Available online at: http://e-jurnal.lppmunsera.org/index.php/JSMI

Jurnal Sistem dan Manajemen Industri

ISSN (Print) 2580-2887 ISSN (Online) 2580-2895

Raw material planning for tapioca flour production based on fuzzy logic approach: a case study

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ARTICLE INFORMATION

Article history:

Received: March 19, 2022
Revised: May 30, 2022
Accepted: June 29, 2022

Keywords:

Defuzzification
Fuzzy logic
Forecasting
Membership function
OEE

A B S T R A C T

The availability of cassava raw materials influences tapioca flour production at small and medium industry's (SMIs) Bogor Regency. Cassava raw material is a crucial factor in producing cassava yields, affecting the amount of tapioca flour production. Planning for cassava raw material must be carried out properly because the quality and quantity of cassava must be maintained to achieve the tapioca flour production target. The results of forecasting the demand for tapioca flour in SMIs using the Multiplicative Decomposition method were 2566 kg with MAD = 173.73 and MAPE = 0.08. Based on the analysis of the effectiveness of the grinding machine, the average value of OEE for one year is 0.32 (32%). Based on the value of demand forecasting results, milling machine OEE and tapioca flour prices, an analysis of cassava raw material needs are carried out using a fuzzy logic approach. The membership set used is Triangular and Trapezoidal Membership Function and Fuzzy Rule Base as many as 81 possibilities. The defuzzification of cassava raw material requirements in SMIs is 17600 kg. Based on the results of defuzzification, the need for raw materials must be increased so that the demand for tapioca flour can be achieved.

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1. INTRODUCTION

Cassava raw materials for the flour processing industry currently have a long shelf life [1]. However, the current problem of tapioca flour production is related to the unstable supply of cassava raw materials at suppliers. This condition causes industries, including SMIs, not to meet market demand optimally. The government's ability to provide strategic policies related to the market is a factor in maintaining cassava product-ion's stability and can provide added value to the industry [2].

The ability of small and medium industries (SMIs) to produce quality tapioca flour is strongly influenced by the ability to manage the availability of cassava raw materials. Cassava is an agricultural product that can be an alternative to producing industrial products with low processing costs [3]. Temperature conditions affect the quality of cassava, which will impact the quality of flour produced [4]. The quality of flour depends on the raw materials used to produce quality yields [5].

The raw material planning process in SMIs must be analyzed using variables that affect the raw material requirements to achieve the flour production target. Production planning is the initial process that the company must carry out so that the availability of raw materials and production machines can run optimally [6]. The availability of raw materials will affect the machine's performance to achieve the production targets set by the company [7]. The availability of materials influences production capacity, so procuring raw materials is one of the success factors of production [8]. The material requirement planning (MRP) method can be done for raw material requirements by considering the variable number of production schedules [9].

The MRP method is a method for preparing raw materials based on the Bill of Material components to meet the needs of the production schedule [10]. The MRP method in raw material management only pays attention to internal variables, namely the production schedule and the number of products produced in the company [11]. The MRP method cannot be used to plan the raw material needs of cassava because it only looks at one variable, namely the production schedule. In comparison, more than one variable must be used in planning the raw material for tapioca flour production.

Variables that affect the determination of the amount of cassava raw material in tapioca flour SMIs include the effectiveness of the grinding machine, forecasting demand, and the selling price of tapioca flour. Raw materials available in production can be integrated with suppliers in one supply chain system [12]. The availability of raw materials will affect the effectiveness of the machine in achieving production targets [13]. Production planning requires support from application development to manage every variable that affects so that production targets are achieved [14].

Based on the need for cassava raw materials in SMIs, it is necessary to plan the number of raw materials using a fuzzy logic approach to identify the vague values of each input and output variable for cassava raw materials. The fuzzy logic approach can provide analysis results related to variables with vague values [15]. This study uses a fuzzy logic approach with membership set variables used. They are overall equipment effectiveness (OEE) milling machine, forecasting demand and selling price of tapioca flour has never been done in previous research. It can help SMIs in planning optimal cassava raw material needs.

