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FUZZY LOGIC APPROACH FOR PREDICTION OF HEALTH INDEX OF FEEDER CABLE BASED ON PARTIAL DISCHARGE PARAMETER

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ABSTRAK

PT PLN (Persero) as the main provider of electricity in Indonesia, has a strong commitment to improving the reliability of electricity distribution. This reliability is reflected through indicators such as SAIDI (System Average Interruption Duration Index), SAIFI (System Average Interruption Frequency Index), and ENS (Energy Not Served), which are caused by disturbances in the 20 kV extension. Preventive efforts to reduce interruptions are mitigated before interruptions occur by conducting an assessment of the 20 kV feeder cable. This assessment provides important variables that can be processed to predict the condition of the cable and determine the next repair steps. The application of data analysis methods such as Fuzzy Logic in processing technical variables such as PDIV (Partial Discharge Inception Voltage), PDEV (Partial Discharge Extinction Voltage) and Partial Discharge charge values can provide more accurate predictions than conventional calculations. The ability of Fuzzy Logic to overcome uncertain problems, results in another view in assessing the health condition of the repeater cable (Health Index). The results of the research are expected to provide more optimal results as an effort to reduce the frequency of faults to support the achievement of company performance.

KEYWORDS PDIV, PDEV, Partial Discharge Charge, Suppression, Cable Assessment, Fuzzy Logic, Health Index

INTRODUCTION

PT PLN (Persero) as the only BUMN engaged in the electricity supply sector in Indonesia, is committed to continuing to provide the best service for the entire community. Based on research by F. Albar et al. (2023), that operational reliability is a major concern for PLN, thus encouraging the company to adopt three *key* performance indicators (*KPIs)* namely SAIDI *(System Average Interruption Duration Index)*, SAIFI *(System Average Interruption Frequency Index)* and ENS *(Energy Not Served)*.

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One of the factors determining the value of SAIDI, SAIFI, and ENS is the intensity and duration when a 20 kV feeder fault occurs. Therefore, efforts to reduce the number of disruptions and accelerate recovery when a disruption occurs are the main focus of PLN. Currently, preventive efforts in the form of cable testing (*assessment*) have been carried out. The assessment also produces *outputs* that can be used as a reference to determine the next step of improvement. But in its application, the results of the *Assessment* have the potential to be processed using *machine learning* technology, which aims to determine more accurate decisions so that the next repair steps can be carried out quickly and precisely.

Mitigating faults by ensuring the health condition of 20 kV cables is an important step in an effort to improve the operational reliability of electric power distribution. A 20 kV cable can be said to be GOOD if it has met the criteria for the cable health value index in accordance with IEEE Std 400.3-2022. One of the parameters that describe the condition of the cable is the variables obtained from the *Partial Discharge Test* process. This data collects variables such as PDIV *(Partial Discharge Inception Voltage),* PDEV *(Partial Discharge Extinction Voltage),* and the number of *Partial Discharge* appearance points. From these variables, a cable health index value can be obtained. But in realization, the cable that has been declared GOOD through the results of the cable health index value after the cable *assessment* activity, several times experienced interference. This condition is an opportunity for improvement by utilizing the *Fuzzy Logic* approach.

Based on the formulation of the problem, the following are the objectives of this thesis:

1. Develop a *Fuzzy Logic* algorithm model that is able to identify and evaluate new variables that may play a role in determining the cable health index.
2. Produce output variables in the form of a more accurate cable health index by considering the complexity of test data through *fuzzy* rules.
3. Minimize cable health index assessment errors that could potentially cause interference *with* the power *line.*

In the research of Romphoyen, D., et al. (2023) it was found that the Fuzzy Logic algorithm has a good level of accuracy in determining the health value of the ground cable (SKTM). These results can be seen from the classification of the cable health index which is worth GOOD by 92.577%. There is a difference in the result value of 0.03% when compared to the Weight Averaged Method which is at 92.54%. This condition indicates that Fuzzy Logic can be used in managing input variables which are the determining value of 20 kV cable health.

In research by Biryulin, et al. (2018), it was found that the *Fuzzy Logic* approach can combine quantitative variables (such as cable loading values, insulation temperature and *partial discharge* values) and qualitative variables (such as environmental factors and HR expertise), in the process of processing *input* variables. So that it can produce a more accurate cable health index. This research also proves the ability of the *Fuzzy Logic* method to handle uncertainty derived from variations in data and qualitative measurement sources.

Based on the premises mentioned, the following hypothesis can be formulated.

Hypothesis 1: The use of the *Fuzzy Logic* algorithm can produce a better index of the health value of the 20 kV cable of a repeater when compared to the conventional method so that it is feasible to use in determining the health index of the 20kV cable.

Hypothesis 2: The use of *Fuzzy Logic* algorithms that can combine quantitative and qualitative variables, will produce a more accurate 20 kV cable health index so that decision making can take place more effectively and optimally. This condition is better when compared to methods that only consider quantitative variables.

