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Determination of Copper Losses for Substation Transformers in Special Region of Yogyakarta using the Fuzzy System

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ABSTRACT

Transformer's efficiency is essential and significantly affects the transformer's performance in delivering power. The efficiency is affected by copper losses, of which value is not constant. To improve a state-owned electricity company in Indonesia (PLN) in increasing the optimization of transformer loading, a more accurate calculation of transformer copper losses is needed. In this study, a new method was proposed to assess the value of copper losses using a fuzzy system, namely the first-order Takagi-Sugeno-Kang (TSK) method combined with Singular Value Decomposition (SVD). The fuzzy system was built based on training data. Upon this data, clustering was carried out with fuzzy c-mean (FCM). The results of the FCM were cluster centers, which were then used to construct membership functions and fuzzy rules. The parameters on the consequent of each first-order TSK fuzzy rule were determined using SVD. The last step was defuzzification to obtain the value of the transformer copper losses. The defuzzification method used was the weight average. The fuzzy system that had been built was tested on all data to determine and obtain the accuracy of the copper losses values. The results of this study indicated that the determination of transformer copper losses with a fuzzy system for training and testing data have accuracies of 99.3354% and 99.6490%, respectively. Furthermore, the first-order TSK method gives better results than that of the zero-order TSK and Mamdani methods.

1. INTRODUCTION

Electricity is the most needed energy source in the modern era. The consumption of electrical energy increases in line with population growth [1]. Electricity has been used in various activities such as entertainment, communication, lighting, learning, work, and transportation [2]. Thus, electricity plays an important role among the sources of energy for life [3].

Electrical energy is distributed by electricity providers to consumers. In Indonesia, a state-owned electricity company, called Perusahaan Listrik Negara (PLN), is a provider and distributor of electrical energy through substations [4]. The substation has several components, one of which is a transformer. Transformers are equipment used to connect electrical power transmission systems at different voltage levels [5]. Some substations in Indonesia use three-phase transformers, including in the Special Region of Yogyakarta. A three-phase transformer serves in distributing electrical energy to customers [6].

Transformers could experience losses in delivering power [5]. One type of losses in a transformer is copper losses. It is caused by the current flowing in the copper wire windings on the primary and secondary sides [7]. Copper losses arise from the load current, which is not constant [8]. In meeting the needs of electrical energy to customers, transformers must have high efficiency to be able to deliver power optimally [9]. Transformer's efficiency can be affected by the value of copper losses [10]. Therefore, it is necessary to determine the calculation of copper losses with good accuracy.

Determination of copper losses can be carried out by using several analytical methods, namely the finite element method and measurements [11]. The analytical method can only be applied to simple transformer structures and cannot be applied to complex winding structures. While the measurement method has the potential to obtain higher accuracy results, the equipment and experiments carried out are complicated [7].

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Several studies have been conducted to determine copper losses in transformers. Research on determining transformer copper losses has been carried out using a winding layer allocation approach utilizing the Dowell analysis method with Maxwell's equations [12]-[15]. The Dowell method exhibits good results in predicting copper losses. However, the Dowell method has the disadvantage that it is difficult to use in transformers with parallel-connected windings [12], [14]. Lin and Fuchs [16] investigated the determination of copper losses using an online losses measurement method when the transformer operates under load conditions. This method is based on voltage and current sensors and the results showed good accuracy.

Intelligent control systems have been used in various applications and fuzzy logic is one of these intelligent systems. The applications of fuzzy logic in control systems are for instances in vehicle control, robots, and stabilization [17]. In several studies, fuzzy logic has also been applied to transformers. Malik *et al.* [18], in their research, used fuzzy logic to predict minimum losses and to design optimal transformers. The result of the study stated that fuzzy logic was feasible to use. In another study, a fuzzy system was applied to design an optimal power converter in the transformer [19] to simulate the transformer's voltage drop accurately with a simple model [20], determine the total copper losses and core losses [21], [22], and improve the diagnostic accuracy of gas analysis in transformers [23].

The fuzzy system has several methods, one of which is the Takagi Sugeno-Kang (TSK) method. The first-order fuzzy TSK has a consequent linear equation that can give high accuracy results with few fuzzy rules [24]. TSK fuzzy system has been used in several studies. Ippolito *et al.* [24] modeled the overload prediction on the power transformer using the TSK fuzzy system and gave good accuracy results with an error of less than 3%.

Based on the description above, there has been no research on determining the transformer copper losses using a fuzzy system. Therefore, in this research, the transformer copper losses are determined by using a fuzzy system. The fuzzy system is chosen because the input variables used contain uncertain values. The advantage of the fuzzy system is that it can model nonlinear functions on data that contains uncertainty. The inference method used is the first-order TSK method combined with the singular value decomposition (SVD) method. TSK fuzzy rules are built using the fuzzy c-means (FCM) method. The FCM method can transform classification into mathematical optimization [25]. From the results of the classification using FCM, the value of the cluster center could be changed into linguistic variables and transformed into fuzzy rules [26]. In this study, the copper losses are determined based on the input variable of load current and transformer voltage from the transformer load data. The calculation of transformer copper losses in this paper emphasizes efforts to improve a state-owned electricity company in Indonesia (PLN) in increasing the optimization of transformer loading, so that in the future, transformer operation management can be integrated with applications developed based on this method.

