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Reduction of Raw Material Inventory Costs with an Operational Management Approach for Beverage Products at Loca Coffee

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A B S T R A C T

Facing significant demand fluctuations has resulted in Loca Coffee experiencing a surge in inventory costs, a lack of control over raw material inventory, and suboptimal service quality. To assist the company, this study aims to reduce inventory costs, minimize order frequency, and improve service quality. To achieve these objectives, an operational management approach is applied in this research. One of the inventory control techniques, Material Requirements Planning (MRP), will be utilized. In implementing an effective MRP system, the Holt-Winter and SARIMA methods will be applied in the forecasting process. Machine learning techniques will be employed for the forecasting model using time series sales data of Loca Coffee products, with Python programming language. As long as the approach is carried out in the appropriate manner, the findings of the research indicate that the implementation of an inventory control system that is based on MRP was successful in achieving a reduction in costs of Rp 10,335,500, a significant decrease in the frequency of orders, and an improvement in the quality of service

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INTRODUCTION

Demand fluctuations pose a significant challenge in the coffee shop industry where sales volume can change drastically within hours, days, or even seasonally. Research shows that 60% of coffee shops struggle to predict demand accurately, with estimated losses reaching 15% of potential revenue due to the inability to meet customer demand during critical times. (National Restaurant Association 2024). Loca Coffee faces challenges with the increasing demand and expectations of young consumers, while the variability of preferences and rapidly changing trends require flexibility in stock management and operational efficiency. This emphasizes the importance of reviewing and optimizing raw material inventory management strategies to meet dynamic demand without burdening the cost structure.

Figure 1. Fluctuation in demand

The graph in Figure 1 represents the highest sales volume for coffee and non-coffee product variants, showing fluctuations in production levels that can suddenly spike during certain periods. The cause of this spike is due to several events taking place on certain days, resulting in an increase in consumer levels at Loca Coffee. Therefore, Loca Coffee is experiencing issues related to its raw material inventory. This issue can pose challenges such as overstock and stockout in inventory management. Excess stock can result in high storage costs, the risk of raw material damage, and tied-up capital. On the other hand, stock shortages can disrupt production continuity, cause potential sales losses, and diminish customer trust.

Facing these issues, operational efficiency through optimal inventory management becomes key to maintaining competitiveness without sacrificing product quality or service quality. This research focuses on efforts to reduce raw material inventory costs through an operational management approach. The complexity of inventory management issues necessitates a systematic approach that can comprehensively integrate various aspects of inventory management. Material Requirements Planning (MRP) as one of the solutions that can be implemented to address the challenges in managing raw material inventory. Material Requirements Planning (MRP) as one of the solutions that can be implemented to address the challenges in managing raw material inventory. . (Heizer et al., 2017).

In the implementation of the MRP system, determining the order lot size becomes one of the important decisions that can affect the effectiveness of inventory control. Lot for Lot (LFL) is one of the lot sizing techniques used to optimize the order quantity of raw materials in this study. Based on several research sources conducted by (Ramadhan dan Widajanti 2024), (Utami dan Widajanti 2024), (Saputra dan Apsari 2024), it has been proven that the Lot for Lot technique is one of the methods that can significantly minimize inventory costs in relation to MRP implementation.

Utilizing information technology is one of the most important things that cannot be improved in today's digital world to maximize MRP in this study. The use of machine learning with the Python programming language as a data processing tool provides flexibility and reliable capabilities in managing the complexity of inventory management calculations. As forecasting methods in this study, the two techniques that will be used are Holt-Winters and SARIMA. (Seasonal AutoRegressive Integrated Moving Average). From previous research by (Wibisono et al. 2024), it is explained that the Holt-Winters method has good capabilities in demand forecasting due to its relatively low error rate. On the other hand, SARIMA is a more complex forecasting method and is more specific for data with seasonal components. By combining elements from the ARIMA (AutoRegressive Integrated Moving Average) model and seasonal components, SARIMA is capable of handling data with more pronounced seasonal fluctuations and accounting for more complex seasonal patterns. According to the findings of the research conducted by (Suseno dan Wibowo 2023), which used the SARIMA method to achieve satisfactory forecasting results, this is consistent with those findings.

