Calculate the probability or likelihood of a lack of inventory. At this stage, there are 2 policies, which are shown in Eq. (2) and Eq. (3). topsep
   a. a backorder occurs if there is a pending order to find a replacement item.

$$P = 1 - \frac{QIC}{Dk} \tag{2}$$

   b. Lost sales occur if the company leaves the order unfulfilled so that the order is canceled.

$$P = 1 - \frac{QIC}{Dk + QIC} \tag{3}$$

3. Based on the P results obtained, determine the z value in the normal distribution table then find the value of $E_{(z)}$ in the normal loss per unit table, then calculate the new Q_0 value.

$$Q_0 = EOQ = \sqrt{\frac{2D(S + kSd\sqrt{LT}\,E_{(z)})}{IC}} \tag{4}$$

4. Repeat steps 2 and 3 until the values of P and Q are fixed or unchanged.
5. Calculate other calculations desired, such as Reorder Point (ROP), Safety Stock (SS), and Total Cost (TC).

where: D – demand per period, Sd – standard deviation of demand, S – setup cost, I – holding cost percentage, k – stock out cost, $E_{(z)}$ – normal loss per unit, LT – lead time, C – price of goods.

Periodic Order Quantity Model

The POQ method is used to overcome lumpy demand that is not always the same during the planning period, this method is the development of the EOQ method which assumes placing an order with a fixed order interval. The use of the EOQ method can be continued to calculate POQ, where POQ determines the size of the order quantity based on the period obtained by dividing the EOQ by demand per period (Heizer et al., 2020). Following are the steps in calculating POQ:

1. Determine the EOQ value.
2. Determine order frequency (f) by dividing the total demand in a year by the EOQ value.

$$f = \frac{D}{EOQ} \tag{5}$$

3. Determine the POQ value by dividing the number of periods per year (N) by the value of f.

$$EOI = \frac{N}{f} \tag{6}$$

Material Requirements Planning

Material Requirement Planning (MRP) is used to determine the amount of each item that will be used in producing the final product, and the time at which each item must be purchased or produced to meet the date specified for the final product (Ramya et al., 2019). MRP assumes that all necessary information is known with certainty, but uncertainties remain (Nahmias & Olsen, 2015). In making MRP, it is needed to enter the form of MPS, Bill of Material (BOM), and inventory records which are then processed into gross requirements, scheduled receipts, projected on hand, net requirements, planned order receipts, and planned order releases (Stevenson, 2018).

Materials and methods

Fig. 2 shows the analysis phase of this study which began with ABC analysis, forecasting using the ARIMA method with the help of Minitab 18 software, aggregate planning based on linear equations of transportation methods with the help of Solver software,