In this research, the methodology used is the SEMMA method (*Sample, Explore, Modify, Model, Assess*). SEMMA is a method developed by the SAS Institute, specifically designed for *data mining* processes and *machine learning* development. SEMMA is designed so that each stage of the process can focus on data exploration and modification so that the initial data that will become *input* variables can become more optimal and qualified to achieve the expected results in modeling. The modification stage is also needed to bring up potential new variables obtained from the initial data processing results. This methodology consists of *data sampling*, *data exploration*, *data modification*, *data modeling, & model evaluation* as shown in Figure I.1 SEMMA.

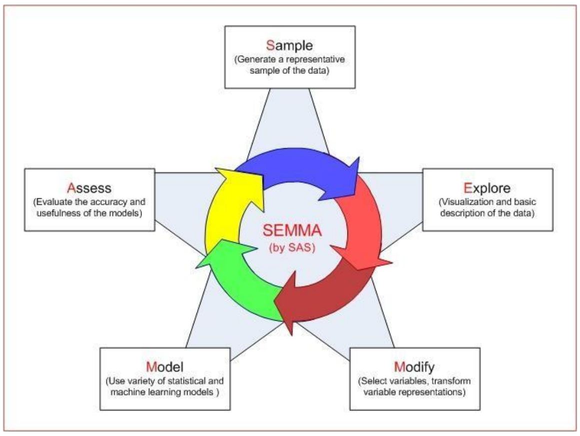


Figure I. SEMMA method

Research Schedule

The research schedule is planned for 5 months with the following details.

Table 2: Research schedule

No	Kegiatan	Jadwal Penelitian																								
		2023										2024														
		November					Desember					Januari					Februari					Maret				
		M1	M2	M3	M4	M5	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
1	Analisis Masalah																									
2	Pengumpulan Data																									
3	Perancangan Sistem																									
4	Pengujian																									
5	Penulisan Laporan Akhir																									

Literature Review

Mamdani Fuzzy Method

The three main steps in the process of forming a *fuzzy logic* algorithm, there is one model that is most commonly used, namely the *Mamdani Fuzzy Inference System (FIS)* Model. This system was developed by Ebrahim Mamdani in 1975 and is known as one of the first widely accepted approaches to the implementation of *fuzzy-based* intelligent control systems.

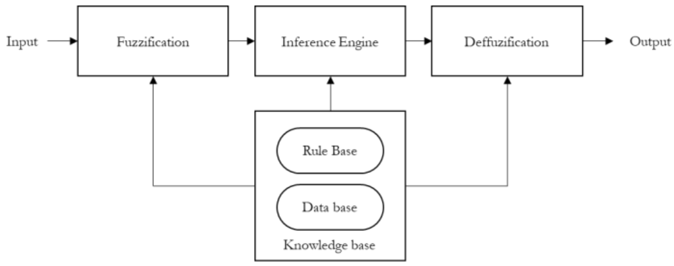


Figure 3. Mamdani Fuzzy Flowchart

Partial Discharge Test

Partial Discharge (PD) is the phenomenon of partial discharge of electric charge on an insulating material of a 20 kV conducting cable when the electric field exceeds the capacity of the insulator, thus causing gradual degradation of the material. Partial Discharge often occurs in cables or electrical equipment operating at high voltage and can be an early indicator of damage to the insulation system. The occurrence of Partial Discharge begins when there are gaps or imperfections in the insulation, such as gas bubbles or cracks, which allow discharge as an electrical charge.

Efforts that can be made to test cable insulation from the potential appearance of Partial Discharge is to conduct a Partial Discharge Test. Based on research by Kiitam et al. (2021), partial discharge measurement is a very important technique to use to diagnose electrical insulation problems that cause material degradation. Partial Discharge Test also produces data related to indications of problems that arise so that it can provide recommendations for the need to replace the cable insulation system.

Partial Discharge Test is carried out through two processes, namely the PDIV (Partial Discharge Inception Voltage) and PDEV (Partial Discharge Extinction Voltage) testing processes. The PDIV value is defined in units of kV (kiloVolt), which indicates the voltage value when partial discharge begins to occur.