LITERATURE REVIEW

Inventory Management

Goods that will be sold or used within a certain period are called inventory. (Ningrum, Asih, dan Sultan 2024). Raw materials, work-in-progress products, and finished goods that are considered business assets ready or to be sold are called inventory. (Singh dan Verma 2018). Inventory management plays a crucial role in achieving supply chain goals, reducing costs, and ensuring that goods are delivered to customers without delay. (Albayrak Ünal, Erkayman, dan Usanmaz 2023).

Forecasting

Forecasting is a scientific and artistic approach to predicting future events. According to (Nur et al. 2024), forecasting involves the quantitative or qualitative estimation of a future phenomenon by analyzing historical data using natural and statistical methods. (Tutupoho, Laitupa, dan Duwila 2024) expand this definition by stating that forecasting is a combination of art and science in projecting past data into the future, either through mathematical models or subjective assessments.

Forecast accuracy

According to (Azari 2024), the calculations used to determine forecasting accuracy are by calculating the values of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error. (MAPE). The accuracy of the forecast will be more precise if the values from the measurements are minimized.

The value of the prediction error rate (RMSE) is a magnitude, and the smaller this value (approaching zero), the more accurate the forecasting results will be. The RMSE value can be calculated using the following equation.

$$RMSE = \sqrt{\frac{\Sigma(y_t - \hat{y}_t)^2}{n}} \quad (1)$$

The MAE value can be calculated using the following formula: MAE shows the average absolute error between the actual value and the forecast result. Here is how to measure the accuracy level of the forecasting model.

$$MAE = \frac{1}{n}\Sigma|y_t - \hat{y}_t| \quad (2)$$

The Mean Absolute Percentage Error method is useful for showing the percentage of forecasting error compared to the actual value. Where the accuracy of the forecasting model will be better if the MAPE value is below 10%. (semakin kecil semakin baik). According to the formula, the MAPE value can be obtained from the following equation.

$$MAPE = \left(\frac{1}{n}\Sigma_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|\right) \times 100\% \quad (3)$$

Time Series

According to (Heizer et al., 2017), time series analysis means dividing past data into small parts and then making projections for future data from those parts. A series of data arranged sequentially with the same time intervals, such as weekly, monthly, or quarterly, is called a time series.

Holt-winters

The main focus of the Holt-Winters method is the level value (α), the slope (α), and the seasonal effect. (Nuranun 2021). This method combines the Holt and Winters approaches to address issues related to trends and seasonal patterns. All parameters have values between 0 and 1. The closer these values are to 0, the smaller the weight influence on the latest data in forecasting future values.

Seasonal Autoregressive Integrated Moving Average

Seasonal Autoregressive Integrated Moving Average is an evolution of the ARIMA method, which combines autoregressive and moving average. However, additionally, this method is specifically designed for seasonal patterned data. (Ibrahim dan Kurniati 2023). According to (Febiola et al. 2024), the SARIMA method is used for forecasting time series data that has a seasonal pattern. The stationarity test on the data to ensure that there are no unstable trends or seasonality is the first step in using this technique. After the data is shown to be stationary, the next step is to analyze the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to find the model. The SARIMA model itself has a non-seasonal component denoted by (p, d, q) and a seasonal component denoted by (P, D, Q), as well as a seasonal period symbolized by S. To determine the parameter p, which is the number of variables used in autoregression, and q, which is the number of variables used in moving average, the autocorrelation function and the partial autocorrelation function of the residuals will be analyzed. After the best model is selected, parameter estimation is carried out to obtain a more precise model.

Material Requirement Planning (MRP)

According to (Bayudhana dan Kamandang 2023), Material Requirement Planning (MRP) is a method applied to control the raw material requirements in the production process of a product. This system helps determine the quantity of materials needed and their availability time to ensure a smooth production process.

According to (Utama et al. 2019), the MRP system is useful for determining the amount of raw materials to be ordered based on production needs by adding calculations of costs that may arise due to inventory, such as storage costs and ordering costs.

Lot Sizing

According to (Heizer, Render, dan Munson 2017), the MRP system is an effective method for production planning and determining net requirements. However, net requirements still require decisions regarding the quantity and timing of orders, known as lot-sizing decisions. In the MRP system, there are several methods for determining lot size, and commercial MRP software typically offers several methods for determining lot size. Here are three commonly used methods to determine lot size:

Lot-for-lot. That is, the lot size determination method produces the quantity needed to meet the production plan. This method aligns with the main objective of the MRP system, which is to meet dependent demand needs.