2. THEORETICAL REVIEW

2.1 Transformer Copper Losses

Copper losses can occur when the transformer is running. The losses occur in the windings when the transformer is loaded [27]. Copper losses can be identified after the transformer losses are known. The transformer losses can be determined from the sum of the final losses of each component of the harmonic current [28]. The total transformer losses are the sum of the copper losses and the core losses. This can be expressed in the equation below [16]:

$$\sum Loss = P_{cu} + P_i \tag{1}$$

where P_{cu} is the copper losses and P_i is the core losses.

The total transformer losses are obtained from the difference between the input power and the output power. This is expressed in Equation (2) [16] below.

$$P_{loss} = P_{in} - P_{out} \tag{2}$$

Transformer losses can be computed when the transformer voltage and current flowing in the transformer are known. Using a known current, the copper losses can be calculated [29].

2.2 First-Order TSK Fuzzy System

There are several fuzzy inference processes in the fuzzy system, including the Mamdani, Tsukamoto, and Takagi Sugeno-Kang (TSK) methods. In this research, the first order TSK model was used where the fuzzy rule can be expressed as [30]:

$$\begin{aligned} &IF\ x_1\ is\ C_1\ and \ldots and\ x_n\ is\ C_n\ THEN \\ &y = b_0 + b_1 x_1 + \cdots + b_n x_n \end{aligned} \tag{3}$$

where C_i is a fuzzy set and b_i is a constant.

2.3 FCM

FCM is a technique of grouping data into several clusters. Determination of a datum in a cluster is based on the degree of membership [31]. The degree of membership of data in a cluster uses the concept of fuzzy logic, that is the data has a degree between 0 to 1 in each cluster. The degree of membership indicates the level of membership of the data in the cluster [32]. The data grouping technique in the FCM method is done using the following steps [33]:

1. Determining the number of clusters (c), power (m), smallest error (ε), and initial matrix (U).
2. Calculating the cluster center using the equation:

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m y_k}{\sum_{k=1}^{n} (\mu_{ik})^m} \tag{4}$$

3. Calculating the matrix U using the equation:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{e} \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{m-1}}} \qquad (5)$$

4. Iterating the procedure from step 2 to 3 until $\left| U^{I} - U^{I-1} \right| < \varepsilon$. If $t = t + 1$, then step 2 is repeated.

FCM results can be used to develop a fuzzy system. The cluster center of the FCM results is used as a fuzzy linguistic variable and then transformed into a fuzzy rule [26].

2.4 *SVD*

The SVD of matrix A of size m × n over real numbers is expressed in Equation (6) [34], *i.e.*:

$$A = U \Sigma V^{T} \qquad (6)$$

where U is an orthogonal matrix of size $m \times m$, V is an orthogonal matrix of size $n \times n$, and $\Sigma = diag(\sigma_1, \sigma_2, \ldots, \sigma_r)$ is matrix $m \times n$ of which the diagonal element is called the singular value of the matrix [35]. If matrices U dan V are expressed as column vectors $U = (u_1, u_2, \ldots, u_n)$ and $V = (v_1, v_2, \ldots, v_n)$, then Equation (6) can be expressed as Equation (7)[36], *i.e.*:

$$A = \sum_{i=1}^{n} \sigma_i u_i v_i^T \qquad (7)$$

3. METHODS

3.1 *Data Description*

The data used in this study were the load data obtained from PT. PLN APJ Yogyakarta in November 2019. The data contained transformer load current in R phase (ampere), S phase (ampere), T phase (ampere), transformer voltage (volt), and copper losses (kW) from 12 transformer substations in Special Region of Yogyakarta with a capacity of 60 MVA with peak load at 10.00 western Indonesian time (WIB) 360 data were obtained, which were then divided into 75% of training data or 270 training data and 25% of testing data or 90 testing data. Tables 1 and 2 show the training and testing data, respectively.

Table 1. Training data.

R Current	S Current	T Current	Voltage	Copper Losses
1082.24	983.04	1062.88	21.1	65.82
1263	1135	1188	20.3	77.88
496	544	531	21.3	26.16
984	969	1003	20.9	58.52
⋮	⋮	⋮	⋮	⋮
895	931	901	20.5	48.63
642	527	550	20.6	28.35

Table 2. Testing data.

R Current	S Current	T Current	Voltage	Copper Losses
689	687	695	20.4	35.09
890.28	845	776	20.5	41.89
1002	1023	1049	20.9	62.76
861	840	952	20.2	44.82
⋮	⋮	⋮	⋮	⋮
837	800	830	20.5	41.34
860	828	832	21	43.73

3.2 *Research Steps*

In this study, data analysis was carried out using a fuzzy system with the first-order TSK method to determine the value of transformer copper losses at the Yogyakarta Special Region substation. The fuzzy system was built using the training data, whereas the testing data was used to test the fuzzy system. The steps in conducting this research are presented in Figure 1.

The research steps were initiated by selecting a substation transformer with a capacity of 60 MVA, namely 12 transformers and 360 data were obtained during the month of November 2019. Before building the fuzzy membership function, the cluster center was determined from the training data using FCM. The results of each variable cluster center were used as the peak of each membership function and used to construct the fuzzy rules. The inference system uses the first-order TSK method. The parameters at the consequent of each fuzzy rule were determined by the SVD method. To establish the accuracy of the model, the system was tested based on the values of Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) for training and testing data, respectively.