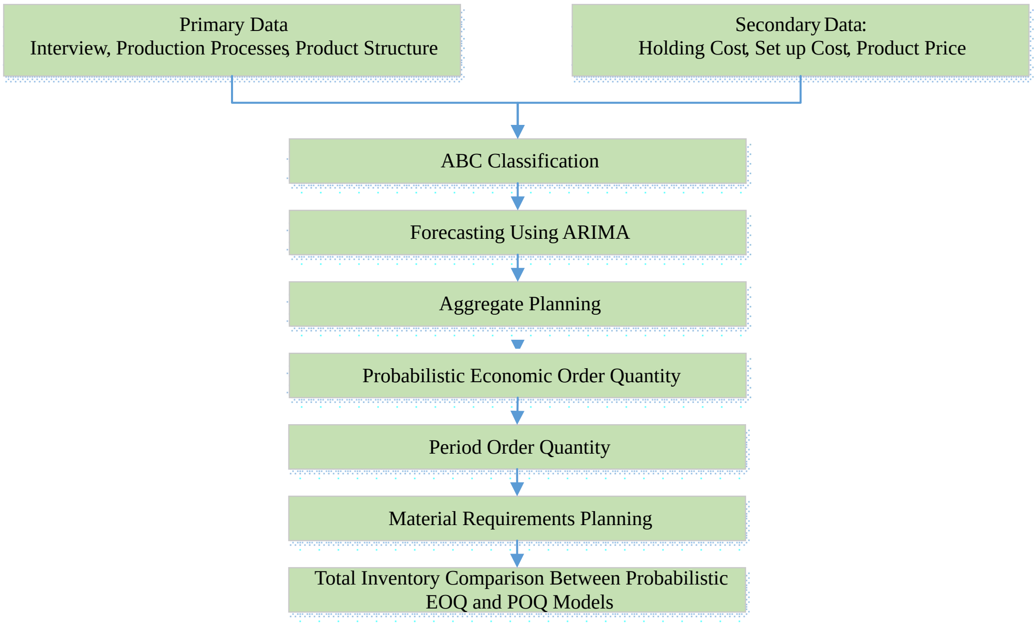

Fig. 2. Research flow chart

MPS, MRP calculations using lot sizing probabilistic EOQ and POQ. Ultimately, this paper compares the results of MRP calculations with probabilistic EOQ and POQ lot-sizing.

Results and discussion

In this section, the discussion covers the ABC classification and followed by the ARIMA forecasting method. After that, aggregate planning is performed before heading to the stage of making a Master Production Schedule (MPS). The output from the MPS is treated as the input for MRP.

ABC classification results

The lumpy demand for raw materials from January 2016 to December 2018 can be seen in Fig. 3. There are five basic costs associated with inventory, namely purchasing costs, storage costs, ordering costs, setup costs, and shortage costs (Stevenson, 2018). Table 2 shows the costs associated with the company's inventory.

Inventory classification is carried out to determine the classification of the use of raw materials processed by the company from January 2016 to December 2018. Table 3 shows the classification results of inventories. Based on calculations that have been made, of the 11 raw materials that the company has, there is 1 raw material that is categorized as A, namely S45C-F, 3 raw materials that are categorized as B, namely

Table 2
Inventory related costs.

Type	Information
Setup cost	IDR 14,285.81
Holding cost percentage	30%
Regular cost	IDR 5,683/kg
Regular capacity for S45C-F	224.48 kg
Subcontract capacity S45C-F	699.26 kg
Subcontract cost	IDR 10,000/kg
Lead time	4 days

Table 3
ABC classification results.

Raw material	Price (IDR)	Percentage (%)	Category
S45C-F	152,674,485	30.41	A
SGT-R	88,817,020	17.69	B
SKD11-R	69,874,830	13.92	B
SLD-R	69,495,730	13.85	B
KS3/SKS3/QKS3-R	46,040,605	9.18	C
S45C-R	29,031,585	5.79	C
KS3/SKS3/QKS3-F	22,994,400	4.58	C
QC11R	14,278,500	2.85	C
SCM415-R	7,020,000	1.4	C
SGT-F	1,230,960	0.25	C
HP4MA-F	619,080	0.13	C
Total	502,077,195		

SGT-R, SKD11-R, and SLD-R, and 7 raw materials which are categorized as C, namely SKS3-R/QKS3-R/KS3-R, S45C-R, SKS3-F/QKS3-F/KS3-F, QC11-R, SCM415-R, SGT-F, and HP4MA-F.

ARIMA forecasting analysis

Demand forecasting is done for category A and B raw materials to determine demand in the coming 12 periods. Forecasting is done by the ARIMA method with the help of Minitab software 18. Calculation results are shown in Table 4.

Aggregate Planning Results

Regular production planning and subcontracting for refinement of S45C-F is carried out to find out the minimum combination of production costs using the aggregate planning method. The results of the linear planning of aggregate planning with the help of Solver's software stated that the minimum total production cost for the S45C-F was IDR 20,149,701. The results are obtained by finding regular production quantities and subcontracts to meet existing demand. Fulfillment of demand is done by considering the number of raw materials that are produced regularly and subcontracts must be less than or equal to each production capacity and the amount of production in each period must be equal to the number of demands.

Master Production Schedule Results

MPS is made for raw materials in categories A and B to find out the amount and when the finished product that the company must make to meet existing demand. The results of the MPS calculation are shown in Table 5.

Probabilistic Economic Order Quantity results

Probabilistic EOQ calculations are performed as a reference and fill in the lot size on the MRP. Table 6 shows the results of the optimum order quantity

Table 4
Tests of forecasting methods.

