Available online at https://journal.rescollacomm.com/index.php/ijqrm/index

International Journal of Quantitative Research and Modeling

e-ISSN 2721-477X
p-ISSN 2722-5046

Vol. 4, No. 1, pp. 20-29, 2023

Inventory Control for MSME Products Using the Q Model with Lost Sales Condition Based on Products Sales Forecasting

Dita Aulia Nissa[1*], Sudradjat Supian[2], Julita Nahar[3]

[1,2,3]*Department of Mathematics, Faculty of Mathematics and Natural Science, Universitas Padjadjaran, Jatinangor, Indonesia*

**Corresponding author email: dita18004@mail.unpad.ac.id*

Abstract

Micro, Small and Medium Enterprises (MSMEs) have an important role in economic development in order to achieve thq quality of economic growth. Intense competition among MSMEs requires MSMEs to have a good inventory control that can help them minimize costs and maximize profits. One of the MSMEs that often experiences problems in inventory control is Sabun Bening Official. To solve the inventory problems in Sabun Bening Official, Holt-Winter Exponential Additive forecasting method is used as a guide to predict future product demand because product demand graph is seasonal and has trend pattern. After getting the value of product demand forecast, inventory control calucaltions are carried out using the Q Model probabilistic inventory method with lost sales condition. The uncertain and fluctuating demand causing the inventory system in Sabun Bening Official is probabilistic and the company will lose sales if it does not able to fulfill customer demands. Based on the research results, product forecasting for the coming period and inventory control policies which include the optimal number of product order, safety stock, reorder point, and product inventory costs can be obtained.

Keywords: Inventory Control, Holt-Winter Exponential Additive, Model Q, Lost Sales

1. Introduction

High population density in some area has an impact on ecomonic growth so it will affect the welfare of the population in the area itself. In order to achieve the quality of economic growth, national development in the economic field is needed, one of which is the empowerment of MSMEs. Micro, Small and Medium Enterprises (MSMEs) have an important role in national economic development. In 2019, Indonesia has 65,456,497 million MSMEs. This number increased by 1.98% when compared to 2018 which has 64,194,057 million. Until 2019, MSMEs accommodated 119,562,843 million workers and contributed 60,51% to the Gross Domestic Product (GDP) at current prices (Source: kemenkopukm.go.id). Intense competition among MSMEs requires MSMEs to have competitive advantages, one of which is good inventory management, so it can help them minimize costs and maximize profits.

One of the MSMEs that often experience problems in inventory management is Sabun Bening Official. The MSME assisted by the Ministry of Cooperatives and Small and Medium Enterprises of Republic of Indonesia is engaged in household needs and sells a variety of products, such as hand soap, softener, detergent, and dish soap. The fluctuating number of products requested by buyers and uncertain demand times are problems that are often encountered by MSME. In addition, the lack of supply due to high demand is a problem that is often experienced by MSME. Those problems lead to risk of lost sales due to the unavailability of products and the increase in ordering costs and inventory costs. If this happens frequently, MSME will suffer losses. Therefore, MSME requires an appropriate policy to meet the uncertain demand of buyers. This problem can be solved by using forecasting methods to determine the amount of demand in the future, then it will be determined the appropriate product inventory policy based on the forecasting results. The state of the art in this research can be seen in Table 1.

Table 1: State of the art research

Researcher	Year	Title	Results
Siregar et al.	2017	Comparison of Exponential Smoothing Methods in Forecasting Palm Oil Real Production	Holt-winter method additive has the lowest error rate.

Mgale et al.	2021	A Comparative Study of ARIMA and Holt-Winters Exponential Smoothing Models for Rice Price Forecasting in Tanzania	Holt-Winter Exponential Additive has a better result than the ARIMA model.
ElHafsi	2021	Optimal production and inventory control of multi-class mixed backorder and lost sales demand class models	Results obtained that the Q model with a back order case is the best model.
Sabit et al.	2020	Policy determination of inventory control of batik fabric using Q and P lost sale probabilistic model through montecarlo simulation approach as the system testing analysis.	Model Q with lost sales case is the most optimal policy.