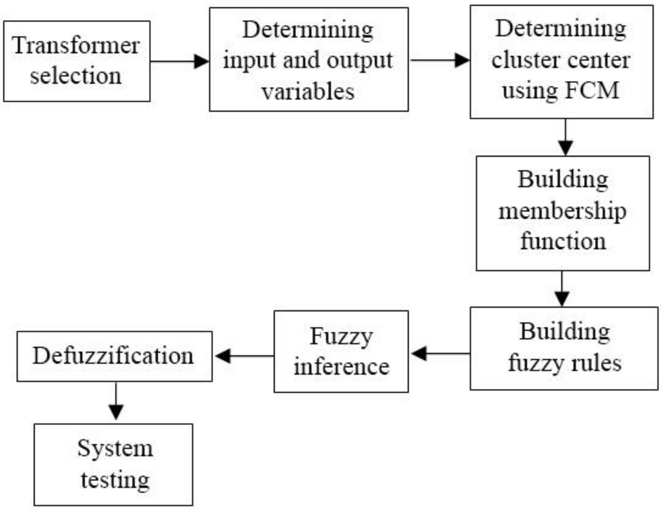

Fig. 1. Research steps.

4. RESULTS AND DISCUSSION

4.1 Determining the Input and Output Variables

This research uses 4 input variables, namely R phase current, S phase current, T phase current, and transformer voltage. The output variable in this study is transformer copper losses.

4.2 Determining the Cluster Center

The test results of several clusters are shown in Table 3. The best accuracy results were used to build the fuzzy system.

Based on Table 3, the fuzzy system is then built using 10 clusters. The cluster center results from the FCM are shown in Table 4. Afterwards, the cluster center is used as the peak of the fuzzy membership function and to construct the fuzzy rules. The cluster center is used to construct 10 fuzzy rules and 10 membership functions at each input variable.

Table 3. Test results of several clusters.

Number of Cluster	Training Data Accuracy (%)	Testing Data Accuracy (%)
4	99.1646	99.3613
6	99.3189	99.4528
10	99.3354	99.6457

Table 4. Cluster center.

No. Cluster	Variables				
	R Current	S Current	T Current	Voltage	Copper Losses
1	1112	1068.3	1098	20.61	68.56
2	1411.8	1364.9	1388.7	20.73	106.67
3	719.14	712.03	720.02	20.58	36.79
4	901.04	877.49	898.78	20.63	47.66
5	995.13	957.32	1001.5	20.67	57.33
6	648.04	653.92	659.3	20.79	33.77
7	431.04	351.79	372.5	20.3	13.99
8	785.13	777.18	786.24	20.62	39.95
9	550.84	564.57	557.06	20.8	27.7
10	1240.4	1175.4	1213.2	20.53	81.09

4.3 Determining the Transformer Copper Losses using the Fuzzy System

a. Building the Membership Function

The membership function is built based on the cluster center. Therefore, each input variable uses 10 fuzzy sets with the membership function using the Gauss curve, which is defined in Equation (8), *i.e.*:

$$g(x;\sigma,c) = \exp^{\left(\frac{-(x-c)^2}{2\sigma^2}\right)} \tag{8}$$

where c is the center and σ is the width of the curve. This study uses the standard deviation of the data to determine the width of the curve. The membership function in each input variable is determined as follows.

1. R phase current (R): Based on the training data, the smallest and largest values of the R phase current are 0 and 1549, respectively, so the universal set is U_R = [0,1549]. The 10 fuzzy sets are defined in the R phase current variable with membership functions of R_1, R_2, R_3,..., R_{10}. The membership function graphs are presented in Figure 2.

$$\mu_{R_1}(x) = \exp^{-\frac{(x-1112)^2}{2(246.4663)^2}}$$

$$\mu_{R_2}(x) = \exp^{-\frac{(x-1411.8)^2}{2(246.4663)^2}}$$

$$\vdots$$

$$\mu_{R_{10}}(x) = \exp^{-\frac{(x-1240.4)^2}{2(246.4663)^2}}$$

2. S phase current (S): According to the training data, the smallest and largest values of the S phase current are 0 and 1545, respectively, so that the universal set is U_S = [0,1545]. The 10 fuzzy sets defined in the S phase current variable have membership functions of S_1, S_2, S_3,..., S_{10}, of which graphs are presented in Figure 3.

$$\mu_{S_1}(x) = \exp^{-\frac{(x-1068.3)^2}{2(232.6904)^2}}$$

$$\mu_{S_2}(x) = \exp^{-\frac{(x-1364.9)^2}{2(232.6904)^2}}$$

$$\vdots$$

$$\mu_{S_{10}}(x) = \exp^{-\frac{(x-1175.4)^2}{2(232.6904)^2}}$$

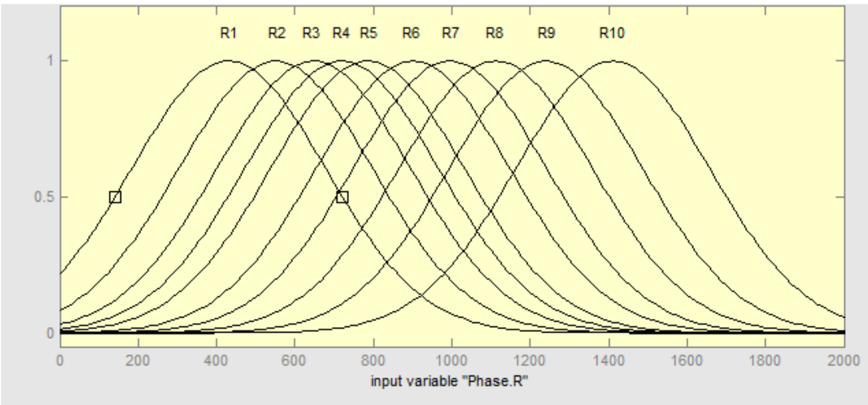

Fig. 2. The membership functions of the R phase variable.