Raw material	Model	Test of significance		Ljung-Box Q statistics		MSE
		Parameter	P-Value	Lag	P-Value	
S45C-F	ARIMA (1,1,1)	AR 1	0.364	12	0.536	30,784.30
		MA 1	0	24	0.551	
	ARIMA (0,1,1)	MA 1	0	12	0.422	30,529.60
				24	0.352	
	ARIMA (1,1,0)	AR 1	0.015	12	0.440	40,820.60
				24	0.482	
SKD11-R	ARIMA (1,1,1)	AR 1	0.736	12	0.548	1,040.93
		MA 1	0	24	0.867	
	ARIMA (0,1,1)	MA 1	0	12	0.606	1,003.27
				24	0.878	
	ARIMA (1,1,0)	AR 1	0.008	12	0.156	1,826.60
				24	0.651	
SLD-R	ARIMA (1,1,1)	AR 1	0.736	12	0.548	1,040.93
		MA 1	0	24	0.867	
	ARIMA (0,1,1)	MA 1	0	12	0.606	1,003.27
				24	0.878	
	ARIMA (1,1,0)	AR 1	0.008	12	0.156	1,826.60
				24	0.651	
SGT-R	ARIMA (1,0,1)	AR 1	0.034	12	0.352	2,123.67
		MA 1	0	24	0.486	
	ARIMA (0,0,1)	MA 1	0,011	12	0.373	2,460.50
				24	0.49	
	ARIMA (1,0,0)	AR 1	0.18	12	0.596	2,570.71
				24	0.843	

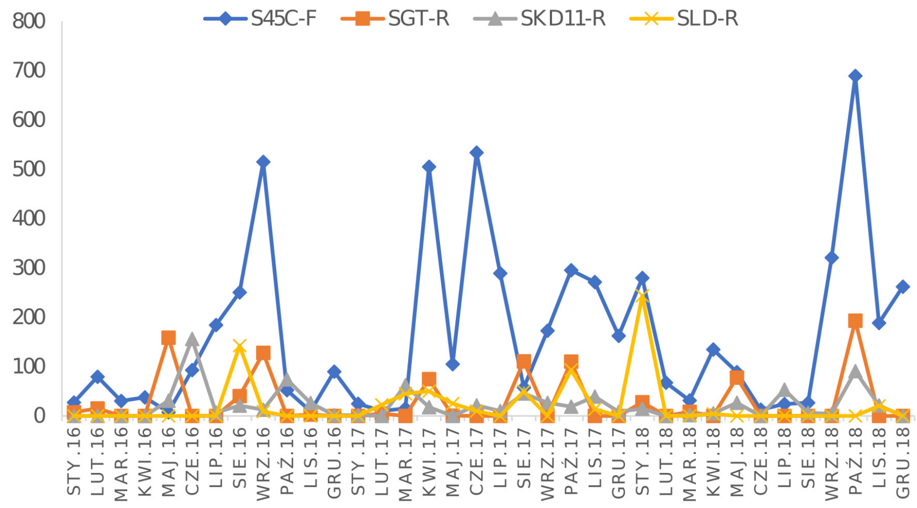

Fig. 3. Demand for raw materials (kg)

indicated by the Q value at the last iteration of each available raw material. This value is used as a reference in determining the number of units to be ordered from suppliers to meet existing demand and is simulated in the MRP table.

Table 5
Master Production Schedule result.

Period	S45C-F	SGT-R	SKD11-R	SLD-R
1	192.375	17.9505	20.4055	5.3693
2	194.592	22.4432	20.2507	17.0063
3	196.81	24.47	20.0959	4.2313
4	199.028	25.3844	19.9411	15.3041
5	201.246	25.7969	19.7863	11.8184
6	203.464	25.983	19.6315	14.9908
7	205.682	26.0669	19.4767	14.3339
8	207.9	26.1048	19.3219	18.204
9	210.118	26.1219	19.1671	16.2102
10	212.335	26.1296	19.0123	20.4155
11	214.553	26.1331	18.8576	19.1293
12	216.771	26.1346	18.7028	22.276

Table 6
Probabilistic EOQ calculation results.