Based on Table 1 and the problems above, the main discussion in this research is to combine the Holt-Winter Exponential Additive forecasting method with the Q Model probabilistic inventory method with lost sales condition to solve inventory problems in MSME.

2. Literature Review

2.1. Inventory Control

Inventory control is a series of control policies to determine inventory levels that must be maintained, when orders to increase inventory must be made, and how large orders must be held (Brown, 2018).

2.2. Probabilistic Inventory Control Method

According to Baker & Urban, (1988), a probabilistic inventory control method is an inventory model where conditions are not known with certainty, but the expected value, variance and distribution pattern can be predicted. The probabilistic inventory control policy is known by the existence of two methods, which are P Model and Q Model. The difference between the two models lies in the time of order.

2.3. Q Model with Lost Sales Condition

Q Model is a probabilistic inventory model related to the determination of operating stock and safety stock. In Q Model, order quantity is the main parameter and the amount of inventory ordered is constant (Kulińska, 2020). In a lost sales condition, when inventory is not available, the buyers is not willing to wait for the product requested until it is available in the warehouse. Buyers will go and look for the product they need elsewhere. Cost formulations considered in inventory control include:

1. Purchase Cost (O_b)
$$O_b = D.P \tag{1}$$
2. rder Cost (O_p)
$$O_p = \frac{AD}{Q} \tag{2}$$
3. Holding Cost (O_s)
$$O_s = \left(\frac{1}{2}Q + ss\right)H \tag{3}$$
4. Shortage Cost (O_k)
$$O_k = C_u \frac{D}{Q^*} N \tag{4}$$

The total inventory cost equation (O_T) can be seen in equation 5.
$$O_T = DP + \frac{AD}{Q} + \left(\frac{Q}{2} + \mathrm{r} - DL\right)h + C_u \frac{D}{Q^*} N \tag{5}$$

To get the inventory solution with the Q Model with lost sales condition, the value O_T needs to be minimized by determining the optimal value of Q^* and r^*. To obtain this value, the Hadley-Within algorithm can be calculated in the following way (Baker & Urban, 1988):

a. Calculate the initial value of Q_1^* with the Wilson formula

$$Q_1^* = Q_w^* = \sqrt{\frac{2AD}{H}} \quad (6)$$

b. Next, the value of the possible shortage of inventory α will be calculated and the value r_1^* will be calculated after

$$\alpha = \frac{HQ_1}{C_u D + HQ_1} \quad (7)$$

$$r_1^* = DL + Z_\alpha s\sqrt{L} \quad (8)$$

c. Then find the value of Q_2^* with the following equation:

$$Q_2^* = \sqrt{\frac{2D(A + C_u N)}{H}} \quad (9)$$

d. Recalculate the value of α and the value of r_2^* using the following equation:

$$\alpha = \frac{HQ_1^*}{C_u D + HQ_1^*} \quad (10)$$

$$r_2^* = DL + Z_\alpha s\sqrt{L} \quad (11)$$

e. If the value of r_2^* relatively equal to r_1^*, then the iteration is finished and it will be obtained $r_1^* = r_2^*$ and $Q_1^* = Q_2^*$. If not, then return to step (c) by replacing the values $r_1^* = r_2^*$ and $Q_1^* = Q_2^*$.

2.4. Forecasting

Forecasting is used to estimate how much demand will be in the future which includes needs in terms of quantity, quality, and time required in order to meet demand for goods (Miller et al, 2017). One of the forecasting methods is the time series method in which the analysis is carried out based on the forecast results which are compiled on the relationship pattern between the variables being sought and the time variable that influences them. The purpose of the time series is to find patterns in historical data series and extrapolate these patterns to the future (Wahyudi, 2017). The types of data patterns in time series are divided into four, which are horizontal, seasonal, cyclical, and trend.