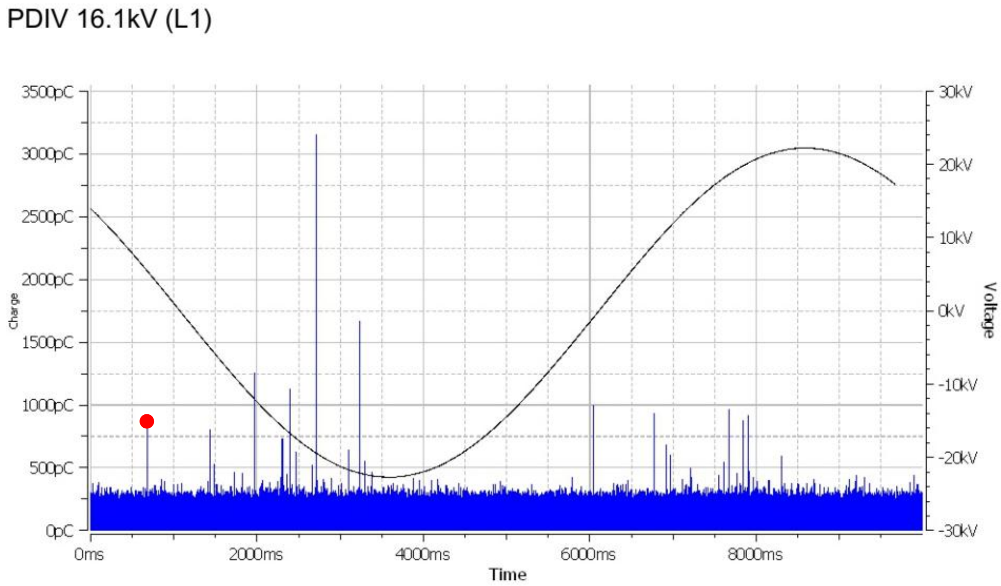


Figure 4. PDIV Graph of Partial Discharge Testing

The PDEV value is defined in units of kV (kiloVolt), which indicates the voltage value when the partial discharge first stops as the voltage begins to gradually decrease.

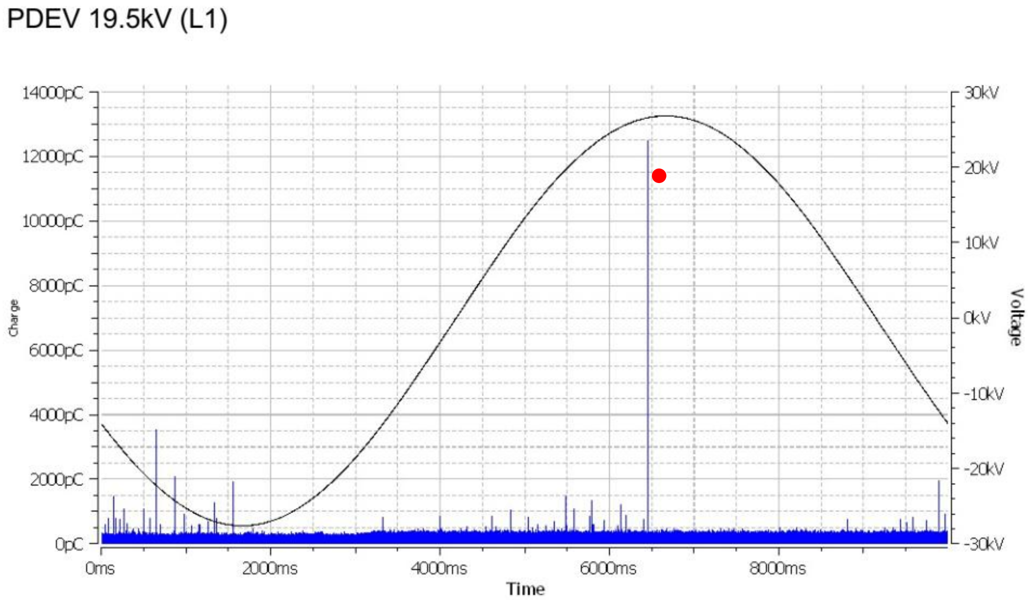


Figure 5. PDEV Graph of Partial Discharge Testing

The SOV value is defined as the nominal voltage used in a medium voltage system in a region. In West Java, the standard usage for cable condition definition through PDIV and PDEV values is as follows:

	Category Sumbu X	Symbol	STATUS
1	PDIV dan PDEV Dibawah Teg Nominal	PDIV & PDEV < Uo	Buruk
2	PDIV diatas Teg Nominal dan PDEV dibawah Teg Nominal	PDIV > Uo & PDEV <Uo	Waspada 1
3	PDIV dibawah Teg Nominal dan PDEV diatas Teg Nominal	PDIV < Uo & PDEV >Uo	Waspada 2
3	PDIV dan PDEV diatas Teg Nominal	PDIV & PDEV > Uo	Baik

Figure 6. PDIV and PDEV Standards in West Java Region

Partial discharge monitoring of high-voltage equipment has the potential to provide information regarding the condition of cable insulation and also provide early warning of potential future damage.

RESEARCH METHOD

Research Flow

Based on the background and literature study that has been described, a flow of this research process is arranged in the flowchart (Figure III.1), including data collection, data pre-processing, fuzzy model formation, fuzzy model testing, and fuzzy model implementation.

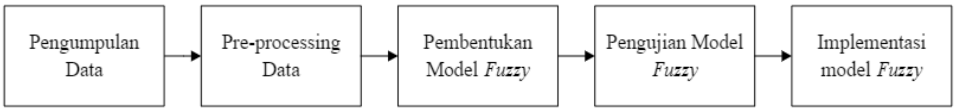


Figure 7. Research flow

Data Collection

Data collection begins with the process of combining data from various sources. In the cable test data, there are cable assessment results such as the value of PDIV, PDEV, Partial Discharge Charge and the point of appearance of *partial discharge*. In the technical specification data source, the value of the repeater load and cable length as well as the repeater fault times are obtained. All of these data refer to a subject, namely the name of the repeater, which can be used as an identity to combine data as shown in the figure.

