Supply and Demand Analysis by using Comparison of Forecasting Method in Motorcycles Tires Manufacturer

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Abstract*— As one of the motorcycle tire manufacturing industries in Indonesia, the company faced the uncertainty of capacity and resources due to the mismatch of forecasts which causes an increase in inventory to 2,207,537 tires, the highest number in the last five years. The purpose of this paper is to analyze differences in sales forecast, demand, supply, and production from January 2015 to February 2020, then to measure the error rate of demand data using POM for Windows with the Naïve Method (NM), Moving Average (MA), Weighted Moving Average (WMA), Exponential Smoothing (ES), Exponential Smoothing with Trends (ESWT), Regression/Trend Analysis (R/TA), and Multiplication Decomposition (MD Seasonal). The lowest error measurement results using the Multiplicative Decomposition (MD Seasonal) method have a Mean Absolute Deviation (MAD) of 303,577 and a Mean Absolute Percentage Error (MAPE) of 14.15%. Using the Multiplicative Decomposition (MD Seasonal) method, demand forecast had been obtained as a reference for capacity planning such as machine resources and manpower planning, so that there were reduced production from 86,000 pcs/day to 60,000 pcs/day and makes the stock inventory decrease to 757,997 pcs.

***Keywords*— forecast, demand, supply, inventory, POM.**

I. INTRODUCTION

As one of the motorcycle tires manufacturing industries in Indonesia, the company is faced with uncertainty of capacity and resources because of the occurrence of the sales forecast mismatches [1]. Sales forecast is the basic capacity for resource requirements calculated and received from the sales division towards the top of the year and used as a reference for planning for the following year.

Another problem is that the lack or excessive availability of buffer stock, so when there is a surge in demand the corporate cannot meet customer needs quickly.

If this continues for a long time, the impact will be very fatal for the company where it is possible for customers to switch to other suppliers, and this of course can reduce the company's revenue [2]. The potential for volume variability approaches to be understood is supply demand mismatch, therefore it is important for the company to deal with supply demand problems [3].

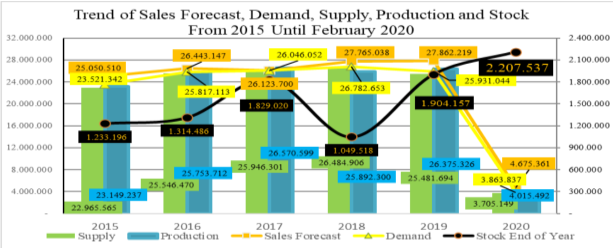


Fig. 1. Trend sales forecast, demand, supply, and stock 2015 to Feb 2020

From Fig. 1, it can be explained that there has been a difference between the forecast and supply, namely 8.3% in 2015, 3.4% in 2016, 0.7% in 2017, 4.6% in 2018, then it raised to 8.5% in 2019 and up to the highest in February 2020 where the difference reached 20.8%. Then, a total of 2,207,537 tires were stocked in February 2020 which became the highest in the last five years as shown in Fig. 2.

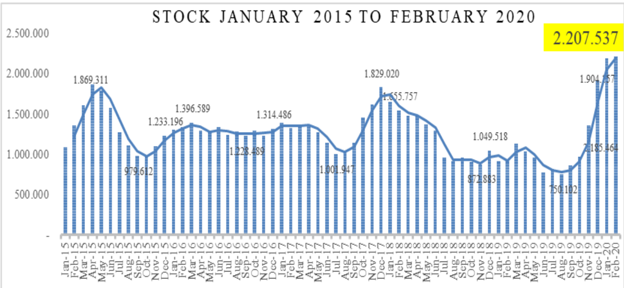


Fig. 2. Stock finish good tire in warehouse form Jan 2015 to Feb 2020

The purpose of this study is to find out the difference between forecast and supply as well to determine the causes of increased stock.