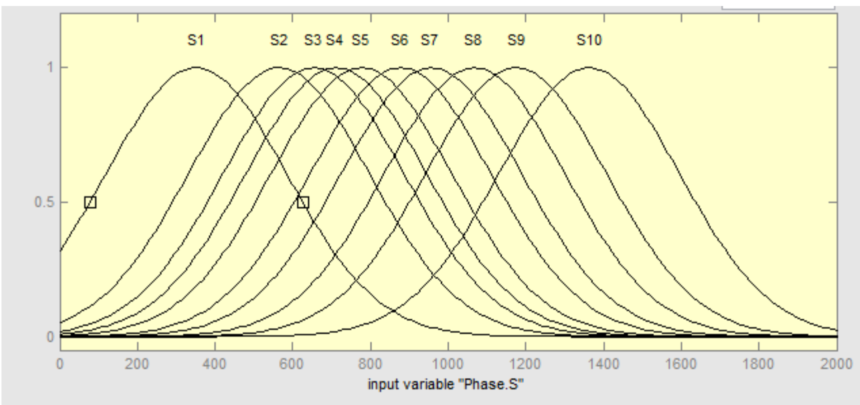

Fig. 3. The membership functions of the S phase variable.

3. T phase current (T): Based on the training data, the smallest and the largest values of the T phase current are 0 and 1600, respectively, thus the universal set is U_T = [0,1600]. Consequently, 10 fuzzy sets are defined in the T phase current variable with membership functions of T_1, T_2, T_3,..., T_{10}. These graphs are given in Figure 4.

$$\mu_{T_1}(x) = \exp^{-\frac{(x-1098)^2}{2(243.4481)^2}}$$

$$\mu_{T_2}(x) = \exp^{-\frac{(x-1388.7)^2}{2(243.4481)^2}}$$

$$\vdots$$

$$\mu_{T_{10}}(x) = \exp^{-\frac{(x-1213.2)^2}{2(243.4481)^2}}$$

4. Transformer voltage (V)*:* Finally, based again on the training data, the smallest and largest values of the voltage are 0 and 21.3, respectively. Therefore, the universal set is U_V = [0,21.3]. Moreover, the 10 fuzzy sets are defined in the voltage variable with membership functions, namely V_1, V_2, V_3,..., V_{10}. The graphs of the membership functions are presented in Figure 5.

$$\mu_{V_1}(x) = \exp^{-\frac{(x-20.61)^2}{2(1.2854)^2}}$$

$$\mu_{V_2}(x) = \exp^{-\frac{(x-20.73)^2}{2(1.2854)^2}}$$

$$\vdots$$

$$\mu_{V_{10}}(x) = \exp^{-\frac{(x-20.53)^2}{2(1.2854)^2}}$$

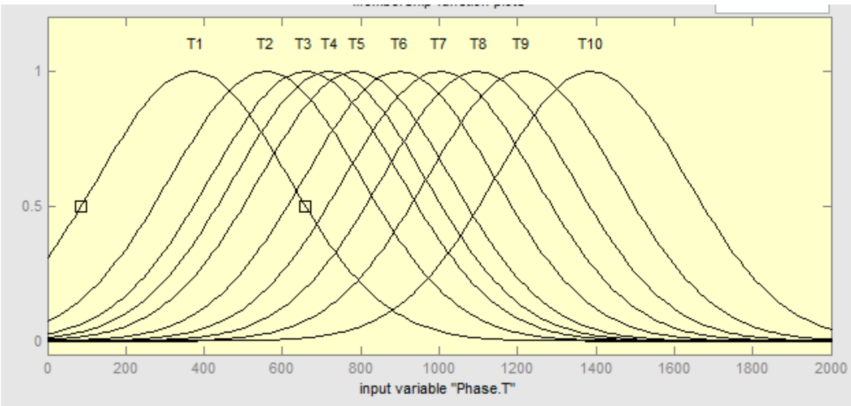

Fig. 4. The membership functions of the T phase variable.

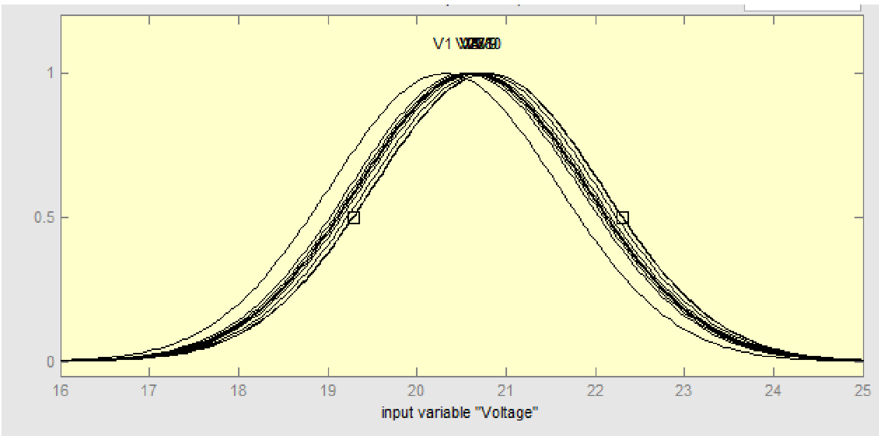

Fig. 5. Voltage variable membership functions.

