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Fuzzy Inference System Tsukamoto–Decision Tree C 4.5 in Predicting the Amount of Roof Tile Production in Kebumen

Tundo[1*], Fajar Mahardika[2]
[1]Departement of Informatics, Universitas 17 Agustus 1945 Jakarta, Indonesia
[2]Departement of Computer Technology, ITS NU Pekalongan, Indonesia
asna8mujahid@gmail.com[1], fajarmahardika@itsnupekalongan.ac.id[2]

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ABSTRACT

Tile is a product that is in great demand by many people. This has become a trigger for producers to improve their management. The company's tile production management is still experiencing problems, namely frequent miscalculations in determining the agreement that must be issued in making tile production from customer requests. One of the efforts made is to predict the production that can be done to get the optimal amount obtained, to get a big profit. In this study, to obtain a prediction of the amount of tile production, computerized calculations were carried out using the Tsukamoto fuzzy logic method. This method uses the concept of rules from the C 4.5 decision tree in the building to make it easier to determine the rules that are built without having to consult an expert because C 4.5 will study existing datasets to serve as a reference in forming these rules according to conditions that often occur. The modeling results produce relevant rules after being compared with the actual results. The results of the comparison of predictions with actual production have an error percentage of 29.34%, with a truth of 70.66% (based on the calculation of the Average Forecasting Error Rate (AFER)). Therefore when implemented in the Tsukamoto Fuzzy Inference System it can produce predictions of tile production that are quite optimum. It is said to be quite optimum because all customer requests are met, either generated by the production prediction itself or the prediction results are added up with inventory data, and all predictions are close to actual production.

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A. INTRODUCTION

Tile is in great demand by various groups (Wati, Rohmah, & Rahmadani, 2021). This condition provides many opportunities for producers to implement strategies to optimize their production (Ezhilmaran & Joseph, 2017). In the industrial era 4.0, the application of technology in various ways, can be done to increase the optimization of tile production. One of the processes carried out is predicting the amount of production from producers.

One of the efforts made in a prediction is by using the Fuzzy Logic method (Tundo & Sela, 2018). Fuzzy logic is logic with a value of similarity (fuzziness) with a value of true or false (Sheena, Ramalingam, & Anuradha, 2017). This concept was implemented and introduced by Lotfi Asker Zadeh in 1965 in fuzzy set theory (Solesvik, Kondratenko, & Kharchenko, 2017). There are several types of fuzzy belonging to the type of Fuzzy Inference System (FIS), namely Sugeno, Mamdani, and Tsukamoto. This study uses the Tsukamoto FIS concept – Decision tree C 4.5 which is used to implement. Use of decision tree C 4.5 to create rules that are built based on collected datasets, then processed using WEKA. These two concepts make the flexible, simple structure, tolerant of the data used, and speed up the creation of rules without expert intervention (Tseng, Konada, & Kwon, 2016).

Several studies support this research, including the application of Mamdani FIS in predicting the amount of woven fabric production (Tundo & Saifullah, 2022). Rules are made automatically using Random Tree with the criteria used are production costs, stock, and demand. The resulting accuracy shows values with results that are close to actual production with an accuracy of 97%. But unfortunately not in detail explained how the concept of Random Tree is used. Furthermore, other predictions are also made with the application of FIS in predicting palm oil production (Tundo & 'Uyun, 2020) carried out using the Tsukamoto method. The rules used are the results of the decision tree J48 and REPTree with the criteria: the amount of oil palm, demand, and supply of palm oil. The decision tree shows values with results that are close to actual production. However, the resulting classification accuracy is lower than J48. Furthermore, there is a wind power prediction using the comparison of Fuzzy Mamdani and Sugeno (Topaloglu & Pehlivan, 2018). The criteria used are wind speed, power density, capacity factor, and suitability factor. The experimental results give a better result using the Sugeno method compared to Mamdani. However, no detailed accuracy results have been submitted yet, it should be explained so that it can be confirmed and seen.

Modeling in this study was carried out using decision tree rules C 4.5 which were then processed with WEKA to form a rule. These rules are used to predict tile production using the FIS Tsukamoto method. The existence of C 4.5 rules makes it easier to determine the rules that are built without having to consult with experts because C 4.5 will study existing datasets to serve as a reference in forming these rules according to conditions that often occur. In addition, evidenced by the accuracy presented (Mujahid & Sela, 2019). The modeling results produce relevant rules after being compared with the actual results. In addition, this research can also assist in estimating predictions of tile production which can estimate related losses or profits that will occur.