II. LITERATURE REVIEW

This research was conducted with reference to previous studies related to forecasting. Demand forecasting is important for efficient supply chain management. The difference between forecast and actual sales determines forecast error. The types of forecast error are classified based on the case where the non-conformity occurs; different products can have different combinations of these types of forecast errors. Lacks a general measure of forecast error and concludes the paper with comments about the desired estimate error size using ABC classification [4]. India's primary energy demand estimated results with the high forecast precision showed that the prediction was compelling which utilized mean absolute percentage error (MAPE) and root mean square error (RMSE) [5]. A case study was conducted in University Health Centre to optimize the overall inventory demand through forecasting techniques using Risk Simulator Software with regression analysis methods for the Panadol 650 mg [6]. Bahir Dar Textile Share Company has a varying demand in the market to implement and evaluate methods of forecasting performance for forecasting sales using POM-QM software. The MAW method was the best technique for accurate sales forecasts [7]. Pessimistic, moderate, and optimistic approaches are forecasting calculation schemes for the forecasting of zakat collection. zakat funds is collected using the MD forecasting method [8].

A. *Sales Forecast (SF)*

Sales Forecasting (SF) is an activity that is normally performed by a sales team to find out how much demand for the product. It is an integral part of business management. Certainly, without a solid idea about future sales, inventory or cash flows could not be managed. SF purpose is to provide information that can be used to make smart business decisions [9].

B. *Forecasting Techniques*

In forecasting there are several types of data patterns including:

- Horizontal data pattern occurs if the data values fluctuate around a constant average value. Such a series will not move until its average value. The data values fluctuate around a constant average value as seen in Fig. 3.

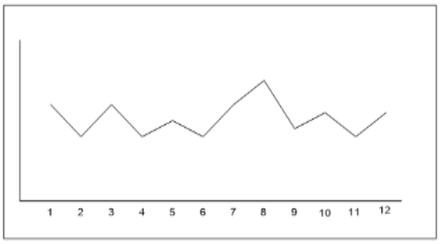


Fig. 3 Horizontal data patterns

- Seasonal data pattern is when a series is influenced by seasonal factors, such as monthly, quarterly in a certain year, and daily at a certain week or time as seen in Fig. 4.

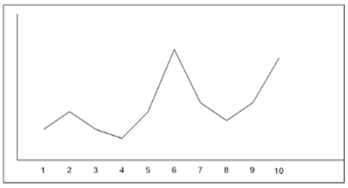


Fig. 4. Seasonal data pattern

- Cycle data pattern is when data is affected by long-run economic fluctuations, such as those related to the business cycle as seen in Fig. 5.

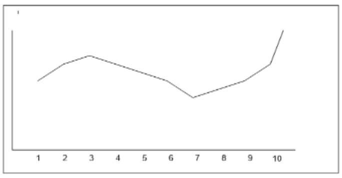


Fig. 5. Cycle data pattern

- Trend pattern appear when in the long term there is an increase or decrease in data as seen in Fig. 6.

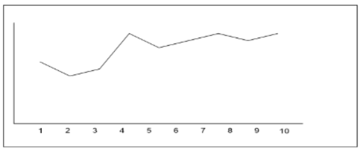


Fig. 6. Trend data patterns

C. *Exponential Smoothing (ES) Method*

The ES method is used in conditions where the weight of the data in one period is different from the data in the previous period, thus forming an exponential function. The exponential smoothing method is divided into four:

- Naïve Method, forecasting using this method is carried out based on the following formula:

$$Ft=Ft - 1+ \alpha\ (A_{(t-1)} - Ft - 1) \quad (1)$$

- Double Exponential Smoothing Method, the following is the equation used in the calculation of double exponential smoothing:

$$S't = \alpha.x_t + (1-\alpha)S'_{t-1} \quad (2)$$

$$S''t = \alpha.S'_t + (1-\alpha)S''_{t-1} \quad (3)$$

$$a_t = S't + (S't - S''t) = 2\, S't - S''t \quad (4)$$

$$b_t = \frac{1}{1-\alpha}(S'\,t - S''\,t) \quad (5)$$

$$F_{tm} = a_t + b_t\ .\ m_t \quad (6)$$

- Exponential Smoothing Method with Trend, the trend correction equation uses the smoothing constant α, which is calculated according to the following formula:

$$T_t = (1-\alpha)\, T_{t-1} + \alpha\, (F_t - F_{t-1}) \quad (7)$$

D. Forecasting Verification and Control

Validation of forecasting methods, especially using the above methods cannot be separated from indicators in measuring forecasting accuracy. However, there are several indicators in measuring forecasting accuracy, but the most frequently used are the MAD, MAPE, and MSE.

