Production Scheduling Based on Smart Forecasting Model of Bottled Mineral Water Products

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PRODUCTION SCHEDULING BASED ON SMART FORECASTING MODEL OF BOTTLED MINERAL WATER PRODUCTS

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Abstract Optimal production planning is a problem that causes product stock buildup at PT Marina. Factors that affect production planning in the company are the conditions of Demand, Safety Stock, and Production Costs. The results of the demand forecasting method chosen are the Moving Average with N = 3 and the Mean Absolute Percentage Error (MAPE) = 0.05 is 68,084 boxes/period with a production cost of IDR 544,672.00/period. The Safety Stock of bottle products in the ninth forecasting period is 8076 Boxes. Based on the three factors above, an intelligent production planning model was developed using a fuzzy logic approach. The result of defuzzification of demand planning for bottle products for the ninth or three months using the Center of Area (COA) method was 59,917 Boxes. Based on the defuzzification of production planning, the total cost of aggregate production planning for the next three months using the chase strategy method is 617,235,300. 1500 ml = 17,105 boxes. Based on the aggregate planning model above, the company can schedule production and raw materials so that the warehouse's product stock management is maintained optimally.

Keywords Forecasting, Safety Stock, Defuzzification, Aggregate, MPS

1. Introduction

Bottled mineral water products have a broad market segment, so companies need optimal production planning to meet market demand. PT Marina is a company engaged in bottled mineral water production. The company carries out the production process with a make to stock system. The current condition is that the company is experiencing product stock buildup, which causes the product to be damaged. Production planning requires a demand forecasting process to implement production scheduling optimally [1]. Production system management based on the number of requests can maintain stock conditions in the warehouse optimally [2].

Limited warehouse conditions and production planning based on product demand that are not optimally planned cause the company to experience product stock buildup. Selection of a production planning model based on the trend of product demand [3]. Production planning starts from identifying demand to determining the schedule for the arrival of raw materials [4]. Demand identification can be made with a forecasting approach by using and analyzing trends in demand data for the previous period [5]. Trend analysis of historical demand data is an initial process to determine the probability of the accuracy of forecasting results [6], [7].

Stock management is currently a company problem because fluctuations in demand often cause a buildup of products in the warehouse. Fluctuation demand can impact stock which can't be identified optimally [8]. Optimal production planning can meet market demand so that products in the warehouse do not experience accumulation because they are optimally distributed [9]. Stock conditions integrated with production planning will prevent product damage due to shelf life [10]. Safety stock management can be carried out using an integrated model with adaptive demand forecasting [11].

Production scheduling is influenced by demand in the strategic phase, where product prices will affect the level of demand [12]. Production costs will affect the aggregate plan to determine the most optimal production costs [13], [14]

The company is currently unable to process demand forecasts accurately, where several variables have vague values to determine the amount of production. Demand forecasting is done by considering various variables, including external variables, which are vague and must be measured by quantification [15]. Determining requests can use variables that have fuzzy values where the Fuzzy Inference System (FIS) will identify forecasting results based on the membership set model built [16], [17]. Demand and final stock conditions have a vague value that can affect the optimal production amount [18], [19]

The company has three variations of bottle packaging products, so in planning production, aggregation is needed for one period to determine the optimal production cost requirements. Aggregate planning can be used to plan production costs by paying attention to variables with a vague value by using a membership set that matches the variables used [20], [21]. Aggregate planning can be used to determine production cost efficiency with optimal labour and inventory management [20], [22].

The novelty of this research is it integrates the production planning process using a fuzzy logic approach to the demand forecasting process based on three variables: demand, safety stock and production costs. The demand planning defuzzification process will become the basis for carrying out aggregate planning and the Master Production Schedule so that the company can plan stock optimally.

2. Materials and Methods

Production planning identifies the amount of production to be carried out based on forecasted demand and customer orders [23]. The stages of developing a production planning model are as follows:

1. Forecasting Method

The Moving Average determines the number of future requests based on the company's average historical data. The Moving Average forecasting model is as follows: [24]

$$MA = \frac{Mn\ 1 + Mn2 + \ldots Mn}{P}$$

The Exponential Smoothing method performs the demand forecasting process by looking at the whole level values of the company's data. The Exponential Smoothing method is as follows: [25]

$$F_{n+1} = F_n + \alpha\ (X_t - F_n)$$

2. Forecasting Error Analysis

Mean Absolute Percentage Error (MAPE) is the percentage of an error rate that is owned based on the absolute value of the error with historical demand data [26]. MAPE can provide an overview regarding the optimal error by comparing several forecasting methods with the following formulation: [27]

$$MAPE = \sum_{n=1}^{X} \{[|(Pn - Bn)/Bn|]/X\} \times 100\%$$

3. Safety Stock

Safety stock management based on product demand can maintain the optimal stock in the warehouse for distribution [9] [28]. The safety stock model based on the level of probability is as follows : [29] [30]

$$\text{Safety Stock} = Z\alpha \times \text{Standard Deviation} \times \sqrt{\text{lead time}}$$

4. Fuzzy Rule Base

Determination of fuzzy membership set boundaries using trapezoidal and triangular graphs by using all possibilities on the fuzzy rules base. The fuzzy rule base is a defuzzification result limit that may occur in the membership set that is built with rules Ri: If Y_1 is AB_1^i and Y_2 is $B_2^{i,}$ and$\cdots Y_m$ is $B_m^{i,}$ Then Y is C^i; i = 1; 2;…n [31], [32]

5. Defuzzification Demand

The defuzzification process uses the Center of Area (COA) method. This method compares the Area and Moment generated from the fuzzy operators used. The defuzzification formulation using the COA method is as follows. [33], [34]

$$\text{Center of Area} = \frac{\int_{y=0}^{z} \mu A(y) x\ dx}{\int_{y=0}^{n} \mu A(b)\ dx}$$

6. Aggregate Planning

Aggregate planning is production planning based on demand management to determine minimum cost requirements, which are influenced by the amount of production, labour, and inventory [35], [36]. With the following formula: [37] [38]

$$\text{Inventory} = \text{Stock}_{t-1} + \text{Production}_n - \text{Demand}_n$$

7. Master Production Schedule

Fluctuations in demand can affect stock conditions, so companies must schedule optimal production to avoid stock buildup [39], [40]. The Master Production Schedule (MPS) consists of managing Gross Requirements Customer Orders, Project on Hand (POH), Production Schedule and Production Receipt with the following formulation: [41], [42]

$$POH = \text{Stock}_{t-1} + \text{JIP Receipt} - \text{Max [Gross Requirement; Customer Order]}$$

3. Results and Discussion

The production problems faced by the company today are related to production planning that is not optimal, causing stock conditions to accumulate in the warehouse. Companies currently need a model related to production planning based on forecasted demand levels which are influenced by three variables that have a vague value, namely the level of demand, safety stock and total production costs, so that they can identify the level of product demand in the future to determine the optimal production schedule.

Currently, the company has increased the number of stocks in the warehouse. The average stock condition with warehouse capacity can be seen in Figure 1.

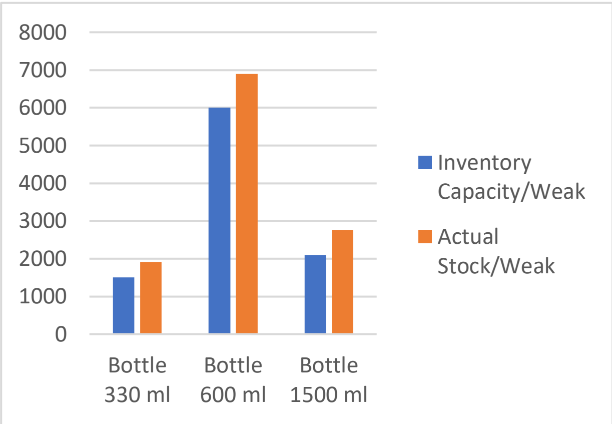

Figure 1 Comparison of stock and warehouse capacity

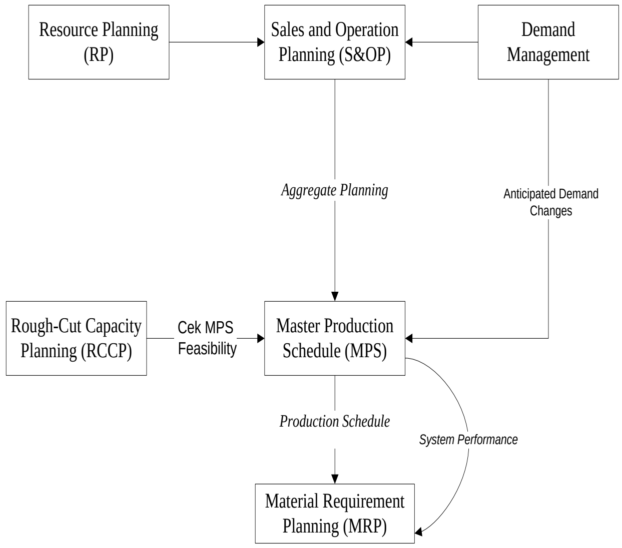

Figure 2 Strategic Level Of Production Planning Control (adapted from [43])