Economic Order Quantity. EOQ is useful when demand is relatively constant. However, in an MRP system, demand can change each period. Therefore, the lot sizing technique using EOQ is often less effective in MRP.

Periodic Order Quantity. Periodic Order Quantity (POQ) is a method for determining the lot size that orders the required quantity within a specific time period, for example, every three weeks.

Machine Learning

A part of artificial intelligence called machine learning focuses on enhancing the ability of computers to learn from available data. In this process, the system is designed to learn independently and make decisions without having to be constantly reprogrammed by humans. This approach enables computers to find the best patterns in decision-making while also adapting to changes that occur. (Rachman, Kusdinar, dan Indrayana 2024).

Python

The design philosophy of Python emphasizes simplicity, readability, and flexibility, making it a useful language for various stages of research and scientific endeavors. Python can be used for general computation, experimental design, building device interfaces, connecting and controlling various hardware/software tools, as well as data analysis and visualization. With these capabilities, Python is well-suited for tasks that require heavy data processing. (Vaughan 2023).

METHODOLOGY

This study uses a descriptive research strategy based on quantitative analysis. The data used in this research comes from two sources: primary and secondary. Primary data was obtained directly from the Loca Coffee archives, through observation and interviews with relevant parties. This primary data includes information about product demand, production schedules, and raw material ordering times. Secondary data is obtained from internal company reports, sales databases, and existing inventory records, which include historical product sales data, raw material stock, and inventory cost information. This research uses an operational management approach, focusing on the application of machine learning algorithms implemented using the Python programming language to analyze and forecast product sales. The forecasting methods that will be applied in the analysis are the SARIMA (Seasonal Autoregressive Integrated Moving Average) model and Holt-Winters to predict demand with seasonal patterns and trends. The MRP technique applied in this study is Lot-for-Lot, which allows for controlling the order quantity according to actual needs, without over-ordering. The inventory management system of Loca Coffee was used to collect data for this research through direct observation and documentation. The data analysis method will use descriptive statistical analysis and forecasting with the mentioned algorithms, as well as cost efficiency evaluation based on the comparison between the traditional MRP method and the proposed implementation. For the forecasting analysis, it will be conducted using Visual Studio Codes with the Python programming language.

RESEARCH RESULT

Sales forecasting plays a very important role in the effective implementation of the Master Production Schedule (MPS). MPS is a master production plan used to determine the production volume and schedule for the final product within a specific period. For MPS to function well, accurate sales forecasting is necessary to predict future product demand.

Forecasting with the Holt-Winters method

The Holt-Winters method is one way to forecast data using time series, which is useful in handling data with seasonal patterns, in addition to trend and level. This method combines three components: level, trend, and seasonality, to produce accurate predictions in situations where the data shows periodic or seasonal variations. To run the machine learning function in forecasting using the Holt-Winters method, exponential smoothing is imported from the statsmodels library.

First, the code will load sales data from a CSV file. This process involves reading an external file and converting it into a data structure that can be further processed in the analysis.

```
# Load Sales Data
file_path = r'C:\Users\asus\AppData\Local\Programs\Python\Project
Skripsi\pjaren.csv' #data location
data = pd.read_csv(file_path, delimiter=';')
data_penjualan = data['ArenLatte']
data_penjualan = data_penjualan.squeeze()
```

Next, the matplotlib library will be used to visualize the sales data in the form of a plot. Data visualization is crucial in analysis because it makes it easier to identify patterns, trends, and relationships in the data in a clearer and more understandable way.

```
# Visualisasi data awal
plt.figure(figsize=(12, 6))
plt.plot(data_penjualan, marker='o', linestyle='-', color='brown',
label='ArenLatte')
plt.title('Data Penjualan Mingguan')
plt.xlabel('Week')
plt.grid(True)
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.ylabel('Penjualan (Cup)')
plt.show()
```

Next, the dataset will be divided into two parts: one for training the model (training data), and one for testing the model's accuracy (testing data). The model will be created to train Holt-Winters Exponential Smoothing on the training data. The parameters used need to be adjusted according to the characteristics of the data to be forecasted.