2.5. Holt-Winter Exponential Additive

Holt-Winter Exponential Additive forecasting is a method used for data that contains trend and seasonal elements, where the seasonal elements indicate a relatively constant seasonal fluctuation. According to Wheelwright (1998), this method is based on three smoothing parameters to obtain forecasting results, which are α, β, and γ. This method requires the best combination of the three parameters in order to get optimal results. The equation used for forecasting with the Holt-Winter Exponential Additive method is as follows:

1. Specifies the values of α, β, and γ
   Determination of model parameters is determined through trial and error which is entering the value of α, β, and γ at intervals (0,1) then selecting the best α, β, and γ that produces the smallest MAPE (Nurhamidah et al, 2020).
2. Specifies the level smoothing value (L_t)
   $$L_t = \alpha(X_t - S_{t-k}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (12)$$
3. Determine the estimated value of the trend (b_t)
   $$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (13)$$
4. Determine the seasonal estimated value (S_t)
   $$S_t = \gamma(X_t - L_t) + (1-\gamma)S_{t-k} \quad (14)$$
5. Determine the forecast value (F_{t+m})
   $$F_{t+m} = L_t + mb_t + S_{t-k+m} \quad (15)$$

In the calculation of the Holt-Winter exponential additive method, it is necessary to initialize the initial value. The equation used to initialize the initial value is as follows:

1. Initialization value for exponential smoothing
   $$L_k = \frac{1}{k}(X_1 + X_2 + X_3 + \cdots + X_k) \quad (16)$$
2. Initialization value for trend smoothing
   $$b_k = \frac{1}{k}\left(\frac{X_{k+1} - X_1}{k} + \frac{X_{k+2} - X_2}{k} + \frac{X_{k+3} - X_3}{k} + \cdots + \frac{X_{2k} - X_k}{k}\right) \quad (17)$$
3. Initialization values for the seasonal smoothing of periods 1 to k
   $$S_t = X_t - L_k\ ;\ t = 1,2,3,\ldots,k \quad (18)$$

2.6. Validation of Forecasting Method Accuracy

In this research, the calculation of forecasting accuracy is used with the Mean Absolute Percentage Error (MAPE). MAPE is a measurement of accuracy by calculating the total percentage between forecasting data that deviates from the actual data (Adnan et al., 2018). The MAPE formula is as follows:

$$\text{MAPE} = \sum_{i=1}^{n} \frac{|PE_t|}{n} \tag{19}$$

$$PE_t = \left(\frac{X_t - F_t}{X_t}\right)(100)$$

The MAPE criteria according to Lawrence (2009) can be seen in Table 2.

Table 2: The MAPE criteria

MAPE	Interpretation
< 10%	High forecasting accuracy
10% - 20%	Good forecasting accuracy
20% - 50%	Reasonable forecasting accuracy
> 50%	Weak and inaccurate predictability

3. Materials and Methods

3.1. Materials

The object of this research is the supply of several types of products at MSME Sabun Bening Official. The MSME is located at Bandung City, West Java. The UMKM is engaged in household needs and selling offline or in person and online through the WhatsApp business platform and Tokopedia and Shopee e-commerce. Products which are the object of this research are hand soap, softener, and detergent. Those three products are the bestseller products and having the high demand from buyers. The sales data for January – August 2022 used for this research. Microsoft Excel and SPSS are the software used.

3.2. Methods

The research method used in this research is descriptive quantitative method. The reason for using the quantitative method is because the research data used is in the form of numbers and being analyzed using a model then the results will be given a discussion. It is said to be descriptive because the results obtained will be described and explained regarding the object under the research through the data that has been collected. As for the research process, data collection methods are obtained as follows:

1) Observation
2) Interview
3) Literature Review
4) Documentary Review

4. Results and Discussion

The data shown are the graph of sales data patterns for *hand soap* , *softener* and detergent products.