Based on the data for the last three months, the company has experienced stock buildup; where this condition is caused by the company not being able to identify demand based on the influencing variables, namely demand, safety stock and total production costs.

Based on this condition, an optimal production planning model is needed to maintain stock conditions based on product demand. The development of this model is based on the company's real conditions and literature studies. Production planning with various products begins with identifying demand by paying attention to the undefined variables, which is a strategic level in the company and can be seen in Figure 2.

The development of a production planning model is carried out by considering the variables that affect demand forecasting. Decision making regarding demand forecasting is influenced by demand, safety stock, and production costs. These three variables are difficult to manage using the model above. In this study, a smart demand forecasting model was developed to identify the three variables with a vague value to be measurable. The development of an intelligent production planning model can be seen in Figure 3.

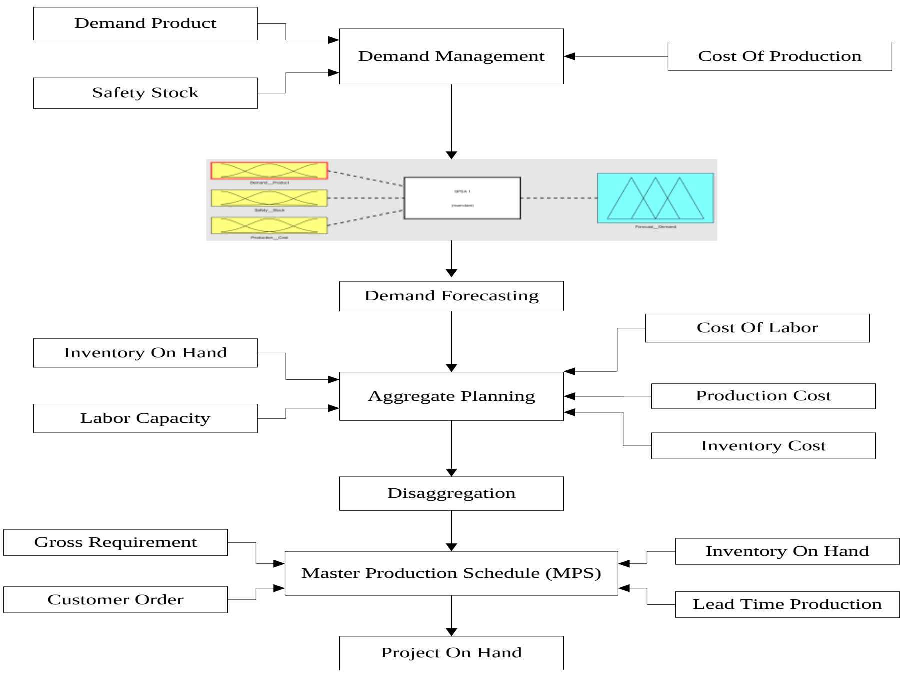

Figure 3 Smart production planning model

Based on the above problems, an intelligent production planning model was developed to determine production schedules at PT Marina to maintain stock conditions in the warehouse. The stages of analysis carried out based on an intelligent production planning model for the management of bottled mineral water products are as follows:

1. Forecasting Demand

   Forecasting compares two methods, namely Moving Average and Exponential Smoothing. These methods determine the number of requests based on the smallest Mean Absolute Percentage Error (MAPE). Historical data used for 24 months is divided into eight periods, each containing three months of historical data and forecasting the demand forecasting process for bottles (boxes) using the POM for Windows application. Bottle demand data input in the period in the POM for Windows application can be seen in Figure 4.

	Demand(y)
1	62890
2	66656
3	62613
4	60756
5	66886
6	65385
7	66192
8	72675

Figure 4 Input bottle demand product on POM for Windows application

The results of the comparison of data processing using the Moving Average method with N = 3 and Exponential Smoothing with $\alpha = 0.05$ in the POM for Windows application can be seen in Figure 5.