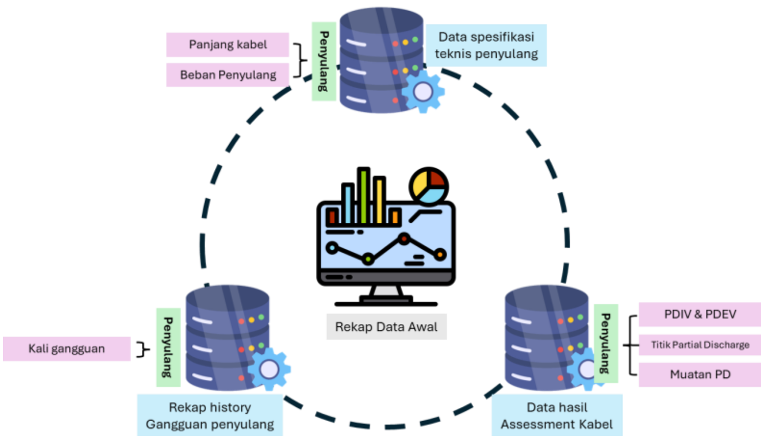


Figure 8. Data Merge Flow

Data *Pre-Processing* and Correlation Analysis of Variables

The data pre-processing stage, the data adjustment process is carried out while still paying attention to the validity of the data, aims to ensure that the data used is of good quality and ready to become the foundation for the formation of fuzzy logic models. At this stage, efforts to find links between the data we already have are the main goal. In the data from the first source, which is a recap of the history of reinforcement interference, data adjustment will be carried out through the process of cleaning, modifying and standardizing data, including overcoming outliers that appear. Furthermore, the data will be tested for correlation with other data sources, namely the assessment data. Correlation testing will use the correlation analysis method where the relationship between the dependent and independent variables will be known. Furthermore, the results of the analysis will be used as justification for determining that the assessment result variables can be used as variables that determine the results of the cable health index through the Fuzzy Logic method.

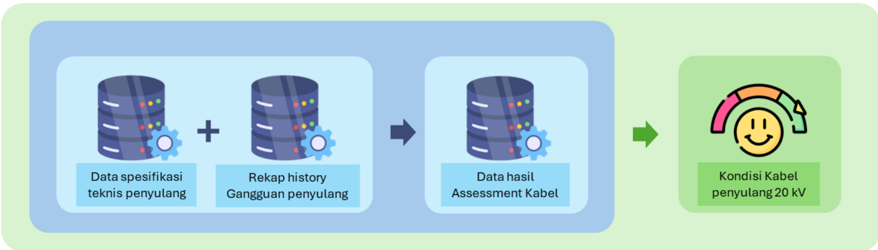


Figure 4. Variable Correlation Testing

Fuzzy Logic Model Design

Furthermore, the stage of fuzzy model formation, where at this stage the design of the model through the fuzzification, inference and deffuzification processes is carried out in stages.

Starting from the fuzzification process, input and output variables are defined into fuzzy linguistic variables using membership functions. Membership functions that can be used include Triangular and Trapezoidal.

After the fuzzification process, fuzzy rule formation is performed using the format "IF..AND..AND..THEN.." . The number of fuzzy rules will be determined by the number of input variables.

The model building stage is followed by the Inference process, with a choice of methods that can be used, one of which is the Min - Max Method. This stage will produce fuzzy output.

The final stage is the deffuzification process, where the fuzzy output will be converted into a numerical output that defines the result of fuzzy logic processing. There are several methods such as Centroid Method and Bisector Method.

Fuzzy Logic Model Testing

After the fuzzy model is formed, iterative model testing is carried out, starting from input - output validation, simulation comparison with real data, to model performance evaluation. Testing aims to validate the model, related to the accuracy of the prediction results using metrics such as Mean Absolute Error (MAE) or confusion matrix and Precision, Recall, F1 Score and Accuracy values. If the test results have error or anomaly conditions, several adjustments can be made such as: changing the shape or range of the membership function, adding or changing fuzzy rules, and trying other deffuzification methods.

RESULTS AND DISCUSSION

Initial Data Collection

The first information obtained from the initial data collection process where the process of combining three types of data sources resulted in the following variables:

1. Repeater identity Information data related to the region, substation, repeater name, cable length, cable type and cross-sectional area.
2. Transmission fault history: information data of cable fault times
3. Partial Discharge Test results: data information on PDIV, PDEV, PD charge, number of PD location points and PD value index referring to the IEEE Std 400.3-2022 partial discharge standard.

From several variables obtained, the selection of input variables that have the potential to determine the cable health index such as cable length, cross-sectional area, repeater load in accordance with the research of Zhang, H., et al. (2006) as well as the variables of fault times, PDIV value, PDEV value, delta PD, number of PDs, number of PD values, number of PD location points and PD density in accordance with the research by Zaeni, A., et al. (2019).

Data *Pre-Processing*

The main focus of the *pre-processing* stage is revamping the initial data, including data type adjustment, elimination of anomalous data, and the establishment of correlation values between selected variables. The anomalous data that is eliminated is data from cable *assessments* that indicate BREAKDOWN or damage. Where in this condition, the cable is declared in a damaged condition. Data correlation aims to find relationships between selected variables, so that it has the potential to model these variables with the *Fuzzy Logic* method. The following is the data on the correlation results between variables.