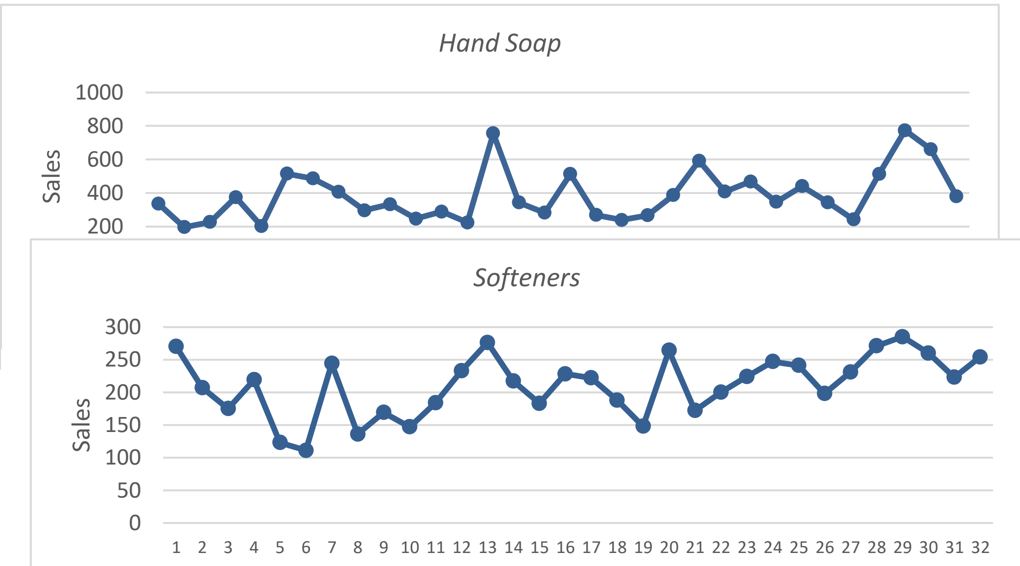

Figure 2: Softener product sales chart

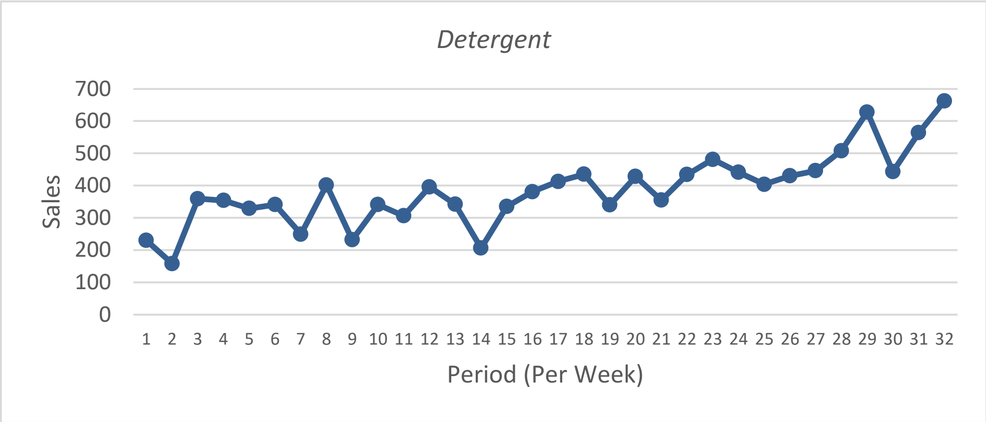

Figure 3: Detergent product sales chart

The sales data pattern for the three products is not fixed but has elements of an increasing trend and repeated in a certain period, so it can be assumed that the data pattern is seasonal. Seasonal element checking is seen from the comparison of each individual value with the average value for each season, where one period will be less than the season's average value and another period will be greater than the season's average value. Accordingly, the three products have a seasonal length of 8 periods.