Forecasting Results

(untitled) Summary

Measure	Value
Error Measures	
Bias (Mean Error)	2116,87
MAD (Mean Absolute Deviation)	3435,67
MSE (Mean Squared Error)	14648120
Standard Error (denom=n-2=3)	4941
MAPE (Mean Absolute Percent Error)	,05
Forecast	
next period	68084

(a) Hasil Error Moving Average

Forecasting Results

(untitled) Summary

Measure	Value
Error Measures	
Bias (Mean Error)	5784,33
MAD (Mean Absolute Deviation)	5784,33
MSE (Mean Squared Error)	43053050
Standard Error (denom=n-2=6)	7576,55
MAPE (Mean Absolute Percent Error)	,09
Forecast	
next period	61213,73

(b) Hasil Exponential Smoothing

Figure 5 Part a and b Tingkat Error Peramalan Permintaan

Based on the comparison results above, the lowest MAPE value is the Moving Average method (N=3). The results of the Error Analysis method selected Moving Average can be seen in Figure 5

.

Details and Error Analysis

(untitled) Solution

	Demand(y)	Forecast	Error	|Error|	Error^2	|Pct Error|
1	62890	58900	3990	3990	15920100	,06
2	66656	59099,5	7556,5	7556,5	57100690	,11
3	62613	59477,32	3135,68	3135,68	9832463	,05
4	60756	59634,11	1121,89	1121,89	1258639,0	,02
5	66886	59690,2	7195,8	7195,8	51779490	,11
6	65385	60050	5335	5335	28462310	,08
7	66192	60316,74	5875,26	5875,26	34518660	,09
8	72675	60610,5	12064,5	12064,5	145552100	,17
TOTALS	524053		46274,63	46274,63	344424400	,69
AVERAGE	65506,63		5784,33	5784,33	43053050	,09
Next period forecast		61213,73	(Bias)	(MAD)	(MSE)	(MAPE)
				Std err	7576,55	

Figure 6 Moving Average (N=3) Error Analysis

Based on a comparison of the lowest Mean Absolute Percentage Error (MAPE) value of 0.05 using the Moving Average (MA) method. Based on these results, the number of company requests in the nine periods using the Moving Average method is 68,084 boxes.

2. Safety Stock

Determination of Safety Stock (SS) for bottled beverage products at PT Marina uses a probabilistic method where the total stock is determined using the value of the probability that it will occur. Determination of Safety Stock uses a production lead time of 3 days, value α = 5% and Service Level = 95%. The results of data processing in determining Safety Stock based on demand data for eight periods can be seen in Table 1.

Table 1 Safety stock calculation data

Period	Demand	$(X\text{-}X_{bar})$	$(X\text{-}X_{bar})^2$
1	62890	-2616,6	6846726,39
2	66656	1149,4	1321062,89
3	62613	-2893,6	8373065,64
4	60756	-4750,6	22568437,89
5	66886	1379,4	1902675,39
6	65385	-121,6	14792,64
7	66192	685,4	469738,89
8	72675	7168,4	51385600,14

Based on the requested data above, the standard deviation value is 3642.646, and the Reorder Point (ROP) value is 204,596 boxes in the ninth period. Based on the standard deviation and ROP values, the Safety Stock can be determined as follows:

$$\begin{aligned}\text{Safety Stock} &= Z\alpha \text{ x Standard Deviation x } \sqrt{\text{lead time}} \\ &= 1{,}28 \text{ x } 3642{,}64 \text{ x } \sqrt{3} \\ &= 8076 \text{ box/period}\end{aligned}$$

3. Production Cost

The total production cost of bottle packaging uses the total production cost based on the company's production plan. The production plan is obtained from the results of demand forecasting. In the ninth period, it was found that the demand forecast value to be realized for production was 68,084 boxes, with an average production cost of IDR 8,000/box. Based on the cost of the amount to be produced, it can be planned that the average production cost is IDR 544,672,000.- This data will be used for the demand defuzzification process.