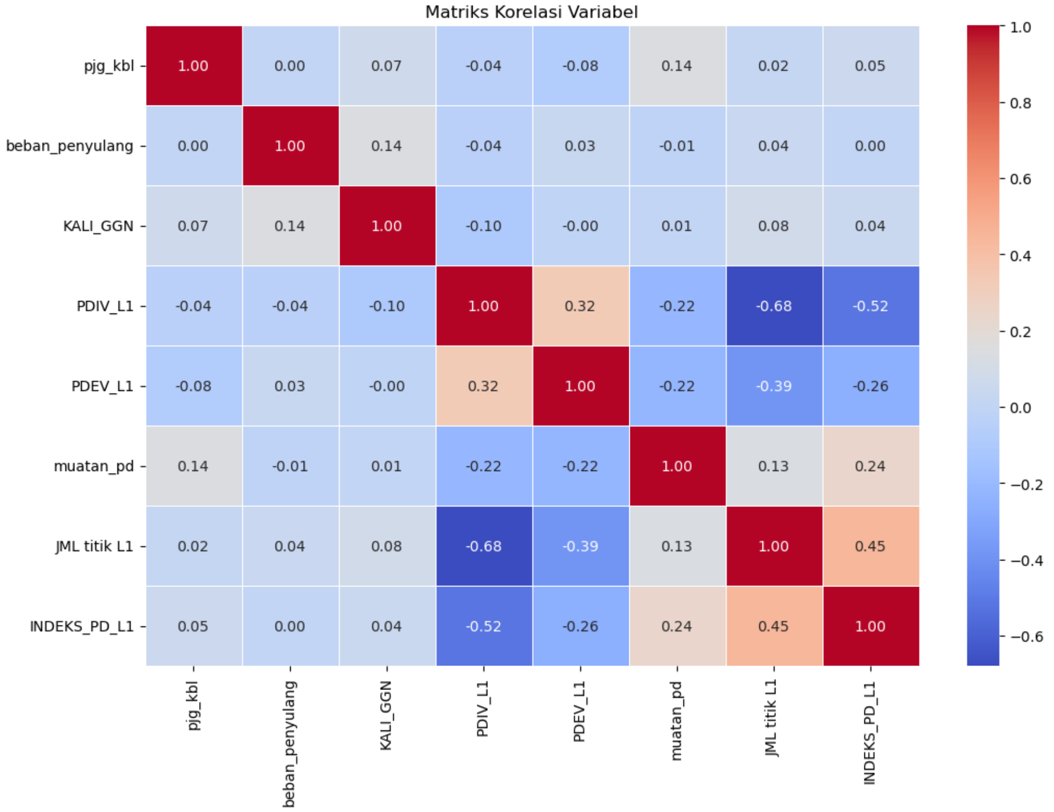


Figure 10. Correlation Matrix between Variables

Some important points from the correlation simulation results are:

1) There is a good correlation between the variables 'PDIV' (voltage at which PD first appears) and 'PDEV' (voltage at which PD starts to disappear) with the variable 'INDEX_PD'. This indicates that the partial discharge index, which determines the health level of the cable, depends on the PDIV and PDEV values as referenced in IEEE Std 400.3-2022. The greater the PDIV and PDEV values, the better the cable health index. Conversely, small PDIV and PDEV values indicate poorer cable condition.
2) There is a good correlation between the variable 'charge_pd' and the variable 'INDEX_PD'. This condition indicates that the partial discharge index, also depends on the amount of charge that is released during the partial discharge test process. The greater the 'charge_pd' value, the worse the cable condition.
3) There is a good correlation between the variable 'JML points' and the variable 'INDEX_PD'. The variable 'JML points' is a variable that defines the point of appearance of partial discharege in a tested cable. This condition also signals that the distribution of partial discharge is a determinant of cable health.

4) In the variables of repeater load, fault times, and cable length, the correlation value with 'INDEX_PD' still produces a small correlation value. This condition needs further testing to see the potential of these variables to affect the cable health index in accordance with research by Zhang, H., et al. (2006).

Fuzzy Logic Model Development

In the next stage, a fuzzy model formation process is carried out which consists of three stages, namely fuzzification, inference, and deffuzification.

Fuzzification

The fuzzification stage aims to convert numerical data from input variables into membership values in a membership function. This membership function will be defined as a linguistic variable. In the initial stage of modeling, the input variables used are PDIV, PDEV and PD Load with the following model:

1) PDIV and PDEV have three categories: BAD (triangle), WARNING (triangle), and GOOD (triangle).