Because the data has elements of trend and seasonality, forecasting with the Holt-Winter Exponential Additive method is chosen. There are three main steps for forecasting using the Holt-Winter Exponential Additive method, which are calculating initialization values, calculating smoothing values with parameters, and calculating forecasting values.

1) Calculating Initialization Value
   Calculations are calculated by using equations 16, 17, and 18. The calculation results for the initialization value of each product are presented in Tables 3 and 4.

Table 3: Product initialization value

Product	Levels (L_8)	Trends (b_8)	Seasonality (S_1)
Hand Soap	344	0.39063	-7
Softeners	185.625	2.375	84.275
detergent	302.75	1.8281	-72.75

Table 4. Seasonal smoothing value period 1 to 8

Hand Soap		Softener		Detergent	
Period	Seasonal (S_1)	Period	Seasonal (S_1)	Period	Seasonal (S_1)
2	-147	2	21.375	2	-144.75
3	-116	3	-10.625	3	56.25
4	32	4	33.375	4	51.25
5	-141	5	-62.625	5	26.25
6	172	6	-74.625	6	38.25
7	143	7	58.375	7	-53.75
8	64	8	-49.625	8	99.25

2) Calculating Smoothing Values with Parameters
   Calculations are calculated by using equations 12, 13, and 14. The results of calculating smoothing values with parameters are presented in Tables 6, 7, 8, 9, 10, 11, 12, 13, and 14.

Table 5. Product parameters

Hand Soap		Softener		detergent	
Parameter	Value	Parameter	Value	Parameter	Value
α	0.0001	α	0.001	α	0.08
β	0.09	β	0.1	β	0.00001
γ	0.507	γ	0.66	γ	0.685

Table 6. The value of smoothing the period 9 to 32 levels of hand soap product

Period (t)	Levels (L_t)	Period (t)	Levels (L_t)	Period (t)	Levels (L_t)	Period (t)	Levels (L_t)
9	344.3866	15	346.7530	21	349.1213	27	351.5080
10	344.7905	16	347.1320	22	349.5098	28	351.8975
11	345.1838	17	347.5422	23	349.9017	29	352,3133
12	345.5667	18	347.9346	24	350.3065	30	352.7257
13	345.9596	19	348.3269	25	350.6931	31	353.1484
14	346.3744	20	348.7125	26	351.1031	32	353.5457

Table 7. The advanced value of trend smoothing period 9 to 32 hand soap product

Period (t)	Trends (b_t)	Period (t)	Trends (b_t)	Period (t)	Trends (b_t)	Period (t)	Trends (b_t)
9	0.39026	15	0.39187	21	0.39336	27	0.39566
10	0.39148	16	0.39072	22	0.39292	28	0.39511
11	0.39165	17	0.39246	23	0.39283	29	0.39697
12	0.39086	18	0.39246	24	0.39391	30	0.39836
13	0.39104	19	0.39245	25	0.39324	31	0.40055
14	0.39318	20	0.39183	26	0.39475	32	0.40026

Table 8. The advanced value of seasonal smoothing for the period 9 to 32 hand soap product

Period (t)	Seasonality (S_t)	Period (t)	Seasonality (S_t)	Period (t)	Seasonal (S_t)	Period (t)	Seasonality (S_t)
9	-27,476	15	69.10321	21	-44.7924	27	-56.251
10	-77.9418	16	-0.96297	22	267.6403	28	-78.3981
11	-106.46	17	70.84843	23	64.03068	29	60.39946
12	-12.3963	18	-77.9382	24	59.70282	30	345.5327
13	-130.84	19	-107.407	25	33.56285	31	187.6479
14	292.4762	20	-47.0327	26	7.15417	32	43.35278