The model will then be applied to forecast training and testing data. After generating the forecasts, the model will then be evaluated on how well it performs by comparing the forecast results with the actual test data. The trained Holt-Winters model will be used to forecast sales values for the next 12 weeks. The forecasting results show how the model predicts trends and seasonality for periods not present in the training or testing data.

Forecasting with the SARIMA model

The next forecasting will use the SARIMA technique, which is an enhancement of the ARIMA model specifically built to handle time series data

```
# training model Holt-Winters
hw_model = ExponentialSmoothing(train,
                                trend='add',
                                seasonal='mul',
                                seasonal_periods=4) #according to
                                                the type of the data
hw_fitted = hw_model.fit()
```

with seasonal patterns. This model is very useful for forecasting data that has recurring variations over specific periods. The SARIMA model consists of non-seasonal components (p, d, q) and seasonal components (P, D, Q) with a seasonal period S. The parameters p (autoregression) and q (moving average) are determined through the analysis of the autocorrelation and partial autocorrelation functions of the residuals. The selection of the forecasting model is done by comparing the values of the Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan and Quinn Criterion (HQ), where the model with the smallest value indicates the best quality and optimal number of parameters. After the data is loaded, the stationarity of the data will be tested using the Augmented Dickey-Fuller test. (ADF test). If the data is stationary, it will proceed to the next stage, and if the data is not stationary, it will undergo data differencing treatment.

```
# stasionarity test
def adf_test(series, column_name):
    print(f"Uji ADF untuk kolom: {column_name}")
    result = adfuller(series, autolag='AIC')
    print(f"ADF Statistic: {result[0]:.4f}")
    print(f"p-value: {result[1]:.4f}")
    print(f"Lag Used: {result[2]}")
    print(f"Number of Observations Used: {result[3]}")
    print("Critical Values:")
    for key, value in result[4].items():
        print(f"   {key}: {value:.4f}")
    if result[1] <= 0.05:
        print("Kesimpulan: Data stasioner")
    else:
        print("Kesimpulan: Data tidak stasioner")
# ADF test application
adf_test(data['ArenLatte'], 'ArenLatte')
```

Data differentiation is the process of analyzing how data evolves and identifying existing patterns or trends. This process can be used to detect unusual data or disruptions, understand the impact of code changes on data, ensure consistency between old and new systems during database migration, and verify data similarity across different locations.The code for differentiating data is as follows.

After the data is stationary, ACF and PACF plots are created to determine the parameters of the ARIMA model. The `plot_acf()` and `plot_pacf()` functions are used to illustrate the autocorrelation and partial autocorrelation in the differenced data, which provide indications for model parameter selection. Before testing the model, the data will be divided into training and testing data.

The SARIMA model will be created with parameters determined for the AR, I, MA (AutoRegressive, Integrated, Moving Average) parts as well as the seasonal component. These parameters are relatively dependent on the identification of ACF and PACF in the data to be forecasted.

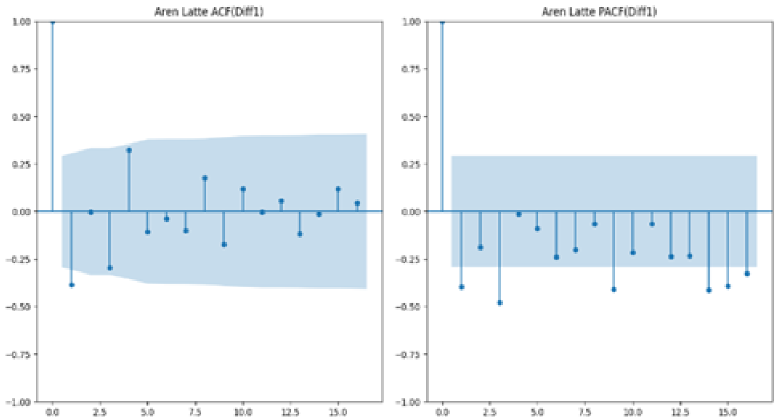

Figure 2. Results of ACF and PACF Visualization for Aren Latte Product

```
# run the SARIMA model
model = SARIMAX(train['ArenLatte'],
                order=(1, 1, 1),
                seasonal_order=(1, 0, 1, 4),
                enforce_stationarity=False,
                enforce_invertibility=False)
results = model.fit(disp=False)
print(results.summary())
```

```
# First differentiation
data['ArenLatte_diff'] = data['ArenLatte'].diff().dropna()
data = data.dropna(subset=['ArenLatte_diff'])
# test data after differentiation
adf_test(data['ArenLatte_diff'], 'ArenLatte_diff')
```

DISCUSSION

After the ideal model is obtained, the model will be used to forecast the train and test data. Next, the evaluation results of the model testing with the smallest value will be examined, and then the model will be used to forecast the next 12 weeks. To create the master production schedule, the evaluation values of the forecasting results will be compared, and then the best forecasting method will be chosen to compile the MPS.