2. RESEARCH METHODS

The research methods used are OEE, demand forecasting, and fuzzy logic for planning raw material requirements. Availability is a measuring tool to see the machine's ability to operate based on available time. Machine availability considers machine operating load time against the amount of unplanned machine downtime. The formulation of machine availability is as follows [16], [17] :

$$\text{Availability} = \frac{\text{Loading Time} - \text{Unplanned Time}}{\text{Loading Time}} \quad (1)$$

Performance is a measuring tool to see the machine's performance in doing production. The utilization of the effective time of the production machine will be compared with the ideal condition of the machine to show the machine's ability to utilize the time available for production. The formulation of engine performance is as follows [16], [17]:

$$\text{Performance} = \frac{\text{Cycle Time x Processed Amount}}{\text{Operating Time}} \quad (2)$$

Quality rate is a measuring tool to see the machine's ability to produce quality products. The machine's ability to produce quality products will be compared with the number of defective goods produced to manage the quality of the products appropriately produced. The formulation of the machine's quality rate is as follows [16], [18]:

$$\text{Quality Rate} = \frac{\text{Processed Amount} - \text{Defect Amount}}{\text{Processed amount}} \quad (3)$$

The effectiveness of the machine can be measured using the OEE method, which pays attention to the machine's ability to operate, produce, and produce the machine's ability to produce quality products [19]. The ideal OEE value based on international standards is 85%. The formulation of OEE is as follows [16], [20]:

$$\text{OEE} = \text{Availability x Performance x Quality Rate} \quad (4)$$

The multiplicative decomposition forecasting method is used for data types with patterns that repeat themselves over time. In the multiplicative decomposition method, the data used have groupings based on different data trends. The weight value of each group of data trends must be determined to determine the forecasting results [21]. The formulation of the Multiplicative Decomposition forecasting method is as follows [22]:

$$Yt = TR_t \text{ x } SN_t \text{ x } CL_4 \text{ x } IR_t \quad (5)$$

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Where Y_t is the observed value of the time series in period t; TRt is the trend factor in period t; SNt is the seasonal factor t in period t; CLt is the cyclical factor in period t and IRt is the irregular factor in period t.

The accuracy test determines the error level resulting from the forecasting results used. This error rate will be used to see how accurate the forecasting results are based on the method used [23]. Analysis of the level of accuracy can use two methods, namely Mean Absolute Deviation (MAD) and Mean Percentage Error (MAPE). The formulation of the two MAD and MAPE methods is as follows [24]:

$$\text{MAD} = \sum_{i=1}^{M}[|Pi - Ai|]/M \quad (6)$$

$$\text{MAPE} = \sum_{i=1}^{M}\{[|(Pi - Ai)/Ai|]/M\} \text{ x } 100\% \quad (7)$$

The triangular membership set can be used for variables with the highest membership degree value. The membership set will form a maximum value based on the parameters developed in the fuzzy [25]. The triangular membership set in the fuzzy model is μF (a, b, c): R → [0,1] [26]

The trapezoidal membership set can be used for variables with a maximum membership degree of more than one value. This membership set can be used if the parameter used has several variable values with a maximum membership degree [27] [25]. The trapezoidal membership set in the fuzzy model is μF (a, b1, b2, c): R → [0,1] [26].

The fuzzy rules base will determine the fuzzy operator based on the degree of membership value obtained from the variable's value. The fuzzy rules used are Ri: If X_1 is A_1^i and X_2 is $A_2^{i,}$ and···X_m is A_m^i Then Y is B^i; i = 1; 2;…n with the fuzzy operator relationship used is "and" so that the selected operator value in the defuzzification process is the "Min" value [28].

The defuzzification process for determining cassava raw materials uses the center of area method. This method compares the area and the moment generated by the fuzzy operators. The formulation of defuzzification using the COA method is as follows [29]:

$$Xcoa = \frac{\int_{x=0}^{n} \mu A(x)x\, dx}{\int_{x=0}^{n} \mu A(x)\, dx} \quad (8)$$

3. RESULTS AND DISCUSSION

The raw material planning model used previously was the material requirement planning. This model used demand data based on the bill of materials structure to produce the product [9]. The basis for developing the MRP model to manage raw materials is product demand data which will be adjusted to the capabilities of the production machine so that the number of raw material needs and the arrival schedule of the required raw materials can be planned [11]. Another model developed for planning raw materials is EOQ. This model assumes the demand is constant, so Re-Order Point (ROP) analysis is required to maintain the availability of raw materials [30].