B. METHODS

1. Data Collection

Data collection was obtained from a tile company, to be precise at TH ABADI from January 2018 - September 2022, through direct interviews with the parties concerned. Data can be seen in Table 1.

Table 1. Dataset

Month	Year	Land (Kg)	Demand	Supply	Production
January	2018	50000	34000	875	20613
February	2018	55000	31600	500	23800
March	2018	53000	29950	400	25016
April	2018	40000	28720	450	24206
May	2018	45000	29860	230	25516
June	2018	42000	29050	300	25107
July	2018	32000	25050	250	27031
August	2018	56000	32550	200	30072
September	2018	45000	30050	250	27558
October	2018	42000	29550	300	25134
November	2018	40000	27700	500	23731

Month	Year	Land (Kg)	Demand	Supply	Production
December	2018	30000	24100	100	26010
January	2019	25000	21050	150	23841
February	2019	20000	18690	340	24317
March	2019	25000	21740	100	23045
April	2019	15400	14230	590	12780
May	2019	15500	14760	330	23544
June	2019	25300	23090	240	25060
July	2019	60000	34590	650	21304
August	2019	35500	28830	220	27118
September	2019	45200	30400	320	25603
October	2019	40500	28240	580	23071
November	2019	38600	27610	270	25056
December	2019	55000	31630	640	21641
January	2020	42000	29440	400	26690
February	2020	56000	32820	380	25826
March	2020	45000	30120	260	27565
April	2020	53000	30760	300	26568
May	2020	52000	30030	370	25481
June	2020	57000	33430	440	24816
.....	.....	.....	.....	.....	.....
.....	.....	.....	.....	.....	.....
May	2022	49000	27790	220	?
June	2022	55000	32560	260	?
July	2022	48000	32120	340	?
August	2022	56000	32740	300	?
September	2022	53000	32600	350	?

Table 1 is a table of total production with unknown production from May to September 2022, so this data is used as test data.

2. Create Rules

Before presenting the automatic C 4.5 generation rules using WEKA, here are the general working steps of the C 4.5 algorithm in building decision trees;

a. Select a variable as root.
b. Create a branch for each value.
c. Divide cases into branches.
d. Repeat the process for each branch until all cases in the branch have the same class.

The process of making rules using WEKA by changing the production output value in the dataset is a fuzzy set (Sheena et al., 2017). This study divides 3 fuzzy sets consisting of Little, Enough, and Many (Tundo, 2022). The initial process for changing the value of production output by determining the minimum, middle, and maximum values (Tundo & Nugroho, 2020). Then it is assumed that the minimum value until it approaches the midpoint is Little, approaches the midpoint until it approaches the maximum value is Enough and the rest is Many. The following are the maximum rules obtained after experiencing 5x test trials, where the maximum rules obtained produce an accuracy of 80%, as shown in Figure 1.

```
Time taken to build model: 0.02 seconds

=== Evaluation on training set ===
=== Summary ===

Correctly Classified Instances          44               80      %
Incorrectly Classified Instances        11               20      %
Kappa statistic                          0.6849
Mean absolute error                      0.1872
Root mean squared error                  0.3059
Relative absolute error                 43.4422 %
Root relative squared error             65.9642 %
Total Number of Instances               55

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
                 0.75      0.047      0.818     0.75      0.783      0.922    Little
                 0.957     0.281      0.71      0.957     0.815      0.888    Enough
                 0.65      0          1         0.65      0.788      0.912    Many
Weighted Avg.    0.8       0.128      0.839     0.8       0.798      0.904

=== Confusion Matrix ===

  a  b  c   <-- classified as
  9  3  0 |  a = Little
  1 22  0 |  b = Enough
  1  6 13 |  c = Many
```

Figure 1. Rule Formation Accuracy Details

Based on the resulting accuracy and detail accuracy for each class based on Figure 1 above, the rules formed by selecting the C 4.5 visual tree from the process produce rules that look like those in Figure 2.