Table 1. Forecast Evaluation

Produk	Comparison of evaluation scores					
	RMSE		MAE		MAPE	
	Holt-Winters	SARIMA	Holt-winters	SARIMA	Holt-winters	SARIMA
Aren Latte	16,27	16,91	12,4	12,5	37,10	43,50
Cafe Latte	7,91	6,23	6,67	5,02	35,11	42,60
Lychee Tea	17,98	17,46	14,62	14,90	47,38	36,33
Lemon Tea	8,14	6,67	6,56	4,93	38,88	27,89

From the comparison results presented in Table 1, the Aren Latte product will use projections from the Holt-Winters method, the Cafe Latte product will use analysis results from the SARIMA method, the Lychee Tea product will use analysis results from the SARIMA method, and the Lemon Tea product will use forecasting results from the SARIMA method.

Bill Of Material is a complete list of materials needed to assemble a finished product. The details of the raw materials for each product will be presented in Figure 3 – Figure 6.

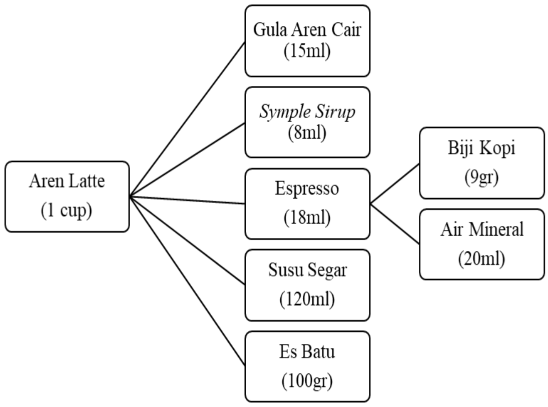

Figure 3. BOM of Aren Latte

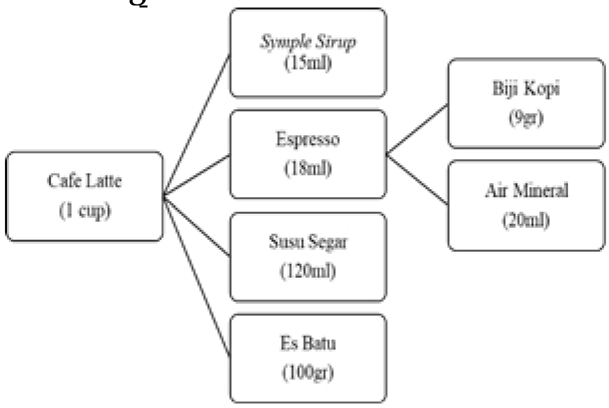

Figure 4. BOM of Aren Latte

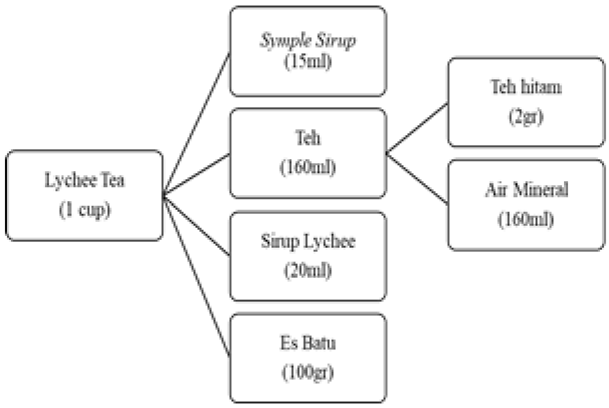

Figure 5. BOM of Lychee Tea

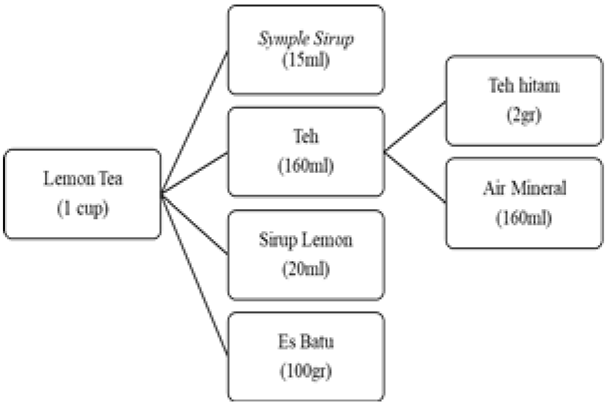

Figure 6. BOM of Lemon Tea

Material Requirement Planning (MRP) is a method that not only controls the raw material requirements in the production process but also takes into account logistics aspects and related costs, such as storage and ordering costs. By combining the calculation of the required material quantities and their availability times, MRP enables companies to plan the production process more efficiently while minimizing potential additional costs arising from suboptimal inventory management. This system functions to maintain the smoothness of production while also controlling expenses that may arise from the imbalance between demand and the supply of raw materials.

Table 2. MRP Simple Syrup

Simple Syrup(litre)	November				December				January			
Lead Time : 0	1	2	3	4	1	2	3	4	1	2	3	4
Gross Requirement	1,67	1,47	1,43	1,33	1,48	1,41	1,50	1,33	1,37	1,30	1,23	1,14