Based on the model used in previous studies, the critical variable used is product demand data to determine the planning of raw material requirements based on the production schedule. This model cannot be implemented in the planning of cassava raw materials because, based on the actual conditions, it is influenced by three variables: the demand for tapioca flour products, the effectiveness of the grinding machine, and the selling price of tapioca flour. The effectiveness of the cassava grinding machine is essential in the tapioca flour production process because the amount of milled cassava produced in this machine will determine the amount of tapioca flour yield.

The variable selling price of tapioca flour is critical because the selling price fluctuates and can affect the number of product orders. It impacts the need for cassava raw materials that must be prepared. Therefore, the research on the planning model of cassava raw material requirements currently being carried out uses these three variables as input using a fuzzy logic approach. This fuzzy approach model can identify an insufficient number of the three variables above to produce an ideal cassava raw material planning. This research on cassava raw materials requirements based on fuzzy logic can be developed by looking at the current supply conditions of SMIs, including the availability of suppliers and supplier performance. This model can be integrated the supply activity of cassava raw materials from the plant to the supplier.

Tapioca flour production is influenced by the ability of milled cassava to produce ground cassava. Ground cassava will be soaked to get the cassava yield. The cassava grinding machine is critical in the cassava production process because this machine has ground cassava used to produce cassava yield in tapioca flour manufacturing.

The effectiveness of the cassava grinding machine is the key to the success of SMIs in producing tapioca flour according to the quantity and quality, so its effectiveness must be analyzed in production. The effectiveness of the cassava grinding machine was analyzed using the overall equipment effectiveness method. The machine's ability to produce ground cassava was determined based on the machine's availability, performance, and quality rate.

The results of the OEE value of the grinding machine will be used as input variables in determining the need for cassava raw materials in the fuzzy membership set model. The results of the effectiveness of the cassava grinding machine for one year using the OEE method can be seen in Table 1. Based on the analysis of the cassava grinding machine for one year, the average value of availability = 65.16%; performance = 53.62%; quality rate = 89.55%, and the average OEE of the cassava grinding machine is 32%. The results of the OEE value of the grinding machine will be entered into the OEE membership set to obtain the membership degree value used for the defuzzification process of cassava raw material needs.

Tapioca flour demand data is obtained from the needs of flour collector cooperatives that SMIs can fulfil. Forecasting tapioca flour demand on SMIs uses demand data for one year. Tapioca flour demand can be seen in Table 2. The condition of cassava raw materials supply from collectors, which is inconsistent in quality and quantity, is the problem with the declining demand for tapioca flour in May and June. The poor quality of cassava raw materials causes a decrease in the quality of tapioca flour, causing the need for collecting cooperatives to decline in May and June. From July to August, the demand for tapioca flour increased because the supply of cassava raw materials was well maintained so that the tapioca flour produced could meet the flour collector's quality standards (water content and colour).

Table 1. OEE results of cassava grinding machine

Month	Availability	Performance	Quality rate	OEE
January	60.87%	47.31%	89.63%	25.81%
February	50.00%	48.43%	89.55%	21.68%
March	60.87%	49.66%	89.50%	27.05%
April	72.73%	56.52%	89.35%	36.73%
May	50.00%	44.58%	89.41%	19.93%
June	50.00%	45.99%	89.53%	20.59%
July	72.73%	56.38%	89.27%	36.60%
August	85.71%	65.45%	90.10%	50.55%
September	72.73%	57.69%	89.53%	37.56%
October	72.73%	61.87%	89.77%	40.39%
November	72.73%	56.07%	89.43%	36.47%
December	60.87%	53.54%	89.51%	29.17%