1) Mean Absolute Deviation (MAD)

Forecasting accuracy will be higher if the value of MAD, MAPE, MSE is getting smaller. MAD is the absolute total value of the forecast error divided by the data. If formulated, the formula for calculating MAD is as follows:

$$MAD = \sum \left| \frac{A_t - f_t}{n} \right| \tag{8}$$

2) Mean Squared Error (MSE)

The average squared error is also known as the forecast error. This forecasting error can also function to calculate the MAD value which was discussed in the previous section. Estimation errors cannot be avoided in forecasting systems but forecast errors must be managed properly. The management of forecast errors will be more effective if forecasters are able to take appropriate action regarding the reasons for these forecast errors. In a forecasting system, the use of various forecasting models will provide different forecast values and different degrees of forecast error. The mean squared error amplifies the effect of a large error rate but minimizes an estimate error rate of less than one unit.

$$MSE = \sum \frac{(A_t - F_t)^2}{n} \tag{9}$$

3) Mean Absolute Percentage Error (MAPE)

MAPE shows the mean absolute error of the estimates as a percentage of the actual data.

$$MAPE = \left(\frac{100}{n}\right) \sum \left| A_t - \frac{F_t}{A_t} \right| \tag{10}$$

E. Checking the Reliability of the Forecasting Model

To determine the reliability of the selected forecasting model, a tracking signal control chart is made. The value of the analysis tracking signal for the forecasting model must be within acceptable limits (maximum± 4). The overall positive values of the tracking signals indicate that the true value of the demand is greater than expected. A good tracking signal has a low RSFE and has a positive error that is equal to or equal to a negative error, so the center of the tracking signal is close to zero.

$$MAD = \frac{\sum(\text{absolut from forecast error})}{n} \tag{11}$$

$$\text{Tracking Signal} = \frac{\text{RSFE}}{\text{MAD}} \tag{12}$$

F. POM for Windows

The POM for Windows program is a computer program package used to solve quantitative problems in production and operations. The word POM is a short form of Production Operation Management. An attractive graphic display and easy operation make the POM for Windows widely used as an alternative computer application to assist decision making, such as determining the right production combination so that maximum profits are obtained. Many analytical tools can be assisted in making decisions. To perform the analysis required data [10].

G. Capacity Planning

Capacity planning is the assessment of the sequence and the arrangement of the resource acquisition or sale. It is a method for decision-making [11]. Operational information is an element of the assembly system which can be used in the planning and control of production processes. In addition to the preparation and control of external procurement and in-house production, the central role of PPC is to plan scheduling, capability, and production program planning related to quantity, production and assembly process demand planning.

Inside the framework of availability and scheduling preparation, the timetable for planning and scheduling of orders shall be determined on the basis of quantity planning, taking into account the available planning and adjustment of production orders, the measurement of their completion times and locations, and availability of comprehensive additive manufacturing machines and staff with detailed scheduling and sequences in place [12].

III. Data Collecting

In this paper, data has been collected from various existing sources and then processed over the last five years from January 2015 to February 2020 for historical data analysis.

As shown in Table 1, it can be explained that the total sales forecast in 2015 is 25.050.510 pcs, in 2016 is 26.443.147 pcs, in 2017 is 26.123.700 pcs, in 2018 is 27.765.038 pcs, in 2019 is 27.862.219 pcs, and the first two month of 2020 the total sales reaches 4.675.361 pcs.

As seen in Table 2, the demand data obtained from the dealer and all customer requests that occurred those months are usually called sales order.

Supply data processed from delivery data to all dealers and customers at the end of each month for the last five years shown in Table 3.