Table 9. The advanced values for period level smoothing 9 to 32 softener product

Period (t)	Levels (L_t)	Period (t)	Levels (L_t)	Period (t)	Levels (L_t)	Period (t)	Levels (L_t)
9	187.8966	15	202.1897	21	216.4182	27	230.6927
10	190.1967	16	204.6371	22	218.7834	28	233.0605
11	192.5569	17	207.0176	23	221.1486	29	235.5034
12	194.92	18	209.3991	24	223.5426	30	237.924
13	197.4203	19	211.7262	25	225.9139	31	240.2876
14	199.8851	20	214.1157	26	228.2765	32	242.6671

Table 10. The advanced value of trend smoothing period 9 to 32 softener product

Period (t)	Trends (b_t)	Period (t)	Trends (b_t)	Period (t)	Trends (b_t)	Period (t)	Trends (b_t)
9	2.36466	15	2.37443	21	2.36998	27	2.3752
10	2.3582	16	2.38174	22	2.36951	28	2.37446
11	2.35841	17	2.38161	23	2.36908	29	2.38131

12	2.35888	18	2.3816	24	2.37157	30	2.38524
13	2.37301	19	2.37615	25	2.37154	31	2.38308
14	2.38219	20	2.37749	26	2.37064	32	2.38271

Table 11. The advanced value of seasonal smoothing period 9 to 32 softener product

Period (t)	Seasonality (S_t)	Period (t)	Seasonal (S_t)	Period (t)	Seasonal (S_t)	Period (t)	Seasonality (S_t)
9	16.216	15	7.1823	21	-18.922	27	-15.168
10	-21.242	16	-1.453	22	-17.183	28	40.451
11	-9.2601	17	15.402	23	4.3239	29	26.234
12	36.48	18	-21.346	24	14.988	30	8.7279
13	30.57	19	-45.208	25	15.193	31	-9.9397
14	-14.077	20	45.327	26	-27.24	32	12.576

Table 12. The advanced value smoothing level period 9 to 32 detergent product

Period (t)	Levels (L_t)	Period (t)	Levels (L_t)	Period (t)	Levels (L_t)	Period (t)	Levels (L_t)
9	304.592	15	319.195	21	349.064	27	385.529
10	320.766	16	317.881	22	362.349	28	390.953
11	316.767	17	332.984	23	374.012	29	410.72
12	320.688	18	345.366	24	375.093	30	412.573
13	321.975	19	345.792	25	376.533	31	420.66
14	311.319	20	348.632	26	378.381	32	436.161

Table 13. The advanced value of trend smoothing period 9 to 32 detergent product

Period (t)	Trends (b_t)	Period (t)	Trends (b_t)	Period (t)	Trends (b_t)	Period (t)	Trends (b_t)
9	1,8281	15	1.8282	21	1.8284	27	1.8286
10	1.8283	16	1.8281	22	1.8285	28	1.8286
11	1.8282	17	1.8283	23	1.8286	29	1.8288
12	1.8282	18	1.8284	24	1.8286	30	1.8288
13	1.8282	19	1.8284	25	1.8286	31	1.8289
14	1.8281	20	1.8284	26	1.8286	32	1,829

Table 14. The advanced value of seasonal smoothing period 9 to 32 detergent product

Period (t)	Seasonality (S_t)	Period (t)	Seasonal (S_t)	Period (t)	Seasonal (S_t)	Period (t)	Seasonal (S_t)
9	−72.642	15	-6.1048	21	10.9915	27	41.199
10	-31.736	16	74.5001	22	30.1513	28	104.024
11	10.3433	17	31.9288	23	71.3641	29	152.299
12	67.7327	18	51.4022	24	68.6139	30	30.3404
13	21.9861	19	-0.7091	25	28.8722	31	120.667
14	-60.095	20	75.7031	26	51.5508	32	176.313

3) Calculating Forecasting Value

Calculations are performed using equation 15. The results of calculating the sales forecasting value of each product are presented in Table 15.