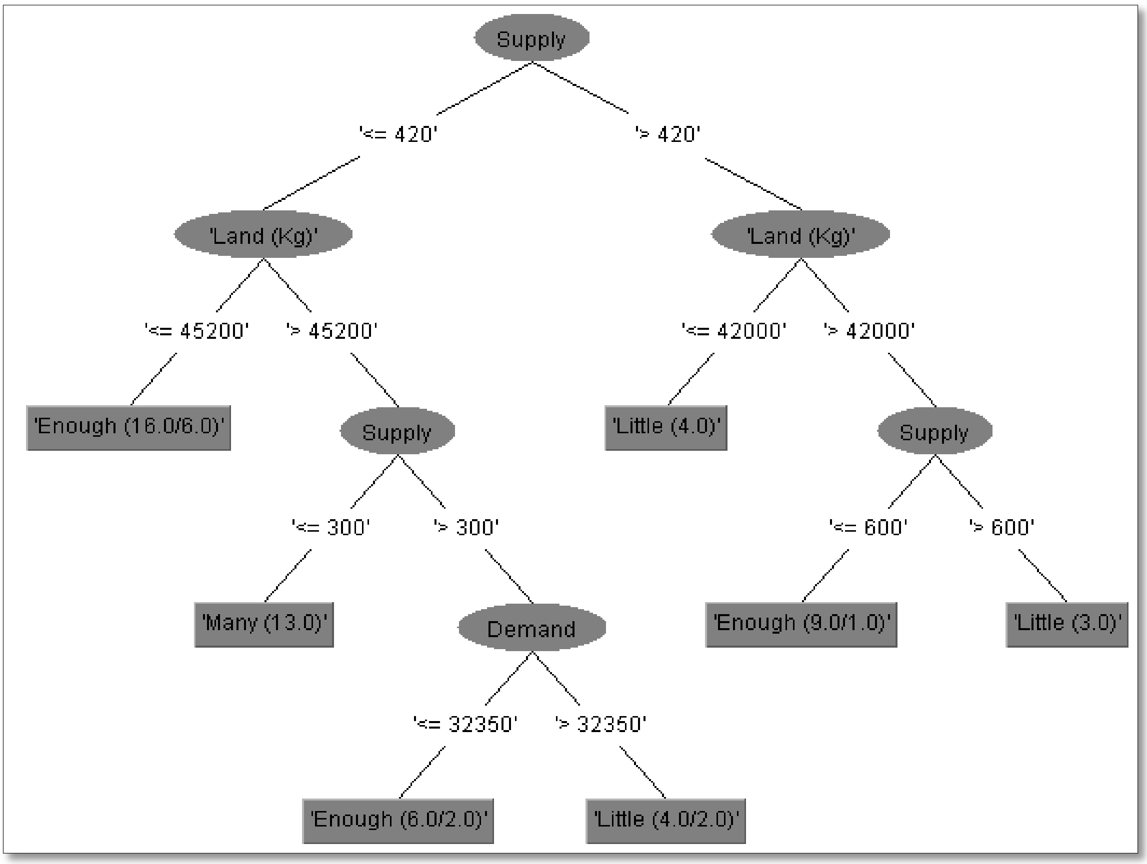

Figure 2. Decision Tree C 4.5

Based on Figure 2, the IF...THEN rule is obtained by writing the classification for each parameter first to make it easier to translate the rules that are formed (Selvachandran et al., 2019). The following classification for each parameter looks like the following.

Supply:
> 600 = Many
300 – 600 = Enough
< = 300 = Little

Land:
> 45200 = Many
42000 – 45200 = Enough
< = 42000 = Little

Demand:
> 32350 = Many
< = 32350 = Little

Based on the classification above, the IF...THEN rules that are formed can be seen in Table 2 (Tundo & Kurniawan, 2019).

Table 2. Rules used

Code	IF ... THEN
R1	IF Supply Enough And Land Enough THEN Production Enough
R2	IF Supply Little And Land Many THEN Production Many
R3	IF Supply Enough And Land Many And Demand Little THEN Production Enough
R4	IF Supply Enough And Land Many And Demand Many THEN Production Little
R5	IF Supply Enough And Land Little THEN Production Little
R6	IF Supply Many And Land Enough THEN Production Little

3. FIS Tsukamoto

Tsukamoto's FIS is a method in which each consequence is in the form of an IF...THEN rule must be represented in the concept of a fuzzy set with a monotonous membership function (Rahmalia, 2021). As for the stages in this method, there are 3 processes to get the output, namely:

a. Formation of Fuzzy Sets
   This process requires a rule model that must exist Tundo (2020), such as fuzzy sets, and representation of membership functions and domains (Haghpanah & Taheri, 2017). This study implements the concept based on Table 3, which is in the form of rules, criteria in fuzzy sets, and membership function representations as shown in Figure 3 and Figure 3.