TABLE I
SALES FORECAST FROM JANUARY 2015 TO FEBRUARY 2020

Period	2015	2016	2017	2018	2019	2020
Jan	2.314.356	2.106.808	2.195.981	2.200.932	2.430.411	2.310.886
Feb	2.204.706	2.221.636	2.199.038	2.132.512	2.198.091	2.364.475
Mar	2.261.338	2.188.969	2.331.949	2.270.779	2.420.943	
Apr	2.161.579	2.345.245	2.301.464	2.434.936	2.423.491	
May	2.224.035	2.328.236	2.325.173	2.467.065	2.420.748	
Jun	2.150.772	2.386.860	1.923.322	1.500.898	1.511.918	
Jul	1.464.684	1.656.020	1.203.643	2.454.843	2.416.273	
Aug	1.962.563	2.232.450	2.333.988	2.527.849	2.460.147	
Sep	1.949.755	2.282.410	2.369.863	2.437.193	2.415.531	
Oct	2.085.179	2.246.755	2.376.059	2.538.003	2.518.828	
Nov	2.161.603	2.292.946	2.392.755	2.471.934	2.484.397	
Dec	2.109.940	2.154.812	2.170.465	2.328.094	2.161.441	
Total	25.050.510	26.443.147	26.123.700	27.765.038	27.862.219	4.675.361

Source: Processed Data

TABLE II
DEMAND FROM JANUARY 2015 TO FEBRUARY 2020

Period	2015	2016	2017	2018	2019	2020
Jan	2.831.195	3.748.002	4.009.837	2.813.624	3.415.215	2.180.397
Feb	1.770.414	1.680.162	2.929.045	2.098.877	1.898.300	1.683.440
Mar	1.884.665	2.063.203	1.889.823	2.190.162	1.926.222	
Apr	1.862.771	2.209.187	1.502.974	2.207.040	2.366.759	
May	1.754.190	2.228.909	2.283.369	2.417.418	3.091.830	
Jun	2.272.375	1.980.733	1.539.073	1.739.118	1.903.612	
Jul	1.805.862	1.781.915	2.257.976	2.721.478	1.705.816	
Aug	3.017.189	1.970.042	1.909.436	2.524.724	2.109.534	
Sep	1.537.701	2.379.366	1.800.552	1.365.107	1.883.535	
Oct	1.717.682	1.664.638	2.074.680	1.944.667	2.145.897	
Nov	1.462.692	2.333.015	1.999.259	3.073.382	1.812.665	
Dec	1.604.606	1.777.941	1.850.028	1.687.056	1.671.659	
Total	23.523.357	25.819.129	26.048.069	26.784.671	25.933.063	3.865.857

Source: Processed Data

TABLE III
SUPPLY FROM JANUARY 2015 TO FEBRUARY 2020

Period	2015	2016	2017	2018	2019	2020
Jan	2.156.940	1.917.234	2.218.756	2.278.151	2.350.363	1.866.419
Feb	1.714.270	2.035.797	2.197.098	2.193.894	2.042.398	1.838.730
Mar	1.958.487	2.195.713	2.270.292	2.328.615	2.112.044	
Apr	1.779.481	2.117.576	2.282.405	2.189.100	2.315.002	
May	1.927.673	2.167.396	2.438.634	2.361.308	2.394.478	
Jun	2.011.246	2.173.394	1.682.523	1.483.042	1.564.383	
Jul	1.506.743	1.566.766	2.421.425	2.432.998	2.309.226	
Aug	2.088.452	2.221.621	2.322.481	2.212.758	2.289.908	
Sep	1.989.224	2.239.548	2.156.902	2.192.630	2.188.919	
Oct	2.019.981	2.316.526	2.071.670	2.413.451	2.301.544	
Nov	2.035.872	2.367.681	2.112.142	2.327.181	1.956.536	
Dec	1.777.196	2.227.218	1.771.973	2.071.778	1.656.893	
Total	22.965.565	25.546.470	25.946.301	26.484.906	25.481.694	3.705.149

Source: Processed Data

Production data processed from production line into warehouse data at the end of each month, shown in Table 4 and inventory data stock seen in Table 5.