b. Building the Fuzzy Rules

According to the clustering results, 10 fuzzy rules are constructed. The first-order TSK fuzzy rules are built based on Table 3 with fuzzy sets shown in Figures 2 to 5. The obtained 10 fuzzy rules are shown as follows:

Rule (1): **"**If R phase current is R_8 and S phase current is S_8 and T phase current is T_8 and the voltage is V_4, then

$$y_1 = b_{10} + b_{11} * R + b_{12} * S + b_{13} * T + b_{14} * V."$$

Rule (2): "If R phase current is R_{10} and S phase current is S_{10} and T phase current is T_{10} and the voltage is V_8, then

$$y_2 = b_{20} + b_{21} * R + b_{22} * S + b_{23} * T + b_{24} * V."$$

$$\vdots$$

Rule (10): **"**If R phase current is R_9 and S phase current is S_9 and T phase current is T_9 and the voltage is V_2, then

$y_{10} = b_{100} + b_{101} * R + b_{102} * S + b_{103} * T + b_{104} * V$"

The parameter b_{ij} is calculated by using SVD method.

c. Defuzzification

Defuzzification is the transformation that maps the fuzzy set to a crisp value at the output [30]. This study used the weight average defuzzification method [30], which is expressed as Equation (9).

$$y = \frac{\sum_{i=1}^{L} y_i(\mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n))}{\sum_{I=1}^{L} \mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)} \qquad (9)$$

Moreover, Equation (9) can also be expressed as Equation (10), *i.e.*:

$$y = \sum_{i=1}^{L} w_i(b_{i0} + b_{i1}x_1 + \cdots + b_{in}x_n) \qquad (10)$$

where $w_i = \frac{\mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)}{\sum_{i=1}^{L} \mu_{i1}(x_1)\mu_{i2}(x_2)\cdots\mu_{in}(x_n)}$

The model parameters are determined by minimizing the objective function J [37], which is expressed in Equation (11).

$$J = \sum_{k=1}^{N} [d(k) - y(k)]^2 = (d - Xb)^T(d - Xb) \qquad (11)$$

where $d(k)$ is the real output for the k^{th} data and $y(k)$ is the first-order TSK output model for the k^{th} data, $d = [d(1)d(2)\cdots d(N)]^T$ and X are matrices of size $N \times [(n+1) \times L]$ with N is the number of data, n is the number of input, and L is the number of rules, whereas $b = [b_{10} b_{11} \cdots b_{1n} \cdots b_{L0} b_{L1} \cdots b_{Ln}]$ is a matrix of size $[(n+1) \times L] \times 1$. Matrix X could be expressed as

$$X = \begin{bmatrix} w_1(1) & w_1(1)x_1(1) & \cdots & w_1(1)x_4(1) & \cdots & w_{270}(1)x_4(1) \\ w_1(2) & w_1(2)x_1(2) & \cdots & w_1(2)x_4(2) & \cdots & w_{270}(1)x_4(2) \\ \vdots & \vdots & & \vdots & & \vdots \\ w_1(270) & w_1(270)x_1(270) & \cdots & w_1(270)x_4(270) & \cdots & w_{270}(270)x_4(270) \end{bmatrix}$$

Equation (11) will reach a minimum value if $\| d - Xb \|$ is minimum. Furthermore, $\min\{\| d - Xb \| : b \in R^{(n+1)\times L}\} = \| d - X\hat{b} \|$ where the vector matrix $\hat{b}$ is shown in Equation (12) [38], *i.e.*:

$$\hat{b} = \sum_{i=1}^{r} \sigma_i^{-1} < d, u_i > v_i = \sum_{i=1}^{r} \frac{u_i^T d}{\sigma^i} v_i \qquad (12)$$

where r is a non-zero singular value. The elements of matrix $\hat{b}$ are used to estimate the parameters b_{ij} of the matrix b. The matrix entries are shown in Table 5.

Table 5. Matrix $\hat{b}$ entries.

Row 1-5	Row 6-10	Row 11-15	Row 16-20	Row 21-25
4.6255E+04	1.7475E+05	2.8921E+03	7.749E+03	-418.5940
-12.5702	-54.3968	-14.9051	-3.2432	0.0163
-10.1348	-57.5249	-18.3512	-4.7049	0.0153
-12.5201	-54.7720	-16.3996	-2.8161	0.1002
4.5071	-450.2119	-1.0814E+03	11.7208	17.0349

Row 26-30	Row 31-35	Row 36-40	Row 41-45	Row 46-50
-0.0213	1.6041E+04	2.3029E+04	-1.5528E+03	3.7302E+03
0.0811	-5.4181	-2.6726	-2.3717	-0.7065
-0.0059	-5.1611	-3.4575	-2.1164	-0.6789
0.1158	-4.5796	-3.3608	-2.5853	-0.8332
-3.6100	145.2935	-416.7054	88.1682	9.2122

The entries of matrix $\hat{b}$ are then used as the consequent parameter of the rule. Subsequently, the fuzzy rules are obtained as follows.

Rule (1): "If R phase current is R_8 and S phase current is S_8 and T phase current is T_8 and the voltage is V_4, then

$y_1 = (4.6255E + 04) + -12.5702 * R + -10.1348 * S + -12.5201 * T + 4.5071 * V$."