4. Defuzzification Demand

Fuzzy logic determines the number of requests based on three decision variables with a fuzzy value. The development of the number of intelligent requests fuzzy model is carried out using the Matlab R2015a application. Based on the conditions in the company, three variables that influence production planning are obtained: demand, safety stock, and production costs. Based on the three variables above, the fuzzy input and output membership sets are developed as follows:

Table 2 Input and output fuzzy demand variable

Variable	Low	Medium	High
Demand	32.500; 37.500; 42.500	40.000; 46250; 52500	50.000; 62.500; 75.000
Safety Stock (SS)	0; 0; 5000; 10.000	8000; 12000; 16000	14.000; 16.000; 22.000; 22.000
Production Cost (x Million)	400; 420; 440	430; 480; 530	500; 560; 620
Fuzzy Forecast Demand	0; 0; 50.000, 75.000	75.000; 90.000; 105.000	105.000; 115.000; 125.000; 125.000

Based on the input variables above, the membership set of each variable can be developed based on its parameter limits. The set of membership input demand forecasting with the triangular type can be seen in Figure 6.

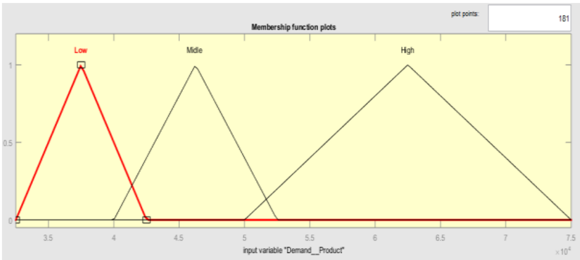

Figure 7 Forecast demand membership function

The results of the request membership set will be used to determine the degree of request membership as follows:

$$\mu demand\ (68.084) = \frac{75.000 - 68084}{75.00 - 62500} = 0,54$$

Based on the parameter limits of the Safety Stock variable, a membership set of fuzzy inputs with Triangular and Trapezoidal types can be developed. The Safety Stock (SS) input membership set can be seen in Figure 7.

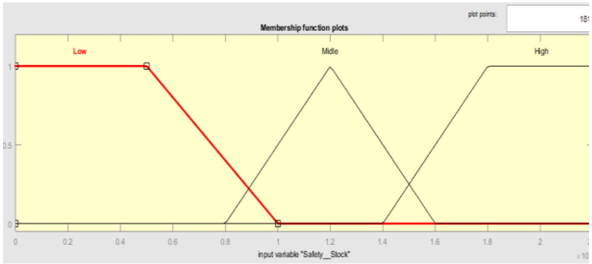

Figure 8 Safety stock membership Function

The results of the calculation of the Safety Stock and the developed membership set can determine the degree of membership as follows:

$$\mu safety\_stock\ (8076) = \frac{10.000 - 8076}{10.000 - 5000} = 0,38$$

Based on the input parameter limits above, the input membership set of the total cost can be developed. The input membership set for the total production costs can be seen in Figure 8.

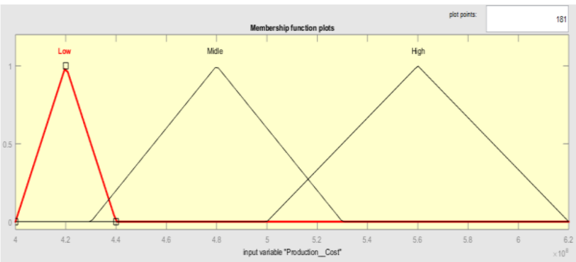

Figure 9 Production cost membership Function

The results of the membership set of production costs have the parameter limits used to determine the degree of membership as follows: (x 1000)

$$\mu Production\_Cost\ \ (544.672.) = \frac{544.672 - 500.000}{560.000 - 500.000} = 0,74$$

The development of the membership degree of each input variable will be used to determine the value of the fuzzy operator. The fuzzy operator uses the "and" function based on the developed fuzzy rules. The fuzzy operator values are as follows:

α = Min (μ demand [0,54] ∩ μ Safety Stock [0,38] ∩ μ_Production Cost [0,74])

α = Min (0,54; 0,38; 0,74)

α = 0,38

Based on the demand forecasting output membership set, the fuzzy operator will determine the defuzzification value. The request planning membership set can be seen in Figure 9.