TABLE IV
PRODUCTION FROM JANUARY 2015 TO FEBRUARY 2020

Period	2015	2016	2017	2018	2019	2020
Jan	2.184.227	2.003.513	2.314.208	2.121.916	2.216.836	2.147.935
Feb	1.976.985	2.063.561	2.150.926	2.101.166	2.051.499	1.867.557
Mar	2.208.063	2.259.684	2.341.294	2.324.997	2.323.215	
Apr	2.043.638	2.093.747	2.286.599	2.214.198	2.229.124	
Period	2015	2016	2017	2018	2019	2020
May	1.852.961	2.145.039	2.357.939	2.272.924	2.318.213	
Jun	1.791.323	2.225.475	1.565.805	1.406.198	1.391.655	
Jul	1.211.351	1.473.922	2.263.408	2.121.478	2.361.097	
Aug	1.917.747	2.264.445	2.391.755	2.180.476	2.223.766	
Sep	1.862.784	2.184.404	2.253.628	2.245.304	2.305.788	
Oct	2.025.466	2.382.577	2.392.826	2.348.749	2.405.446	
Nov	2.160.693	2.316.974	2.273.348	2.303.292	2.341.565	
Dec	1.913.999	2.340.371	1.978.863	2.251.602	2.207.122	
Total	23.149.237	25.753.712	26.570.599	25.892.300	26.375.326	4.015.492

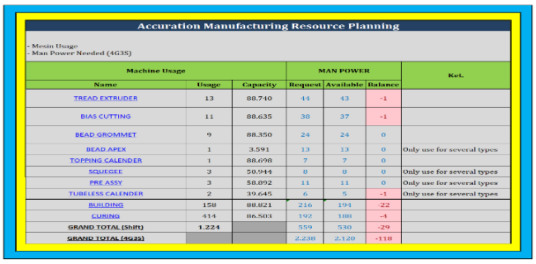
Source: Processed Data

TABLE V
INVENTORY FROM JANUARY 2015 TO FEBRUARY 2020

Period	2015	2016	2017	2018	2019	2020
Jan	1.090.610	1.307.840	1.389.104	1.655.757	916.429	2.185.464
Feb	1.354.529	1.335.014	1.328.280	1.541.937	920.678	2.207.537
Mar	1.604.646	1.396.589	1.370.021	1.481.775	1.130.056	
Apr	1.869.311	1.293.166	1.364.467	1.477.242	1.037.937	
May	1.794.393	1.270.102	1.272.769	1.370.763	960.585	
Jun	1.575.072	1.333.610	1.148.043	1.291.313	778.864	
Jul	1.277.986	1.240.523	1.001.947	955.093	824.360	
Aug	1.106.228	1.283.069	1.049.731	912.769	750.102	
Sep	979.612	1.228.489	1.142.094	961.644	865.966	
Oct	982.380	1.294.708	1.461.197	901.972	965.933	
Nov	1.104.476	1.232.136	1.621.590	872.883	1.360.325	
Dec	1.233.196	1.314.486	1.829.020	1.049.518	1.904.157	
Total	1.090.610	1.307.840	1.389.104	1.655.757	916.429	2.185.464

Source: Processed Data

The historical data collection of machines used for production and manpower with a total of 80.000 pcs/day is shown in Fig.7.



Accuration Manufacturing Resource Planning

- Mesin Usage
- Man Power Needed (4G3S)

Machine Usage			MAN POWER			Ket.
Name	Usage	Capacity	Request	Available	Balance	
TREAD EXTRUDER	13	88.740	44	43	-1	
BIAS CUTTING	11	88.635	38	37	-1	
BEAD GROMMET	9	88.350	24	24	0	
BEAD APEX	1	3.591	13	13	0	Only use for several types
TOPPING CALENDER	1	88.698	7	7	0	
SQUEGEE	3	50.944	8	8	0	Only use for several types
PRE ASSY	3	58.892	11	11	0	Only use for several types
TUBELESS CALENDER	2	39.645	6	5	-1	Only use for several types
BUILDING	158	88.821	216	194	-22	
CURING	414	86.503	192	188	-4	
GRAND TOTAL (Shift)	1.224		559	530	-29	
GRAND TOTAL (4G3S)			2.238	2.120	-118	

Fig. 7. Machine and manpower capacity

IV. RESULTS AND DISCUSSIONS

A. Movements Demand

From Fig. 8, irregular demand movements greatly affect sales forecasts, production plans, and supply to customers, causing warehouse stock conditions in August 2019 to rise to the highest level in February 2020.