Rule (2): "If R phase current is R_{10} and S phase current is S_{10} and T phase current is T_{10} and the voltage is V_8, then

$y_2 = (1.7475E + 05) + -54.3968 * R + -57.5249 * S + -54.7720 * T + -450.2119 * V$."

$\vdots$

Rule (10): "If R phase current is R_9 and S phase current is S_9 and T phase current is T_9 and the voltage is V_2, then

$$y_{10} = (3.7302E + 03) + -0.7065 * R + -0.6789 * S + -0.8332 * T + 9.2122 * V \text{ ."}$$

Then, using Equation (9), the TSK model (13) is obtained.

$$y = \frac{\sum_{i=1}^{10} y_i(\mu_{i1}(x_1)\mu_{i2}(x_2)\mu_{i3}(x_3)\mu_{i4}(x_4))}{\sum_{i=1}^{10} \mu_{i1}(x_1)\mu_{i2}(x_2)\mu_{i3}(x_3)\mu_{i4}(x_4)} \quad (13)$$

Equation (13) is then used to determine the transformer copper losses in the training and testing data.

d. Determining Error and System Accuracy

In this study, as there are actual data with a value of 0 that produce the same prediction value, which is also 0, the MAPE calculation is only carried out on non-zero data. The MAPE and MSE values from the training and testing data based on the first-order TSK fuzzy system are presented in Table 6.

Furthermore, a comparison of the accuracy values for determining transformer copper losses is carried out with the first-order TSK, zero-order TSK, and Mamdani fuzzy systems. This comparison is shown in Table 7. The results show that the first-order TSK fuzzy system has better accuracy than both zero-order TSK and Mamdani methods.

The values of copper losses from the real data and first-order TSK model can be observed in Figure 6. Based on Figure 6, the copper loss values are affected by the load value, which is represented by the current and voltage values of the transformers. There are some transformers whose copper loss values exceed the values listed in the manual book. This condition is caused by factors other than the load value, namely the transformers' age and cooling condition.

The transformer loss values based on the prediction and real data for each transformer in all substations can be seen in Figures 7, 8, 9, and 10.

Table 6. The values of MAPE and MSE.

Type of Data	MAPE (%)	MSE
Training	0.664605	0.108066
Testing	0.354325	0.194703

Table 7. Comparison of the accuracy of the test results.

	First-Order TSK (%)	Zero-Order TSK (%)	Mamdani (%)
Training Data	99.3354	97.1957	96.2799
Testing Data	99.6457	97.2341	96.4882

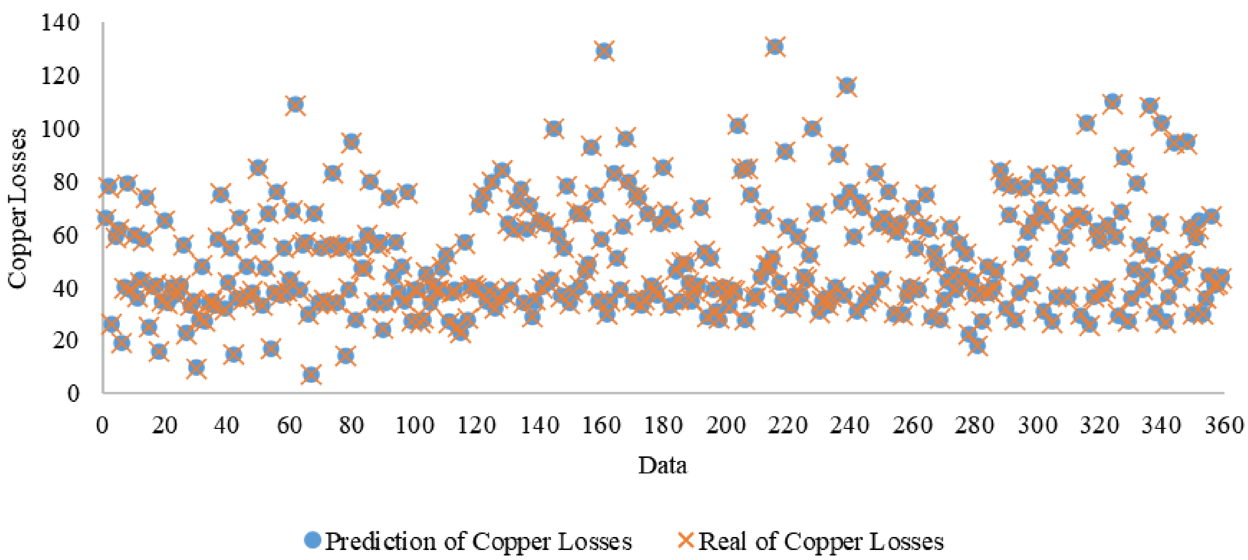

Fig. 6. The real data and fuzzy model prediction results of copper losses.