Table 2. Tapioca flour demand

Month	Cassava raw material (Kg)	Tapioca flour demand (Kg)
January	10019.35	2069.50
February	10255.50	2118.27
March	10516.85	2091.80
April	11968.85	2380.60
May	9441.01	1950.04
June	9738.44	1862.48
July	11938.78	2465.96
August	14726.43	2862.82
September	12979.38	2616.64
October	13101.28	2505.62
November	12616.47	2452.64
December	11338.68	2342.00

http://dx.doi.org/10.30656/jsmi.v6i1.4594

Demand forecasting can be analyzed using the seasonal method, with the seasonal trend divided into two seasons: January to June and July to August. Forecasting accuracy using seasonal method was analyzed using the POM for windows application to see the error rate of forecasting results. Measurement of the error rate with high accuracy can be done by looking at the consistency (reliability) of errors using the MAD and MAPE values [31]. Calculation of the error rate of the forecasting results with the seasonal method can be seen in Table 3. The sessional forecasting method is used to predict the production of tapioca flour, which has seasonal conditions. This condition is caused by farmers' decline in cassava production so that they cannot meet the production needs of SMIs.

Based on the forecasting results, tapioca flour production increased in period 13 because the production data for periods 8-12 was stable. Due to the ability to supply raw materials for cassava collectors in that period to meet the needs of SMEs, this condition shows the tendency of the forecasting trend to increase starting in period 13 following forecasting results. The results of this demand forecasting data can be used if SMIs can ensure the availability of cassava raw material stock.

The results of the seasonal forecasting show the number of requests in the January period of the following year showing the value of MAD = 173.73 and MAPE = 0.08. MAPE results show a value of 0.8, so this condition shows the error rate of forecasting results is good and can be used. Based on the error analysis results, the forecast for tapioca flour demand in January the following year is 2566 kg.

The selling price of tapioca flour based on the production quality at SMIs is Rp. 9500/kg, the purchase price from the cooperative or tapioca flour collectors. This price will be used in the membership set of tapioca flour selling prices in developing a fuzzy model for ordering raw materials.

Based on the results of observations and interviews in SMIs, it was found that the parameter value limits followed the actual conditions that occurred in the field related to the demand, the effectiveness of milling machines, and the selling price of tapioca. The limitations of each parameter consist of the low, medium, and high for each variable used. The appropriate type of membership set is triangular and trapezoidal in defuzzification of raw material requirements. The parameter limit for each variable becomes the parameter value limit for the calculation results in each analytical method used to calculate the raw material requirements using the defuzzification process.

Based on observations and interviews with SMIs actors, a membership set model for machine effectiveness was obtained using the OEE value. The membership set used for the OEE variable is the triangular membership function. The parameters used consist of three, namely Low [0, 0.15, 0.3], Medium [0.25, 0.45, 0.65], and high [0.55, 0.7, 0.85]. The membership function graph of OEE can be seen in Fig. 1.

Table 3. Calculation of the error rate of the forecasting results

Month	**Tapioca flour demand (Kg)**	**Forecast demand (Kg)**	**Error**	**|Error|**	**Square error**	**Absolute percentage error**
January	2069.50	2027.32	42.18	4218	1779.15	0.020
February	2118.27	2136.82	-18.55	18.55	344.10	0.009
March	2091.80	2117.18	-25.38	25.38	644.14	0.012
April	2380.60	2229.48	151.12	151.12	22837.25	0.063
May	1950.04	2207.04	-257.00	257.00	66049.00	0.132
June	1862.48	2322.14	-459.65	459.65	211278.12	0.247
July	2465.96	2296.90	169.07	169.07	28584.66	0.069
August	2862.82	2414.79	448.03	448.03	200730.88	0.156
September	2616.64	2386.75	229.89	229.89	52849.41	0.088
October	2505.62	2507.45	-1.83	1.83	3.35	0.001
November	2452.64	2476.61	-23.97	23.97	574.56	0.010
December	2342.00	2600.11	-258.11	258.11	66620.77	0.110