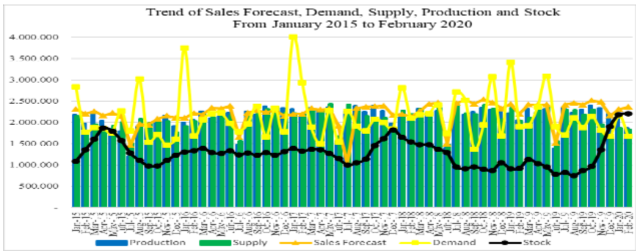


Fig. 8. Trend of sales forecast, demand, supply, production and stock from January 2015 to February 2020.

With evidence of the error rate of demand on sales forecast, supply, production, and stock as in Table 6, MAPE obtained respectively 22.17%, 16.81%, 20.31% and 79.86% demand.

TABLE VI
ERROR DEMAND

Item	**Demand**			
n = 62	Sales Forecast	Supply	Production	Stock
Bias	-96.095,71	- 29.548	- 3.313	- 858.073
MAD	460.712,82	355.607	425.592	884.151
MSE	334.105.132.176	257.821.717.285	310.072.980.754	1.169.694.757.823
MAPE	22,17%	16,81%	20,31%	79,86%

Source: Processed Data

B. Recommended Demand Forecast

The data processing steps carried out for demand forecast using POM for Windows. From the comparison of demand forecast, it is known that the calculation by Multiplicative Decomposition (Seasonal) is better that forecasting demand methods and more suitable to be applied in March to December 2020, because it has a lower error rate. The forecast error rate, MAD (Mean Absolute Deviation) of 303.577, MSE (Mean Square Error) of 157,938,700,000 and MAPE of 14.15% can be seen in Table 7.

C. Demand Forecast Result

By using the Multiplicative Decomposition (Seasonal) demand forecasting method, as shown in table 4.3, the demand forecast for March 2020 is 1,778,651 pcs, April 2020 is 1,566,382 pcs, May 2020 is 1,684,382 pcs, June 2020 is 1,566,204. pcs, July 2020 is 1,590,114 pcs, August 2020 is 1,476,026, September 2020 is 1,495,845 pcs, October is 1,385,848 pcs and November 2020 is 1,401,576 pcs. The result is shown in Fig. 9, Bias of -185, MAD of 271.858, MSE of 116.151.400.000 and MAPE of 12,79%.

TABLE VII
RECOMMENDED DEMAND FORECAST METHOD

Method	**MAD**	**MSE**	**MAPE**
Naïve Method	615.479,0	680.744.500.000	28,87%
Moving Average	468.724,3	425.326.800.000	21,64%
Weighted Moving Averages	468.766,4	434.873.500.000	21,50%
Exponential Smoothing	461.080,4	373.704.600.000	21,93%
Exponential Smoothing with Trend	543.541,6	543.561.600.000	25,42%
Regression/Trend analysis	404.990	293.935.833.012	18,63%
Multiplicative Decomposition (Seasonal)	303.577	157.938.700.000	14,15%

Measure	Value	Future Period	Unadjusted Forecast	Seasonal Factor	Adjusted Forecast
Error Measures		13	1.740.061	1,02	1.778.651
Bias (Mean Error)	- 185	14	1.693.950	0,98	1.656.382
MAD (Mean Absolute Deviation)	271.858	15	1.647.838	1,02	1.684.382
MSE (Mean Squared Error)	116.151.400.000	16	1.601.726	0,98	1.566.204
Standard Error (denom=n-2-2=8)	417.405	17	1.555.614	1,02	1.590.114
MAPE (Mean Absolute Percent Error)	12,79%	18	1.509.503	0,98	1.476.026
Regression line (unadjusted forecast)		19	1.463.391	1,02	1.495.845
Demand(y) = 2.339.514,0		20	1.417.279	0,98	1.385.848
-46.111,71 * time		21	1.371.168	1,02	1.401.576
Statistics		22	1.325.056	0,98	1.295.670
Correlation coefficient	0,442	23	1.278.944	1,02	1.307.307
Coefficient of determination (r^2)	0,195	24	1.232.832	0,98	1.205.492
		25	1.186.721	1,02	1.213.039
		26	1.140.609	0,98	1.115.313

Fig. 9. Demand forecast with multiplicative decomposition (seasonal)

Then in Fig. 10 is the graph of demand forecast which shows a downward trend in the demand forecast for the following months.