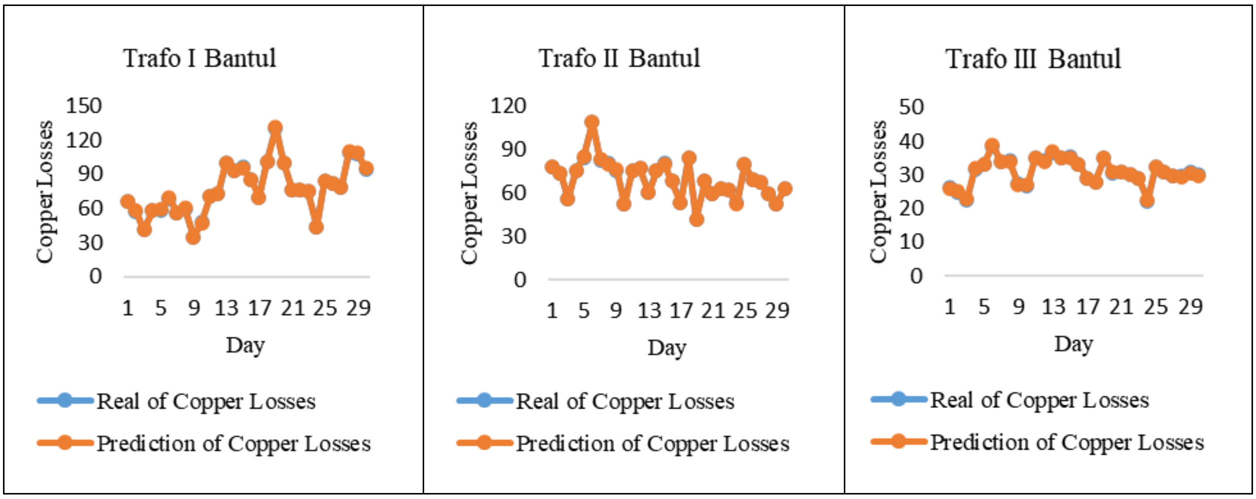

Fig. 7. Transformer copper losses in Bantul.

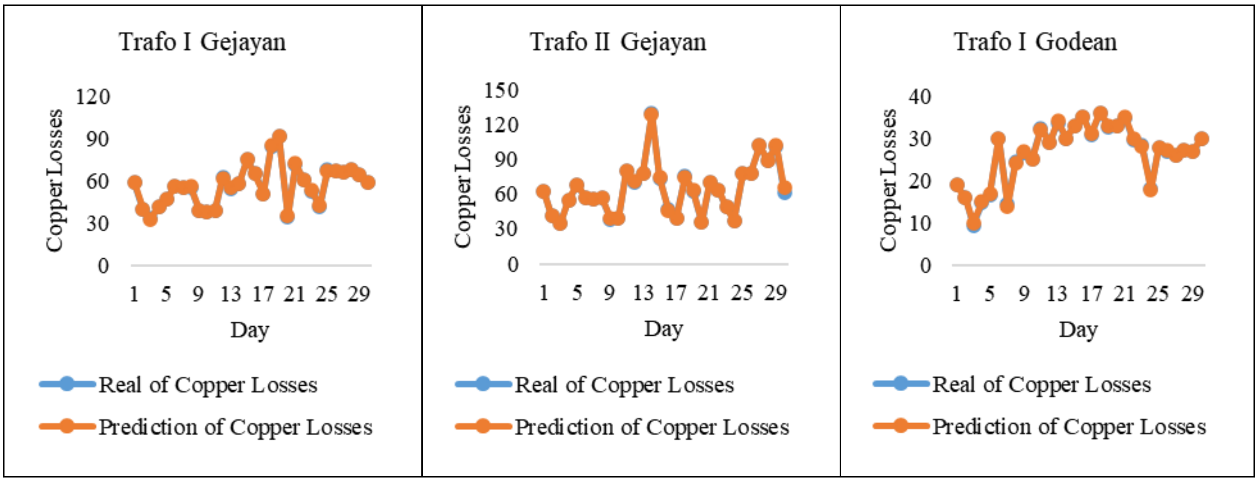

Fig. 8. Transformer copper losses in Gejayan (Transformers I and II) and Godean (Transformer I).

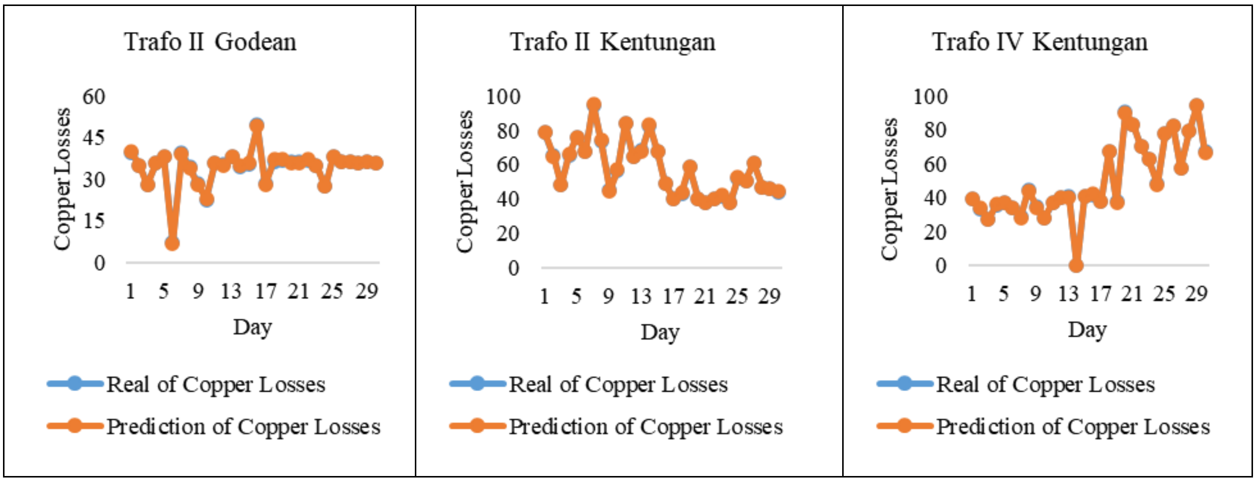

Fig. 9. Transformer copper losses in Godean (transformer II) and Kentungan (transformers II and IV).