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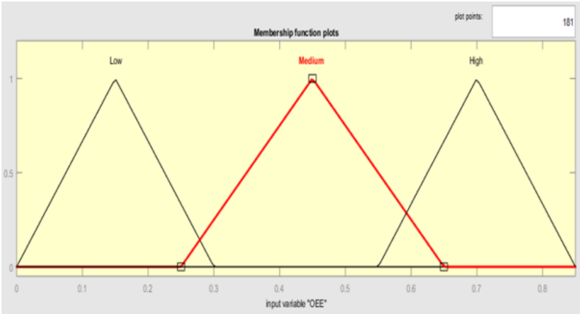

Fig. 1. Membership function graph of OEE

The calculation of the OEE of milled cassava for one year obtained the average OEE value of 0.32 (32%). According to the Seichi Nakajima standard, the condition of this OEE value is terrible because it is below the ideal standard, which is at least 85%. This condition is caused by the quality and quantity of cassava raw materials that cannot meet production needs. The availability and performance values of the machine are under ideal conditions.

The results of the OEE calculation will be the value of the variable in the OEE membership set to determine the value of the degree of fuzzy membership. The result of calculating the degree of OEE membership is $\mu_{OEE\_medium\ (a,b,c)} = 0.35$. The degree of OEE membership will then determine the value of the fuzzy operator used in the raw material defuzzification process.

The membership set for tapioca demand uses triangular and trapezoidal types where the degree of membership is obtained from the results of demand forecasting using the seasonal method. The parameters demand forecasting used consist of three, namely Low [1000, 1000, 1500, 2000], Medium [1800, 2200, 2600], and High [2400, 2800, 3600, 3600]. The membership function graph for tapioca flour demand (Kg) can be seen in Fig. 2.

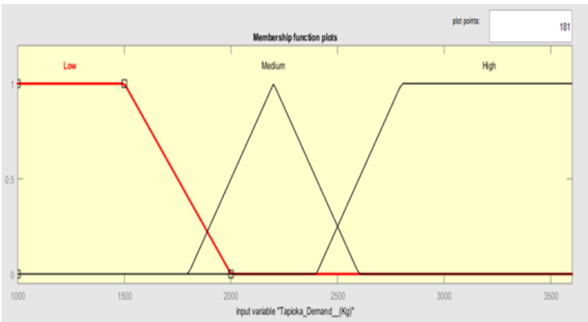

Fig. 2. Membership function graph for tapioca flour demand (Kg)

The forecasting results using the multiplicative decomposition method showed that the demand for tapioca flour in January was 2566 kg. This condition shows that SMIs must prepare the quality and quantity of raw materials.

The results of the demand forecasting will then be entered into the membership set model to determine the degree of membership. The degree of membership of the resulting requests $\mu\_{Demand\_high\_(a,b,c,d)} = 0{,}42$. The degree of membership of the request will then be used to determine the value of the fuzzy operator that will be used in selecting the fuzzy operator that will be used in the process of defuzzification of raw material requirements.

The selling price of flour at SMIs is influenced by the quality of the tapioca flour produced, and one of them is influenced by the quality of the raw cassava material used. The flour price membership set uses the trapezoidal and triangular membership functions. The parameters of selling price used consist of three, namely Low [5000, 5000, 7000, 9000], Medium [8000, 10000, 12000], and High [11000, 12000, 15000, 15000]. The membership function of the selling price graph in SMIs can be seen in Fig. 3.

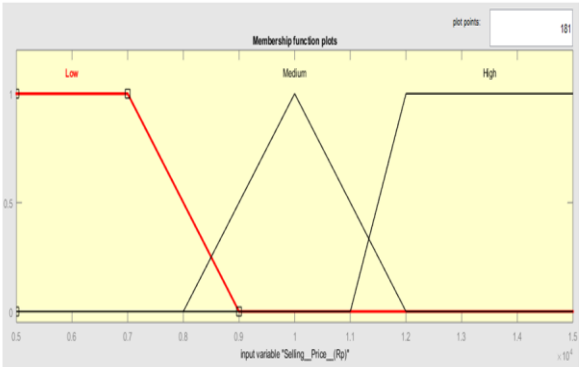

Fig. 3. The selling price membership function graph (x 10000)

Based on the condition of selling tapioca flour to collectors or cooperatives, the selling price during the observation period was Rp. 9500/kg. The selling price of tapioca flour is determined by the fuzzy membership degree based on the membership set used. The degree of membership of the selling price generated based on the membership set is $\mu_{Selling\ proice\_Medium\_(a,b,c,d)} = 0{,}75$.