Table 15. Product sales forecasting results from 15 August 2022 to 24 October 2022

Hand Soap		Softeners		Detergent	
Period	Forecasting (F_{t+m})	Period	Forecasting (F_{t+m})	Period	Forecasting (F_{t+m})
33	388	33	260	33	467
34	362	34	220	34	491
35	298	35	235	35	483
36	277	36	293	36	548
37	416	37	281	37	598
38	701	38	266	38	477

39	544	39	249	39	570
40	400	40	274	40	627
41	391	41	279	41	481
42	365	42	239	42	506
43	302	43	254	43	497

Based on calculations through equation 19, the result is that the MAPE value of the three products is less than 20% where the MAPE of hand soap is 18.236%, softener is 14.1957%, and detergent is 13.6989%.

After knowing the results of product forecasting, then a normality test will be carried out on product sales data. The normality test uses the Kolmogorov-Smirnov test with the test hypothesis:

H_0 : $The\ observed\ frequency\ distribution\ is\ normal$

H_1 : $The\ observed\ frequency\ distribution\ is\ not\ normal$

with the following test criteria:

a. If the significant value $> 0{,}05$ then H_0 accepted
b. If the significant value $< 0{,}05$ then H_0 rejected

Calculations are calculated with SPSS software to carry out the Kolmogorov-Smirnov Test process.

One-Sample Kolmogorov-Smirnov Test

		Hand_Soap	Softener	Detergen
N		32	32	32
Normal Parameters[a,b]	Mean	387.13	210.94	386.66
	Std. Deviation	152.726	46.558	111.341
Most Extreme Differences	Absolute	.132	.114	.141
	Positive	.132	.068	.141
	Negative	-.107	-.114	-.115
Test Statistic		.132	.114	.141
Asymp. Sig. (2-tailed)		.166[c]	.200[c,d]	.108[c]

a. Test distribution is Normal.
b. Calculated from data.
c. Lilliefors Significance Correction.
d. This is a lower bound of the true significance.

Figure 4: Kolmogorov-Smirnov test result

Based on Figure 4, the significance value for each product is greater than 0.05. This shows that it is H_0 accepted and the data is normally distributed. Because the data is normally distributed, the data can be used in inventory control calculations using the Q Model probabilistic inventory method with lost sales condition.

The data needed for the probabilistic inventory method calculation process Q Model with lost sales conditions can be seen in Table 16. Calculations are performed using equations 6, 7, 8, 9, 10, and 11. The inventory control calculation results for each product are presented in Table 17, 18, and 19.

Table 16. Q Model probabilistic inventory method calculation data with lost sales condition

Product	Hand Soap	Softener	Detergent
Number of Requests per Week (D)	404	259	522
Purchase Cost (P)	IDR 6,500	IDR 7,500	IDR 6,500
Order Cost (A)		IDR 58,800	
Holding Cost (H)	IDR 842	IDR 952	IDR 842
Shortage Cost (C_u)	IDR 4,500	IDR 4,500	IDR 11,500
Lead Time (L)		0.142 week	
Standard Deviation(s)	122.4	22.16	54.5

Table 17. Hadley-Within calculation results for hand soap product inventory

Iteration	Q^*	α	Z_α	r^*	$f(Z_\alpha)$	$\psi(Z_\alpha)$	N
1	238	0.0992	1.28	117	0.1714	0.0455	5
	279	0.11	1,2	112	0.1942	0.0561	6
2	286	0.11	1.19	112	0.1942	0.0561	6

Table 18. Calculation results Hadley-Within softener product inventory

Iteration	Q^*	α	Z_α	r^*	$f(Z_\alpha)$	$\psi(Z_\alpha)$	N
1	178	0.12	1.14	46	0.2059	0.0621	1
	186	0.13	1.11	46	0.2059	0.0621	1

Table 19. The results of the Hadley-Within calculation of detergent product inventory

Iteration	Q^*	α	Z_α	r^*	$f(Z_\alpha)$	$\psi(Z_\alpha)$	N
1	270	0.0364	1.79	110	0.0790	0.0143	1
	295	0.039	1.75	110	0.0790	0.0143	1

Based on the calculations that have been carried out using the probabilistic Q Model method with lost sales conditions, the optimal number of orders, reorder point, safety stock, and total costs are obtained. The calculation results can be seen in Table 20.