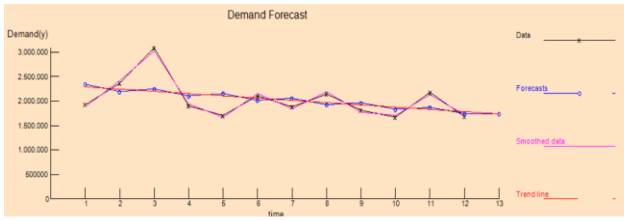


Fig. 10. Demand forecast

With evidence of the error rate of demand forecast on demand, supply, production, and stock as in table VIII, MAPE is obtained respectively 22.17%, 16.81%, 20.31% and 79.86%.

TABLE VIII
DEMAND FORECAST

Item	**Demand**			
n = 11	Demand Forecast	Supply	Production	Stock
Bias	1.776,07	- 6.939	- 15.819	- 164.024
MAD	143.910,40	125.351	58.908	267.547
MSE	87.568.706.133	77.174.557.969	51.595.148.185	174.888.390.803
MAPE	295.920	277.803	227.146	418.197

As seen in Fig. 11, inventory decrease from 2.207.537 pcs in February 2020 to 757.997 pcs in November 2020, by using demand forecast with Multiplicative Decomposition (Seasonal) method and control of production planning and resource planning which initially produced 86,000 pcs each day, it decreased to 60,000 pcs each day (obtained by day's shared demand forecast).

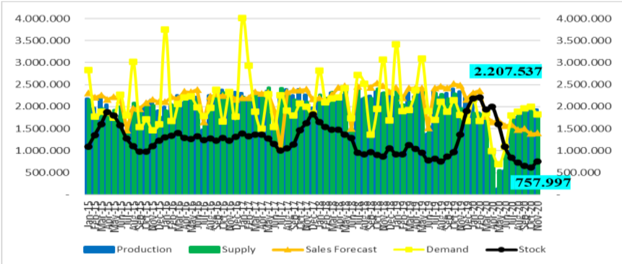


Fig. 11. Trend of sales forecast, demand, supply, production and stock from January 2015 to November 2020.

D. Resource Planning

From the calculation of the available capacity that has been compared with the required capacity, it can be concluded that the available capacity exceeds the capacity required of both the machine and manpower for production with a total of 60.000 pcs/day as in Fig. 12.

Accuration Manufacturing Resource Planning

- Mesin Usage
- Man Power Needed (4G3S)

Machine Usage			MAN POWER			Ket.
Name	Usage	Capacity	Request	Available	Balance	
TREAD EXTRUDER	9	60.435	35	43	8	
BIAS CUTTING	8	60.981	30	37	7	
BEAD GROMMET	6	60.800	19	24	5	
BEAD APEX	1	3.101	13	13	0	Only use for several types
TOPPING CALENDER	1	60.980	7	7	0	
SQUEGEE	2	32.750	6	8	2	Only use for several types
PRE ASSY	2	37.346	8	11	3	Only use for several types
TUBELESS CALENDER	1	24.132	4	5	1	Only use for several types
BUILDING	111	60.541	169	228	59	
CURING	292	60.400	130	188	58	
GRAND TOTAL (Shift)	873		421	564	143	
GRAND TOTAL (4G3S)			1.684	2.256	572	

Fig. 12. Resource planning.

V. CONCLUSIONS AND RECOMMENDATIONS

From Fig. 8, irregular demand movements greatly affect sales forecasts, production plans, and supply to customers, causing warehouse stock conditions in August 2019 to rise to the highest level in February 2020 and by using demand forecasts with the Multiplicative Decomposition method (Seasonal) and production control and resource planning which initially produced 86,000 pcs per day then decreased to 60,000 pcs per day.

Based on data analysis and the discussion that has been concluded, the authors provide several suggestions. Firstly, for the calculation of forecasting, it is hoped that the POM for Windows software used by the author in this study will be one of the professionals. Secondly, for companies as input and predictor of forecasting in decision-making and planning systems, the level of production capacity in the future is needed. Thirdly, based on these results, there are still shortcomings as an evaluation for further research. As for the suggestions for the development of this research, it is necessary to develop a wider range of variables in order to obtain better and perfect forecasting results.

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