Based on the parameters used in the three variables of the input membership set, namely machine OEE, tapioca flour demand, and the selling price of tapioca flour, fuzzy rules are

http://dx.doi.org/10.30656/jsmi.v6i1.4594

obtained that will be used to determine the moment and area in the process of defuzzification of cassava raw material needs. The Fuzzy Rule Base model using the Matlab application can be seen in Fig. 4.

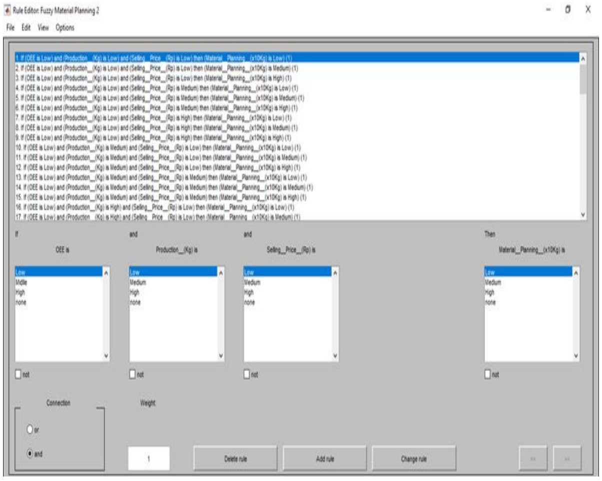

Fig. 4. Result of fuzzy rule base

Input variables, namely OEE, forecasting of demand and selling prices that occur in SMIs, and the output variable of the number of raw materials, the number of possible Fuzzy rule bases that can occur is 81 possibilities. All possibilities in this membership set can occur because the parameter values used in the membership set are actual conditions in SMIs.

Based on the value of the membership degree of the fuzzy input variable, the value of the fuzzy operator can be determined based on the selected fuzzy rules. The results of the fuzzy operators used are as follows:

α = Min (μ OEE [0,35] ∩ μ Prod[0,42] ∩ μ_Selling Price [0,75])

α = Min (0,35; 0,42 0,75)

α = 0,35

Based on the fuzzy rules, cassava raw material needs defuzzification can be carried out using the center of area (COA) method. The COA method will compare the value of the area and moment based on the fuzzy rules that occur in SMIs. The parameters of the cassava raw material planning used consist of three, namely Low [1000, 1000, 1200, 1500], Medium [1400, 1700, 2000]; and High [1800, 2200, 2500, 2500]. The cassava raw material planning membership function graph can be seen in Fig. 5.

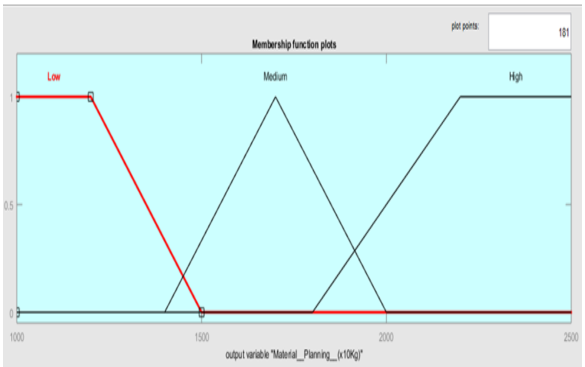

Fig. 5. Cassava raw material planning membership function

Based on the results of determining the area with the fuzzy operator used is α = 0.35, it can be determined the area that occurs in the process of defuzzification of cassava raw material needs. The area obtained in the defuzzification process for cassava raw material needs is as follows:

WA 1 = (14000-1000) x 0.35 = 140

WA 2 = $\frac{(15000-14000)}{2}\ x\ 0.35 = 175$

WA 3 = $\frac{(15000-14000)}{2}\ x\ 0.35 = 175$

WA 4 (19000-15000) x 0.35 = 1400

WA 5 = $\frac{(20000-19000)}{2}\ x\ 0.35 = 175$

WA 6 = $\frac{(19280-18000)}{2}\ x\ 0.35 = 490$

WA 7 = (25.000-19280) x 0.32 = 1960

There are seven regions in the membership set of raw material needs, where each part has an area according to the parameters of the raw material requirements. The total area obtained in the defuzzification process is 4515.