Table 3. Fuzzy Set Rules Model

Parameter	Criteria	Fuzzy Set	Domain
Input	Land	Little	[15400 – 27050]
		Enough	[15400 – 62000]
		Many	[50350 – 62000]
	Demand	Little	[14230 – 19515]
		Enough	[14230 – 35370]
		Many	[30085 – 35370]
	Supply	Little	[95 – 290]
		Enough	[95 – 875]
		Many	[680 – 875]
Output	Production	Little	[12780 – 18210]
		Enough	[12780 – 34500]
		Many	[29070 – 34500]

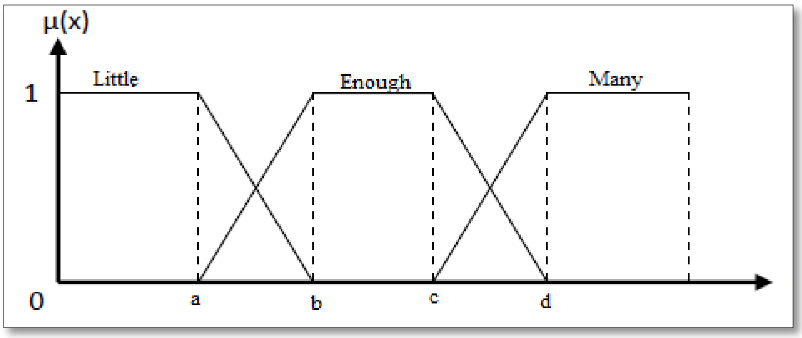

Figure 3. Membership Function

Based on Figure 3, the formula for the degree of membership for each set on the criteria looks like this (Geman, Chiuchisan, & Aldea, 2017) :

$$\mu_{[Little]}(x)\begin{cases}0 & x \geq b\\ \frac{b-x}{b-a}, & a \leq x \leq b\\ 1 & x \leq a\end{cases} \quad (1)$$

$$\mu_{[\boldsymbol{Many}]}(x)\begin{cases}0 & x \leq c\\ \frac{x-c}{d-c}, & c \leq x \leq d\\ 1 & x \geq d\end{cases} \quad (2)$$

$$\mu_{[Enough]}(x)\begin{cases}0 & x \leq a,\ x \geq d\\ \frac{x-a}{b-a}, & a \leq x \leq b\\ \frac{d-x}{d-c}, & c \leq x \leq d\\ 1 & b \leq x \leq c\end{cases} \quad (3)$$

b. Application Function Implication

Tsukamoto's FIS method in applying this concept uses the implication function Min (Sumitra & Supatmi, 2019). The form of this function is If.....Then.... And using the AND operation, where the rules formed in this study use the decision tree C 4.5. The following is an illustration of the implication function application.

$$\mu A \cap B = \min(\mu A[x], \mu B[y]) \quad (4)$$

with:
μA[x] = the membership degree value of the fuzzy solution up to the rules i;
μB[y] = value of the degree of membership of consequent fuzzy rules i;

c. Deffuzy
At the defuze stage, changes are made to the results of concluding the Tsukamoto fuzzy inference system to output in the form of crisp values or firm values using the Weighted Average Method process, in general, it is formulated (Jalota & Agrawal, 2019):

$$z^* = \frac{\sum(a*z)}{\sum a} \quad (5)$$

4. Accuracy

Accuracy at this stage is used to measure the success rate of a method that has been used (Hamsa, Indiradevi, & Kizhakkethottam, 2016). In this method, the accuracy calculation uses the Average Forecasting Error Rate (AFER) method with the formula:

$$\text{AFER} = \frac{\sum\left(\frac{|A_i - F_i|}{A_i}\right)}{n} \; x \; 100\,\% \quad (6)$$

Where Ai is the actual data in the data and Fi is the predicted value for the i data. Meanwhile, n is the amount of data (Tuan et al., 2020).

C. RESULT AND DISCUSSION

1. Calculation of FIS Tsukamoto

The following is an example of calculating the prediction of the amount of manual production using FIS Tsukamoto based on test data, which will be used as an example of the manual calculation, namely, in August 2022, with a land inventory of 49,000 Kg, a demand of 27,790, and an existing supply of 220.