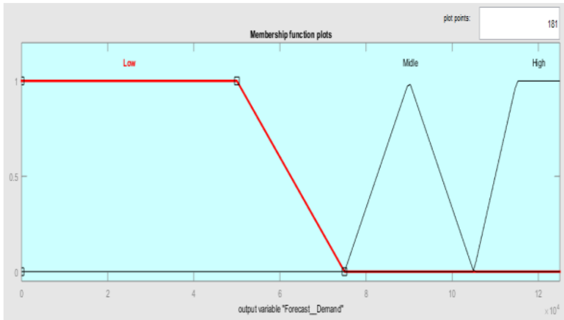

Figure 10 Defuzzification demand membership function

The fuzzy rule developed on this demand forecasting model has 81 rules that may occur in defuzzification. Based on the developed Fuzzy Rule Base, the moment value and area can be determined to determine the demand:

W1 = (65.380-0) x 0,38 = 25158, 23

W2 = $\frac{(75.000-6380)x0,38}{2}$ = 1850,89

W3 = $\frac{(80.772-75.000)x0,38}{2}$ = 1110,52

W4 = (99228-80772) x 0,38 = 7101,87

W5 = $\frac{(105.000-99.228)x0,38}{2}$ = 1110,53

W6 = $\frac{(108.848-105.000)x0,38}{2}$ = 740,35

W7 = (125.000-108.848) x 0,38 = 6215,30

The total area that occurs based on the operator and the fuzzy rule base is 43287.69. Based on the area, the defuzzification process can determine the moment. The moment that occurred was as follows:

Moment 1 = $\int_{0}^{65380} 0,38\ x\ dx$

Moment 2 = $\int_{65380}^{75000} 3x - 0,00004x2\ dx$

Moment 3 = $\int_{75000}^{80772} 0,000173\ x2 - 13x\ dx$

Moment 4 = $\int_{80772}^{99228} 0,38\ x\ dx$

Moment 5 = $\int_{99228}^{105000} 7\,x - 0{,}00066\,x2\;dx$

Moment 6 = $\int_{105000}^{108848} 0{,}0001\,x2 - 10{,}5\,x\;dx$

Moment 7 = $\int_{108848}^{125000} 0{,}38\,x\;dx$

The moment of the fuzzy operator that occurs is 2,593,661,509.34. The moment and area results are then used to determine demand defuzzification using the Center of Area (COA) method. Based on the results of defuzzification using the COA method, the optimal demand for bottled products for the 9th period was 59,917 boxes. The results of defuzzification processing using the Matlab application can be seen in Figure 11.

Figure 11 Fuzzy result for demand forecasting on Matlab application

Based on the demand defuzzification process results, aggregate production planning will be carried out with the ninth period's product demand level of 59,917 boxes.

5. Aggregate Planning

The aggregate planning of PT Marina's bottle packaging products considers demand conditions. Based on the defuzzification results, the demand for the next three months (1 period) is 59,917 boxes and will be converted into demand data per month. Based on the results of converting demand data from 2021-2022 from January to March can be seen in Table 3.

Table 3 Demand forecasting conversion

Month	Percentage Contribution	Demand Forecasting
January	30,64%	18360
February	34,58%	20719
March	34,78%	20837

The development of the aggregate plan must consider the condition of the company. The current condition of the company is as follows:

a. The number of production workers is 14 people
b. The capacity of workers is 1250 boxes/month
c. The worker's salary is IDR 70,000/day
d. Production costs 8800/box
e. Inventory fee 1750/box
f. Hire fee IDR 35,000/person
g. Initial stock 765 boxes.

The results of the defuzzification of demand and company conditions can then be developed in an aggregate model using the Chase Strategy. Chase strategy is an aggregate planning method that assumes the forecasted demand and planned production will be the same. Aggregate planning using the chase strategy method for bottled beverage products at PT Marina can be seen in Table 4.

Table 4 Aggregate Planning Bottle Product

Component	January	February	March
Resources			
Contract Worker	15	17	17
Production	18360	20778	20778
Demand Forecasting	18360	20719	20837
Inventory	765	824	765
Cost			
Salary	26.250.000	29.750.000	29.750.000
Layoff	-	-	-
Hire	35.000	70.000	-
Production	161.568.000	182.846.400	182.846.400
Inventory	1.338.750	1.442.000	1.338.750
Total Cost	189.191.750	214.108.400	213.935.150

Aggregate planning is carried out for three months, from January to March 2023. The results of aggregate planning show the amount of production, inventory, and labour the company must prepare for. The total aggregate planning cost the company must prepare for the next three months to carry out the production process is IDR 617,235,300.

6. Master Production Schedule (MPS)

Production planning for bottled mineral water production in the company requires a disaggregation process because the company has 3 product variants, namely 330 ml, 600 ml, and 1500 ml. The percentage of disaggregation can be seen in Table 5.