Table 20. The results of the calculation of the probabilistic method Q Model with lost sales condition

Product	Order Size (Q^*)	Reorder Point (r)	Safety Stock (ss)	Total Cost (O_T)
Hand Soap	286 liters	112 liters	54 liters	IDR 2,913,606
Softener	186 liters	46 liters	9 liters	IDR 2,127,959
detergent	295 liters	110 liters	35 liters	IDR 3,671,798

5. Conclussion

The results showed that the Holt-Winter Exponential Additive forecasting method is a good method to use to predict the demand for hand soap, softener, and detergent products in the MSME Sabun Bening Official because forecasting calculations for the three products produce a MAPE value of less than 20%. It is also obtained the optimal number of products ordered for each order (Q), indicators the company will reorder (r), the amount of safety stock (ss) that MSME need to provide, and the expected total inventory cost (O_T).

References

Adnan, F., Damayanti, P., Fajarianto, G. W., & Prihandoko, A. C. (2018). Winter exponential smoothing: sales forecasting on purnama jati souvenirs center. In *2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)* (pp. 680-683). IEEE.

Baker, R. A., & Urban, T. L. (1988). A deterministic inventory system with an inventory-level-dependent demand rate. *Journal of the operational Research Society*, *39*(9), 823-831.

Brown, S., Bessant, J., & Jia, F. (2018). *Strategic operations management*. Routledge.

ElHafsi, M., Fang, J., & Hamouda, E. (2021). Optimal production and inventory control of multi-class mixed backorder and lost sales demand class models. *European Journal of Operational Research*, *291*(1), 147-161.

Kulińska, E., Giera, J. and Kolchanov, A. (2020). The Impact of Supply Disruption on the Standing Order System in the FMCG Supply Chain The Impact of Supply Disruption on the Standing Order System in the FMCG Supply Chain 80, *European Research Studies Journal*, *XXIII(1*), 79-88.

Lawrence, D. Kenneth. Et al. 2009. Fundamentals of Forecasting Using Excel. Industrial Press, Inc. New York.

Mgale, Y.J., Yan, Y. and Timothy, S. (2021). A Comparative Study of ARIMA and Holt-Winters Exponential Smoothing Models for Rice Price Forecasting in Tanzania, *OALib, 08(05),* 1–9.

Miller, J., Varghese, G., Holland, R., & Coolbaugh, T. (2017). Large Scale Dispersant Stockpiles–Product Selection Considerations and Inventory Management. In *International Oil Spill Conference Proceedings* (Vol. 2017, No. 1, p. 2017263). International Oil Spill Conference.

Nurhamidah, N., Nusyirwan, N. and Faisol, A. (2020) 'Forecasting Seasonal Time Series Data Using the Holt-Winters Exponential Smoothing Method of Additive Models', *Jurnal Matematika Integratif*, 16(2), p. 151.

Sabit, M. I., Mansur, A., & Firdaus, F. (2020, April). Policy determination of inventory control of batik fabric using Q and P lost sale probabilistic model through montecarlo simulation approach as the system testing analysis. In *AIP Conference Proceedings* (Vol. 2217, No. 1, p. 030114). AIP Publishing LLC.

Siregar, B., Butar-Butar, I. A., Rahmat, R. F., Andayani, U., & Fahmi, F. (2017). Comparison of exponential smoothing methods in forecasting palm oil real production. In *Journal of Physics: Conference Series* (Vol. 801, No. 1, p. 012004). IOP Publishing.

Wheelwright, S., Makridakis, S., & Hyndman, R. J. (1998). *Forecasting: methods and applications*. John Wiley & Sons.