Step 1:

Look for the membership degree value of each criterion based on the modeling that has been made in Table 3 and Figure 3. The following is the value of each membership degree of each criterion.

$$\mu_{land-little}[49000] = 0$$
$$\mu_{land-enough}[49000] = 1$$
$$\mu_{land-many}[49000] = 0$$
$$\mu_{demand-little}[27790] = 0$$
$$\mu_{demand-enough}[27790] = 1$$
$$\mu_{demand-many}[27790] = 0$$

$\mu_{supply-little[220]} = \frac{290-220}{290-95} = 0{,}3590$

$\mu_{supply-enough[220]} = \frac{220-95}{195} = 0{,}6410$

$\mu_{supply-many[220]} = 0$

Step 2:

The implication function application uses the MIN function, for each rule, to find the a and z values for each rule. Where the value of a and z is a parameter to produce a weighted average. Each Rule will have a and z as many rules as are formed like the following calculation;

R1: IF Supply Enough And Land Enough THEN Production Enough

$\alpha_1 = \mu_{supply-enough} \cap \mu_{land-enough}$

$= \min(0{,}6410; 1) = 0{,}6410$

Due to R1, R3 for THEN Production Enough so that it uses a rising linear membership degree representation. So there is a Z value that occurs 2 times.

<-> $\frac{Z1-12780}{18210-12780} = 0{,}6410$	<-> $\frac{34500-z2}{34500-29070} = 0{,}6410$
<-> $\frac{Z1-12780}{5430} = 0{,}6410$	<-> $\frac{34500-z2}{5430} = 0{,}6410$
<-> Z1 – 12780 = 0,6410 x 5430	<-> 34500 – Z2 = 3481
	-Z2 = 3481 – 34500
<-> Z1 – 12780 = 3481	-Z2 = -31019
Z1 = 3481 + 12780 =16261	Z2 = 31019

R2: IF Supply Little And Land Many THEN Production Many

$\alpha_2 = \mu_{supply-little} \cap \mu_{land-many}$

$= \min(0{,}3590; 0) = 0$

Due to R2 for THEN Production Many, it uses the increasing linear membership degree representation in finding z.

<-> $\frac{Z3-29070}{34500-29070} = 0$

<-> $\frac{Z3-29070}{5430} = 0$

<-> Z3 – 29070 = 0 X 5430

Z3 = 0 + 29070

Z3 = 29070

R3: IF Supply Enough And Land Many And Demand Little THEN Production Enough

$\alpha_3 = \mu_{supply-enough} \cap \mu_{land-many} \cap \mu_{demand-little}$

$= \min(\ 0{,}6410\ ;\ 0;\ 0\ ) = 0$

<-> $\frac{Z4-12780}{18210-12780}$ = 0
<-> $\frac{Z4-12780}{5430}$ = 0
<-> Z4 – 12780 = 0 x 5430
<-> Z4 – 12780 = 0
Z4 = 0 + 12780 =12780

<-> $\frac{34500-z5}{34500-29070}$ = 0
<-> $\frac{34500-z5}{5430}$ = 0
<-> 34500 – Z5 = 0
-Z5 = 0 – 34500
-Z5 = -34500
Z5 = 34500

R4: IF Supply Enough And Land Many And Demand Many THEN Production Little

$$\alpha_4 = \mu_{supply-enough} \cap \mu_{land-many} \cap \mu_{demand-many}$$
$$= \min(0{,}6410 ; 0 ; 0) = 0$$

Due to R4, R5, and R6 for THEN Production Little it uses a linear membership degree representation down in finding z.

<-> $\frac{18210-Z6}{18210-12780}$ = 0
<-> $\frac{18210-Z6}{5430}$ = 0
<-> 18210 – Z6 = 0
-Z6 = 0 – 18210
Z6 = 18210

R5: IF Supply Enough And Land Little THEN Production Little

$$\alpha_5 = \mu_{supply-enough} \cap \mu_{land-little}$$
$$= \min(0{,}6410; 0) = 0$$

<-> $\frac{18210-Z7}{18210-12780}$ = 0
<-> $\frac{18210-Z7}{5430}$ = 0
<-> 18210 – Z7 = 0
Z7 = 18210

R6: IF Supply Many And Land Enough THEN Production Little

$$\alpha_6 = \mu_{supply-many} \cap \mu_{land-enough}$$
$$= \min(0 ; 1) = 0$$

<-> $\frac{18210-Z8}{18210-12780}$ = 0
<-> $\frac{18210-Z8}{5430}$ = 0
<-> 18210 – Z8 = 0
Z8 = 18210

Step 3:

Results or output can be obtained from the calculation of the weighted average, namely;

$$Z^*=\frac{a1*z1+a1*z2+a2*z3+a3*z4+a3*z5+a4*z6+a5*z7+a6*z8}{0{,}6410+0{,}6410+0+0+0+0+0}$$

$$Z^*=\frac{0{,}6410*16261+0{,}6410*31019+0*29070+0*12780+0*34500+0*18210+0*18210+0*18210}{1{,}282}$$

$$Z^*=\frac{30306{,}5}{1{,}282}\approx 23640$$

After all of the test data from May to September 2022 is calculated, predictions for tile production are produced as shown in Table 4.