The membership set of raw materials obtained in tapioca flour SMIs will produce moments based on the fuzzy operators obtained. The membership set of raw material requirements will then create a moment that will be used to determine the number of raw materials needed by the COA method. The moment of demand for cassava raw materials will be compared with the area in the defuzzification process. The membership set for raw material needs and the moments obtained based on the membership set of the raw materials obtained.

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$$
\text{Fx (Material Planning)} \begin{cases} 0 & x \leq 1000 \\ 0{,}35 & 1000 \leq x \leq 14000 \\ \dfrac{15000\text{-}X}{3000} & 14000 \leq x \leq 15000 \\ \dfrac{X\text{-}14000}{3000} & 14000 \leq x \leq 15000 \\ 0{,}35 & 15000 \leq x \leq 19000 \\ \dfrac{20000\text{-}X}{3000} & 19000 \leq x \leq 20000 \\ \dfrac{X\text{-}18000}{4000} & 18000 \leq x \leq 19400 \\ 0{,}35 & 19400 \leq x \leq 25000 \end{cases}
$$

$$\text{Moment 1}: \int_{1000}^{14000} 0.35 \text{ x dx}$$

$$\text{Moment 2}: \int_{14000}^{15000} 5x - 0.00033 \text{ x2 dx}$$

$$\text{Moment 3}: \int_{14000}^{15000} 0.00033 \text{ x2} - 4{,}67x \text{ dx}$$

$$\text{Moment 4}: \int_{15000}^{19000} 0.35 \text{ x dx}$$

$$\text{Moment 5}: \int_{19000}^{20000} 6.67x - 0.00033 \text{ x2 dx}$$

$$\text{Moment 6}: \int_{18000}^{19400} 0.00025x2 - 4.5x \text{ dx}$$

$$\text{Moment 7}: \int_{19400}^{25000} 0.35 \text{ x dx}$$

The results of the defuzzification process for cassava raw material planning using the Matlab application can be seen in Fig. 6.

Fig. 6. The results of the defuzzification for cassava raw material planning

Based on the results of defuzzification with a comparison between moment and area in the COA method, the amount of cassava raw material needed that SMIs must prepare is 17600 Kg. The current availability of cassava raw materials in Table 2 shows that the average cassava raw material used for one year is 11553,42 kg. This condition indicates cassava raw materials' availability is below the raw material defuzzification value of 17600 kg. Based on this condition, SMIs must increase the supply of raw materials following the defuzzification of cassava raw material requirement value to fulfil the demand for tapioca flour cooperatives.

Previous research is related to planning cassava raw materials for production using the EOQ method, where demand is obtained from capacity production data. The need for cassava raw materials is influenced by using raw materials in the production process, and production capacity will affect the point of reordering the required cassava raw materials [32]. Raw material planning using a fuzzy logic approach in this study can provide a more accurate value because uses three variables that influence the success of tapioca flour production because it can identify the vague value of each variable used.

4. CONCLUSION

Planning for cassava raw material needs in SMIs is influenced by the effectiveness of the milling machine, demand forecasting, and the selling price of tapioca flour. Based on the results of the analysis of the effectiveness of the flour milling machine, the OEE value is 0,32 (32%), and the forecast for tapioca flour demand is 2566 kg with MAD 173.73 and MAPE 0.08, so the optimal cassava raw material that must be prepared based on the defuzzification process is 17,600 kg. The following research must be done to evaluate suppliers to increase the quality of the cassava raw materials sent and the flour yield.

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