Scheduled Receipts												
Project on Hand	5,00	3,33	1,86	0,43	4,10	2,62	1,21	4,71	3,38	2,01	0,71	4,48
Net Requirements				0,90			0,29				0,52	
Planned Order Receipts				5,00			5,00				5,00	
Planned Order Released				5,00			5,00				5,00	

Table 3. MRP Lemon Syrup

Lemon Syrup (litre)	November				December				January			
Lead Time : 1	1	2	3	4	1	2	3	4	1	2	3	4
Gross Requirement	0,35	0,19	0,27	0,27	0,26	0,25	0,24	0,24	0,23	0,22	0,21	0,21
Scheduled Receipts												
Project on Hand	2,00	1,65	1,46	1,19	0,92	0,66	0,41	0,17	0,93	0,70	0,48	0,27
Net Requirements								0,07				

Planned Order Receipts								1,00				
Planned Order Released							1,00					1,00

Table 4. MRP Lychee Syrup

Lychee Syrup (litre)	November				December				January			
Lead Time : 1	1	2	3	4	1	2	3	4	1	2	3	4
Gross Requirement	0,66	0,76	0,56	0,60	0,62	0,62	0,62	0,60	0,60	0,58	0,58	0,56
Scheduled Receipts												
Project on Hand	2,00	1,34	0,58	0,02	1,42	0,80	0,18	1,56	0,96	0,36	1,78	1,20
Net Requirements				0,58			0,44			0,22		
Planned Order Receipts				2,00			2,00			2,00		
Planned Order Released			2,00			2,00			2,00			

Table 5. MRP Palm Sugar Syrup

Palm Sugar Syrup (litre)	November				December				January			
Lead Time : 1	1	2	3	4	1	2	3	4	1	2	3	4
Gross Requirement	0,69	0,35	0,72	0,43	0,59	0,30	0,60	0,36	0,46	0,24	0,48	0,29
Scheduled Receipts												
Project on Hand	2,00	1,31	0,96	0,24	1,81	1,22	0,92	0,32	1,96	1,50	1,26	0,78
Net Requirements				0,19				0,04				
Planned Order Receipts				2,00				2,00				
Planned Order Released			2,00				2,00					

Table 6. MRP Coffee Beans

Coffee Beans (Kg)	November				December				January			
Lead Time : 1	1	2	3	4	1	2	3	4	1	2	3	4
Gross Requirement	0,69	0,53	0,64	0,49	0,62	0,49	0,64	0,44	0,59	0,45	0,48	0,39
Scheduled Receipts												
Project on Hand	3,00	2,31	1,78	1,14	0,65	0,03	4,54	3,90	3,46	2,87	2,42	2,03
Net Requirements						0,46						
Planned Order Receipts						5,00						
Planned Order Released					5,00							