Itera-tion	S45C-F		SGT-R		SKD11-R		SLD-R	
	Q	P	Q	P	Q	P	Q	P
0	110.93	0.8712	23.85	0.9693	16.71	0.9259	14.61	0.9152
1	112.39	0.8695	24.2	0.9688	16.8	0.9255	15.52	0.91
2	112.42	0.8695	24.21	0.9688	16.81	0.9255	15.57	0.9097
3	112.42	0.8695	24.21	0.9688	16.81	0.9255	15.57	0.9097

Periodic Order Quantity results

POQ calculation is done after knowing the value of EOQ. Table 7 shows the POQ values where ordering raw materials to suppliers must be done every 1 period for raw materials S45C-F, SGT-R, and SKD11-R as well as for raw materials SKD11-R done every 2 periods.

Table 7
POQ calculation results.

Raw Material	EOQ	Average Demand	POQ
S45C-F	112.42	204.573	1
SGT-R	24.21	24.8932	1
SKD11-R	16.81	19.5541	1
SLD-R	15.57	14.9408	2

Material Requirements Planning results

The calculation of MRP is done for each raw material that is in categories A and B from the results of ABC analysis where the source of demand for each raw material comes from the results on the MPS. MRP analysis was carried out using lot sizing probabilistic EOQ and POQ. The results of the calculation of saving costs and MRP message costs with probabilistic EOQ lot sizes and POQs are shown in Table 8.

The result of MRP calculations shows different lot-sizing techniques with the lowest total cost. On one hand, the POQ model produces the lowest cost for planning S45C-F, SGT-R, and SKD11-R with the total cost of each raw material IDR 171,429. On the other hand, the probabilistic EOQ model is chosen for SLD-R with a total cost of IDR 2,882,410.

Table 8
Total Cost Based on Different Lot-sizing.

Raw Material	EOQ Probabilistic (IDR)	POQ (IDR)
S45C-F	3,195,780	171,429
SGT-R	3,414,171	171,429
SKD11-R	2,723,243	171,429
SLD-R	2,882,410	3,431,427

Conclusions

ABC analysis is made to find out how important each raw material is based on the value of its use over the past 3 years. Based on calculations that have been made, of the 11 raw materials that the company has, there is 1 raw material that is categorized as A, namely S45C-F, 3 raw materials that are categorized as B, namely SGT-R, SKD11-R, and SLD-R, and 7 raw materials which are categorized as C, namely SKS3-R/QKS3-R/KS3-R, S45C-R, SKS3-F/QKS3-F/KS3-F, QC11-R, SCM415-R, SGT-F, and HP4MA-F. The raw materials that are categorized "A" and "B" are further analyzed because both categories represent more than 50 percent of the raw materials that the company has.

Aggregate planning is carried out so that the company can maximize the normal capacity of finishing grinding. Aggregate planning is created with the help of Solver software to produce a minimum total production cost. The total costs generated amounted to IDR 20,149,701. MRP is made to illustrate when raw materials must be available and processed to fulfill the demand. Based on the analysis of MRP calculations that have been carried out on S45C-F, SGT-R, SKD11-R, and SLD-R using lot-sizing EOQ probabilistic and POQ it is known that the POQ method produces the lowest cost for planning S45C-F, SGT-R, and SKD11-R with a total cost of all raw materials are IDR 171,429 and for SLD-R the probabilistic EOQ method was chosen with a total cost of IDR 2,882,410.

To produce a more optimal solution, subsequent studies can be more detailed on the cost of operating a grinding machine used in the process of refinement of each raw material. Different raw materials certainly have different thickness levels, therefore it requires observation to record the length of time needed to refine each type of raw material. The results obtained certainly illustrate the cost of refinement of each material that is more accurate if it converts demand into a narrower period, such as weekly or daily to find out the exact demand that comes every day. Besides, another step is to use other forecasting methods that allow obtaining the number of forecast predictions with a lower error value. Future studies can use other lot sizing methods that enable lower total costs to be obtained. Also, the objective function in terms of minimizing the total cost, total pollution, and total human risk at the same time can be implemented (Tirkolaee et al., 2022).

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