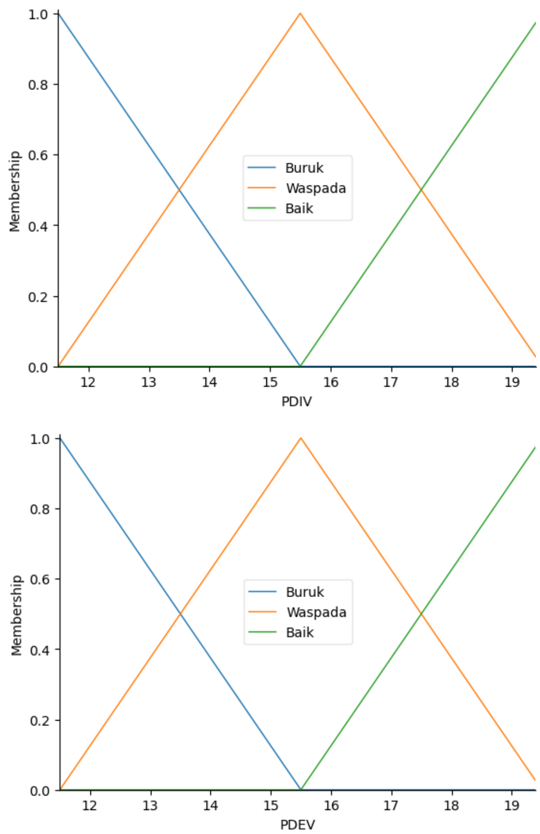


Figure 11. Membership Function PDIV and PDEV

2) PD charges have three categories: BAD (trapezoidal), WARNING (triangle), and GOOD (triangle).

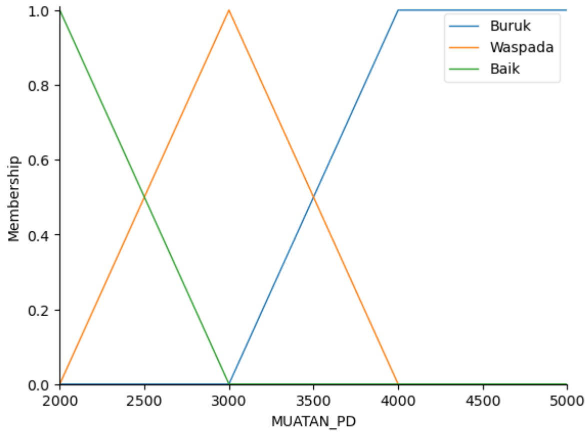


Figure 12. PD Charge Membership Function

The membership function will convert the numerical value of each input variable into a membership level that indicates the level of each linguistic definition according to predetermined limits.

Inference

The inference stage aims to determine the output based on the rules that have been set previously. At this stage, the rules created will use inputs that have been fuzzified or have been in the form of linguistic variables. The following is a list of predetermined rules:

Table 1. Fuzzy Rules

Rules	pdiv	pdev	load_pd	output
Rule 1	Good	Good	Good	Good
Rule 2	Good	Good	Alert	Simply
Rule 3	Good	Good	Bad	Alert
Rule 4	Good	Alert	Good	Good
Rule 5	Good	Alert	Alert	Alert
Rule 6	Good	Alert	Bad	Alert
Rule 7	Good	Bad	Good	Simply
Rule 8	Good	Bad	Alert	Simply
Rule 9	Good	Bad	Bad	Bad
Rule 10	Alert	Good	Good	Good
Rule 11	Alert	Good	Alert	Simply
Rule 12	Alert	Good	Bad	Alert
Rule 13	Alert	Alert	Good	Good
Rule 14	Alert	Alert	Alert	Alert

Rules	pdiv	pdev	load_pd	output
Rule 15	Alert	Alert	Bad	Bad
Rule 16	Alert	Bad	Good	Simply
Rule 17	Alert	Bad	Alert	Bad
Rule 18	Alert	Bad	Bad	Bad
Rule 19	Bad	Good	Good	Simply
Rule 20	Bad	Good	Alert	Alert
Rule 21	Bad	Good	Bad	Bad
Rule 22	Bad	Alert	Good	Bad
Rule 23	Bad	Alert	Alert	Very Bad
Rule 24	Bad	Alert	Bad	Very Bad
Rule 25	Bad	Bad	Good	Bad
Rule 26	Bad	Bad	Alert	Very Bad
Rule 27	Bad	Bad	Bad	Very Bad

Deffuzzification

The deffuzification stage aims to convert fuzzy output values into more defined numerical values, so that they can be used in further analysis or as decisions. At this stage, the resulting output will define the condition of the repeater cable according to the results of the fuzzy processing that has been carried out. The steps taken in the deffuzification process are as follows:

1) After all the rules are executed, the system will produce fuzzy output in the form of membership degree values for categories such as VERY BAD, BAD, WASPADA, GOOD and GOOD.

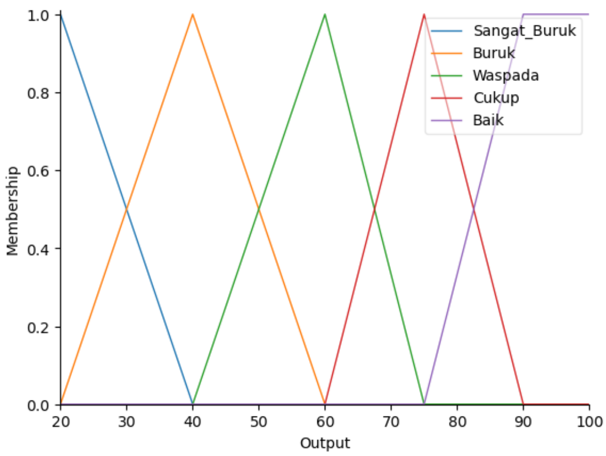


Figure 13. Membership Function Output

2) The system will use the python function fuzz.interp_membership to calculate the membership of the deffuzified value in each category.