Table 5 Percentage of disaggregation product

Product	Price/Box	Income	Disaggregation
Bottle 330 ml	13000	260.520.000	23,41%
Bottle 600 ml	15000	534.750.000	48,05%
Bottle 1500 ml	17500	317.730.000	28,55%

Based on the disaggregation results, each product's production can be determined for one month. The disaggregation results for three months of bottled water products can be seen in Table 6.

Table 6 Disaggregation production

Product	January	February	March
Bottle 330 ml	4298	4864	4864
Bottle 600 ml	8821	9983	9983
Bottle 1500 ml	5241	5932	5932

The results of product aggregation will be scheduled into a Master Production Schedule (MPS). The MPS results for a 330 ml product with a production lead time of 1 week and an initial stock of 250 can be seen in Table 7.

Table 7 MPS product bottle 330 ml

Component	1	2	3	4	5	6	7	8	9	10	11	12
Gross Requirement	1075	1075	1075	1075	1216	1216	1216	1216	1216	1216	1216	1216
Customer Order	520	720	880	750	910	835	1050	960	1150	1200	870	920
Projected On Hand	895	1050	1265	1510	1534	1474	1508	1432	1566	1670	1714	498
JIP Receipt	1450	1230	1290	1320	1240	1156	1250	1140	1350	1320	1260	0
JIP Schedule	1230	1290	1320	1240	1156	1250	1140	1350	1320	1260	0	0

The 660 ml product has a production lead time of 1 week with an initial stock of 7500 boxes. The results of the Master Production Schedule (MPS) for January to March 2023 are determined based on the lead time and the number of requests. The MPS results can be seen in Table 8.

Table 8 MPS product bottle 600 ml

Component	1	2	3	4	5	6	7	8	9	10	11	12
Gross Requirement	2205	2205	2205	2205	2496	2496	2496	2496	2496	2496	2496	2496
Customer Order	220	230	350	780	1250	1230	1100	1200	980	3300	2200	1750
Project On Hand	1625	2700	495	1640	2594	3387	4011	4765	5609	2309	2999	503
JIP Receipt	3250	3280	0	3350	3450	3289	3120	3250	3340	0	3186	0
JIP Schedule	3280	0	3350	3450	3289	3120	3250	3340	0	3186	0	0

The 1500 packaged product has a production lead time of one week, where the initial stock for this product is 1340 boxes. Based on demand forecasting and production lead time, the Master Production Schedule can be seen in Table 9.

Table 9 MPS product bottle 1500 ml

Component	1	2	3	4	5	6	7	8	9	10	11	12
Gross Requirement	1310	1310	1310	1310	1483	1483	1483	1483	1483	1483	1483	1483
Customer Order	980	1070	1230	1100	1326	1289	1340	1120	1456	1200	1230	1289
Project On Hand	860	970	1420	110	307	504	781	1068	1275	1535	1782	299

Component	1	2	3	4	5	6	7	8	9	10	11	12
JIP Receipt	1790	1420	1760	0	1680	1680	1760	1770	1690	1743	1730	0
JIP Schedule	1420	1760	0	1680	1680	1760	1770	1690	1743	1730	0	0

Production scheduling using the Master Production Schedule (MPS) method can provide clear information related to production schedules and the ability of the stock to maintain demand fluctuations.

Based on the analysis results from the Master production schedule, the average stock for 330 ml= 1343 boxes, 600 ml packaging = 2719 boxes and 1500 ml packaging = 909 boxes for 12 weeks (3 months). This condition shows that there is no stacking because it is still below the maximum capacity of the warehouse for storing products in bottled packaging.

4. Conclusion

Based on the results of demand planning defuzzification, it was found that the demand value was 59,917 boxes, and the total aggregate production cost using the chase strategy method was Rp. 544,672,000. Based on the results of the Master Production Schedule (MPS), the average stock of the company's products for three months, namely January to February 2023, obtained the highest stock of bottles 330 ml = 1670 boxes/weak, 600 ml = 2719 boxes/weak and bottle 1500 ml = 909 boxes/weak. This condition indicates that the stock condition is well maintained because it is still below the warehouse capacity, namely for warehouse capacity of bottle 330 ml = 1500 boxes/week, bottle 600 ml = 6000 boxes/week and bottle 1500 ml = 2100 boxes/week. This condition shows that production scheduling using demand defuzzification techniques can maintain stock stability in the warehouse. The next research must be developed is a model for optimizing raw material planning to maintain availability according to the planned production schedule.

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