Table 4. Predicted Results of Test Data

Month	Land	Demand	Supply	Production Predictions
May	49000	27790	220	23640
June	55000	32560	260	22461
July	48000	32120	340	22315
August	56000	32740	300	21059
September	53000	32600	350	22785

2. Analysis of Comparative Results

The predicted results are compared directly with actual production, in detail shown in Figure 4. Real production results are shown in a yellow bar chart, while predictions are shown in green. Predictions have less value and are closer to their real value, as shown in Figure 4.

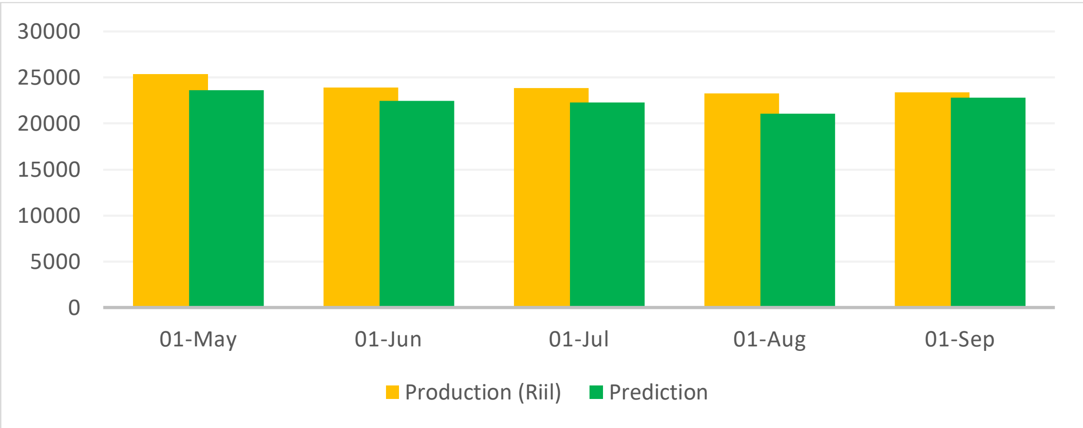

Figure 4. Comparison of Predictive Results

The prediction comparison results (Table 4) were tested using the Average Forecasting Error Rate (AFER) method. The values obtained have error and truth values as shown in Table 5 and Figure 5.

Table 5. Results of Test Data Prediction Error

Land	Demand	Supply	Real Production (A)	Production Predictions (F)	|A-F|	|A-F|/A
49000	27790	220	25360	23640	1720	0.067823
55000	32560	260	23910	22461	1449	0.060602
48000	32120	340	23830	22315	1515	0.063575
56000	32740	300	23300	21059	2241	0.09618
53000	32600	350	23400	22785	615	0.026282
			Average			0.293436
			In Percent			29,34%

Based on the calculation, the error value obtained with AFER is 29.34%, so the accuracy of the truth obtained is 70.66%.

D. CONCLUSION AND SUGGESTIONS

The results of the study show that FIS Tsukamoto – Decision tree C 4.5 can predict tile production at TH ABADI Kebumen. The prediction results with actual production from May to September 2022 using AFER have an error percentage of 29.34% with a truth value of 70.66%. The overall results of predictions on actual production did not exceed anything, so it can be concluded that the FIS Tsukamoto - Decision tree C 4.5 method is sufficiently optimum in providing predictive estimates. It is said to be quite optimum because all customer requests are met, either generated by the production prediction itself or the prediction results are added up with inventory data, and all predictions are close to actual production. This research also shortens the time in making rules because it is sufficiently processed with decision tree C 4.5 using WEKA, so there is no need for expert intervention. The rules that are formed from decision tree C 4.5 using WEKA can be accounted for due to the resulting accuracy, where the accuracy of the rule formation reaches 80%. Suggestions for future researchers can make comparisons with other FIS, namely Mamdani and Sugeno, as well as the decision tree that is formed can use other than C 4.5 to find out the differences in each of the methods used.

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