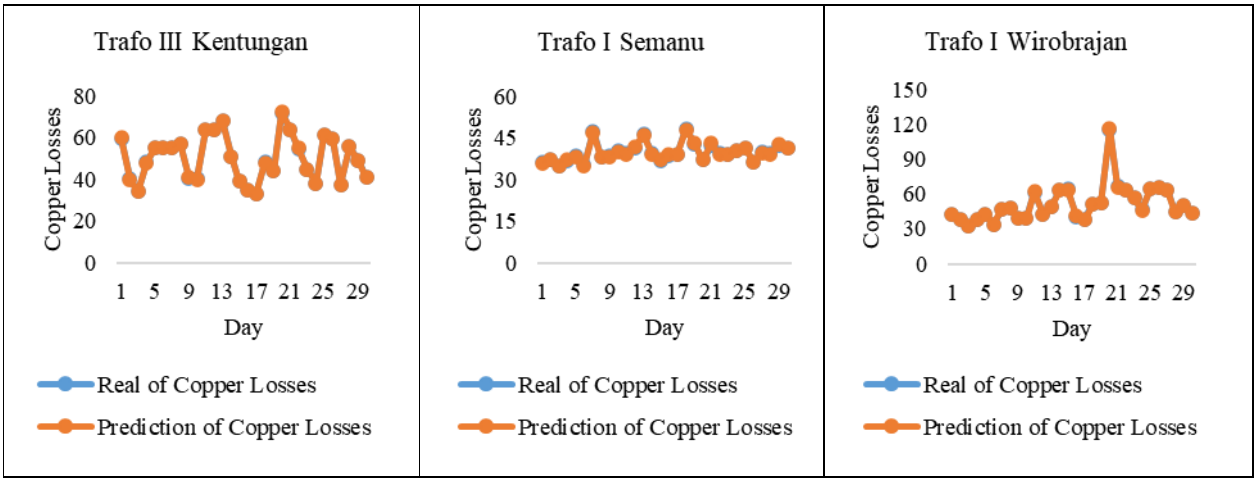

Fig. 10. Transformer copper losses in Kentungan (transformer III), Semanu (transformer I), and Wirobrajan (transformer I).

Table 8. Average value of copper losses for all transformers.

transformer	average of real copper losses	average of copper losses based on the fuzzy model		
		Lowest value	Highest value	average
Trafo I BNL	76.5025	35	131	76.6016
Trafo II BNL	69.3081	42	109	69.2212
Trafo III BNL	30.9093	22.3485	39	30.9002
Trafo I GJN	56.6427	33	91	56.7076
Trafo II GJN	64.2665	35	129	64.4963
Trafo I GDN	26.5620	10	36	26.6326
Trafo II GDN	34.3412	7	49	34.3090
Trafo II KTN	57.7247	38	95	57.7885
Trafo IV KTN	49.8434	0	94.4211	49.8051
Trafo III KTN	50.2988	33	72	50.2810
Trafo I SMU	39.8065	35	48	39.7378
Trafo I WBN	51.5281	33	116	51.5016

Figures 7 to 10 depict graphs of daily copper losses for 30 days of all the transformers at Yogyakarta substations. Based on Figure 7, the daily copper loss values on transformer III Bantul are relatively more stable compared to the transformers I and II Bantul. Based on Table 8, the lowest average copper loss occurs on transformer III Bantul, which is 30.9002 kW, whereas transformer I Bantul has the highest average copper loss of 76.6016 kW. In Figure 8, the copper loss values of transformer I Godean are relatively increasing from the first day until the end of the month. Furthermore, Table 8 also shows that transformer I Godean has the lowest average copper loss of 26.6326 kW compared to the average copper losses of transfomers I and II Gejayan. Figure 9 and Table 8 show that the daily copper loss values on transformer II Godean are relatively stable around the average of 34.3090 kW, while the highest average copper loss occurs on transformer II Kentungan of 57.7885 kW. Moreover, Table 8 shows that the lowest copper loss on transformer IV Kentungan is 0 kW because the aforementioned transformer was not in operation for a day. Finally, based on Figure 10, the daily copper losses on transformer I Semanu are more stable compared to the copper losses on transformer III Kentungan and transformer I Wirobrajan.

5. CONCLUSION

In this study, a first-order TSK model is built using the

FCM and SVD methods to determine transformer copper losses at the substations in the Special Region of Yogyakarta, Indonesia. FCM is used to construct fuzzy rules, and SVD is used to determine the parameters on the consequent of each fuzzy rule. The value of copper losses from the system is obtained using the weight average defuzzification process. The proposed method gives better accuracy than zero-order TSK and Mamdani models. From the calculation results of all transformers, an average copper loss value of 50.806 kW is obtained. The highest copper loss value is 131 kW from transformer I at the Bantul substation, while the lowest copper loss is 7 kW from transformer II at Godean substation. Copper losses from most of the calculation results still meet the standard value for transformer copper losses. The copper loss values on the transformers are affected by the current and voltage values of the transformers. Only a few transformers exhibited copper losses that exceed the standard value. Transformer copper losses affect the performance of a transformer, so that by knowing the value of copper losses in all transformers at the Yogyakarta substation, PLN can evaluate the performance of the transformer continuously. In the future, transformer operation management can be integrated with applications developed based on this method.

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