Table 7. MRP Fresh Milk

Fresh Milk (litre)	November				December				Januari			
Lead Time : 1	1	2	3	4	1	2	3	4	1	2	3	4
Gross Requirement	9,24	6,96	8,64	6,48	8,28	6,60	8,52	6,48	7,32	6,00	6,48	5,16
Scheduled Receipts												
Project on Hand	36	26,76	19,8	11,16	4,68	20,40	13,80	5,28	22,8	15,48	9,48	3,00
Net Requirements					3,60			1,20				2,16
Planned Order Receipts					24,00			24,00				24,00
Planned Order Released				24,00			24,00				24,00	

The determination of Planned Order Released is decided based on considerations of the minimum order quantity from suppliers and/or the minimum order frequency to minimize overstock or high inventory costs. As for the components in the bill of material, MRP is not applied due to considerations of abundant inventory and/or flexible inventory types.

With the inventory planning using the MRP method that has been implemented, the company has the option to reduce its inventory costs. Initially, Loca Coffee had a stockout cost of Rp2,472,000. After the implementation of MRP, this cost was eliminated because the amount of raw material inventory per product was determined. In addition, the implementation of MRP also helps in reducing other inventory costs, namely ordering costs, with a reduction amounting to Rp10,335,500.

Table 8. Comparison of Inventory Cost

Method	Ordering Cost	Stockout Cost	Total Inventory Cost
Conventional	Rp11.170.500	Rp2.472.000	Rp13.642.500
MRP	Rp3.307.000	-	Rp3.307.000

The results of this study are comparable to the research conducted by (Riotama dan Sunarso 2024), which found that the implementation of MRP can improve the effectiveness of expenditures for raw material inventory compared to other methods such as Fixed Production Level (FPL), Economic Order Quantity (EOQ), and Production Order Quantity (POQ).

In terms of order frequency, there is a significant difference before and after the implementation of MRP. Initially, Loca Coffee placed orders based solely on estimates and with unmeasured order quantities, resulting in high inventory costs for the company. Here is the data comparing the order frequency between the company's method and the MRP method. The data was taken over the same period, which is the last 3 months of actual data and 3 months of MRP implementation results.

Table 9. Order Frequency

Raw Material	Conventional Method	MRP Method
Fresh Milk	5	2
Lemon Syrup	1	1
Lychee Syrup	4	3
Palm Sugar Syrup	4	2
Coffee Beans	4	1

From the data presented in Table 9, it can be seen that the frequency has decreased due to the implementation of the MRP system. This indicates that with the application of MRP, the company can reduce how often raw materials are ordered, thereby reducing inventory costs. This result is in line with previous research by (Ramdani, Suhendra, dan Putra 2024), which obtained optimal inventory costs and ideal ordering frequency through the application of the MRP method.

After the implementation of Material Requirement Planning at Loca Coffee, it indirectly has a positive impact on the company's operations. With the projection of demand, the ordering of raw materials has a positive impact on the company's inventory control. This is in line with previous research by (Devi et al. 2024) which investigated several companies in Indonesia, indicating that inventory control and production planning can have impacts such as inventory cost savings, determining optimal order quantities, and improving efficiency in order frequency.

CONCLUSIONS AND RECOMMENDATIONS

In inventory control, the Material Requirement Planning (MRP) method has proven effective in reducing inventory costs, optimizing purchase frequency, and improving the quality of products and services provided to consumers. As a recommendation, Loca Coffee can utilize the results of this research to reduce inventory costs in facing market fluctuations and consider implementing an automated inventory monitoring system with early warning alerts. Additionally, future research could explore the use of hybrid models, such as combining SARIMA with the Random Forest machine learning algorithm, for more accurate raw material demand predictions, as well as considering external data such as weather, holiday calendars, or social trends that affect product demand.

ADVANCED RESEARCH

The researcher acknowledges that there remain significant shortcomings in language, writing, and presentation format, reflecting the researchers' limited knowledge and abilities. Consequently, the researcher anticipates constructive criticism and suggestions from multiple parties to enhance the article's quality. Additionally, future research could explore the use of hybrid models, such as combining SARIMA with the Random Forest machine learning algorithm, for more accurate raw material demand predictions, as well as considering external data such as weather, holiday calendars, or social trends that affect product demand.

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