3) The selected value will use the maximum value of the membership value that has been generated. For example, if the membership value of GOOD is higher than the memberships in other categories, then the output will be grouped into GOOD.

Fuzzy Logic Model Testing

At this stage, Fuzzy Logic Model testing is carried out which aims at how well the model has been made. The parameter is the success of the model to classify according to existing data. At this stage, the existing data used as a reference is the index obtained from the realization of the cable assessment as follows:

A. Membership Function Evaluation

This evaluation aims to provide data on the success of the Fuzzification phase in translating membership function values into linguistic functions that will be processed through fuzzy rules. Tests were carried out from several sample input data from the PDIV, PDEV, and PD Load values as follows:

Table 2. Membership Function Evaluation Data

PENGUJIAN MEMBER PDIV					PENGUJIAN MEMBER PDEV					PENGUJIAN MEMBER MUATAN PD				
PDIV	PDIV Buruk	PDIV Waspada	PDIV Baik	PDIV Result	PDEV	PDEV Buruk	PDEV Waspada	PDEV Baik	PDEV Result	MuatanPD	MuatanPD Buruk	MuatanPD Waspada	MuatanPD Baik	MuatanPD Result
5	1,00	0,00	0,00	Buruk	4	1,00	0,00	0,00	Buruk	1750	0,00	0,25	0,25	Baik
12	0,86	0,14	0,00	Buruk	14	0,29	0,71	0,00	Waspada	2300	0,00	0,80	0,00	Waspada
18	0,00	0,34	0,66	Baik	22	0,00	0,00	1,00	Baik	72300	1,00	0,00	0,00	Buruk
3	1,00	0,00	0,00	Buruk	6	1,00	0,00	0,00	Buruk	2020	0,00	0,52	0,00	Waspada
20	0,00	0,00	1,00	Baik	19	0,00	0,12	0,88	Baik	3500	0,50	0,00	0,00	Buruk
7	1,00	0,00	0,00	Buruk	9	1,00	0,00	0,00	Buruk	5010	1,00	0,00	0,00	Buruk
15	0,00	1,00	0,00	Waspada	16	0,00	0,78	0,22	Waspada	1167	0,00	0,00	0,83	Baik
21	0,00	0,00	1,00	Baik	23	0,00	0,00	1,00	Baik	87832	1,00	0,00	0,00	Buruk
8	1,00	0,00	0,00	Buruk	10	1,00	0,00	0,00	Buruk	4342	1,00	0,00	0,00	Buruk
11	1,00	0,00	0,00	Buruk	13	0,57	0,43	0,00	Buruk	60343	1,00	0,00	0,00	Buruk

From the simulation results above, the ability of the Fuzzy Model to translate the existing *membership function* values is very good. The larger *membership function* value when an input value intersects two *membership functions*, is used as a definition to translate the linguistic function of the input.

B. Testing *Precision, Recall*, *F1 Score* and *Accuracy*

This test aims to obtain information related to the ability of the model to make predictions properly and correctly. Testing is done by comparing the *output of Fuzzy Logic* processing with the realization data from the cable *assessment* results. In the *Precision* test, a value of 0.894 was obtained, indicating that of all categories classified by the model as much as 89.4% of the data is truly relevant to the appropriate category. In the *Recall* test, a value of 0.834 was obtained, where 83.4% of the data could be detected by the model properly. Next is the *F1-Score* test, a value of 0.55 is obtained, which indicates a fairly good balance between the *precision* and *recall* values. For the *Accuracy* value, a value of 0.8343 was obtained. The average value indicates that the model has been said to be quite good, but there are still opportunities to improve the accuracy and detection of the model.

C. *Mean Absolute Error* (MAE) Testing

The results of *Precision, Recall* and *F1 Score* testing that leave room for improvement are also continued by measuring the *Mean Absolute Error* (MAE) value. A result of 0.263 was obtained, where this result is still said to be quite good but there is potential for further improvement in order to increase accuracy and reduce errors.

From the three model tests carried out, it can be concluded that the *Fuzzy Logic* Model created works well, although it leaves room for improvement.

Comparison of Data Processing Results

At this stage, a comparison will be made between the results of the cable health index obtained from the *Fuzzy Logic Model* system and the realization of the cable *assessment*. The curve is obtained from data processing using smoothing with *Moving Average.* The following results were obtained:

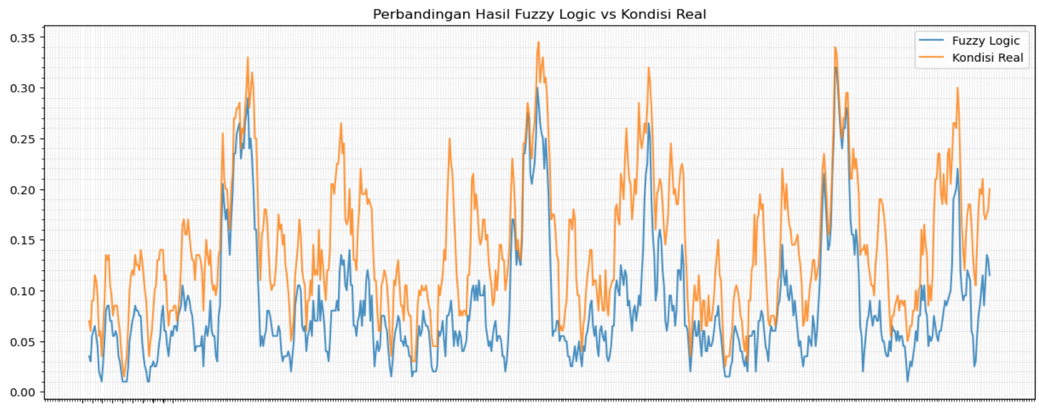
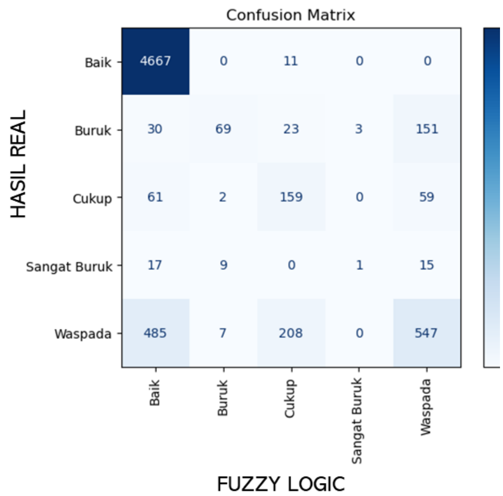


Figure 14. Comparison Curve of Fuzzy Logic Results and Real Conditions

The difference in the amount of data between the realization of the cable *assessment* results compared to the calculation with *Fuzzy Logic* for each category is as follows:



FUZZY LOGIC	KONDISI REAL	JUMLAH DA
Baik	Cukup	61
Baik	Waspada	485
Baik	Buruk	30
Baik	Sangat Buruk	17
Cukup	Baik	11
Cukup	Waspada	208
Cukup	Buruk	23
Waspada	Cukup	59
Waspada	Buruk	151
Waspada	Sangat Buruk	15
Buruk	Cukup	2
Buruk	Waspada	7
Buruk	Sangat Buruk	9
Sangat Buruk	Buruk	3

Figure 15. Comparison of Number of Cable Health Index Data

The difference in the results of the index categories between the *Fuzzy Logic* Method and the realized results of the cable *assessment* gives the view that there are differences in the interpretation of the results between the two. There are five differences in results that need special attention and further observation, among others:

1) *Fuzzy Logic* category results are GOOD, but WORSE than *real* conditions.
2) The *Fuzzy Logic* category results are GOOD, but VERY WORSE than the *real* condition.
3) The *Fuzzy Logic* category result is a GOOD value, but a WORSE value than the *real* condition.
4) The result of the *Fuzzy Logic* category is Alert, but it is WORSE than the *real* condition.
5) The result of the *Fuzzy Logic* category is Alert, but it is VERY WORSE than the *real* condition.

Comparison of *Fuzzy Logic* Model Quality with Other Methods

This research also tested the model by comparing the Fuzzy Logic model with two other machine learning methods, namely the Artificial Neural Network and Support Vector Machine methods.

1) In the Artificial Neural Network (ANN) method, the precision value is 0.8428, recall is 0.8575 and F1 Score is 0.8400.
2) In the *Support Vector Machine* (SVM) method*,* the *precision* value is 0.7500*, recall is* 0.8302 and *F1 Score* is 0.7826.

In terms of the evaluation of ANN and SVM models, the *Fuzzy Logic* method has the highest *F1 - Score* value, giving the interpretation that there is a very good balance between *precision* and *recall* values. In the context of decision making, a model with a high *F1 Score* can provide greater confidence that the prediction results are accurate and comprehensive. Similarly, the *accuracy* value of the model is 0.8343, higher than the *accuracy* level of the SVM method. This condition provides an interpretation that 83.43% of the predictions produced have results that match the real conditions.

CONCLUSIONS

The research findings indicate that the Fuzzy Logic model designed to predict the health index of repeater cables performs well, achieving high precision (0.894), recall (0.834), F1-score (0.855), and accuracy (0.8343). When compared to other machine learning methods, Fuzzy Logic outperforms Support Vector Machine (SVM) and Artificial Neural Network (ANN) in terms of F1-score, demonstrating its balanced predictive capability. However, discrepancies were observed in five specific categories where Fuzzy Logic predictions categorized cables as being in better condition than their actual state, potentially leading to inaccurate maintenance decisions. These discrepancies highlight the importance of careful interpretation and validation of model outputs before execution.

For future research, it is suggested that repeated cable health assessments be conducted over time to improve prediction accuracy, as a single test cannot determine the actual condition of a cable. Additionally, inconsistencies between partial discharge activity and actual cable failures, as referenced in IEEE 400.2 - 2013, necessitate cautious interpretation of test results. Establishing new standards for cable health index determinants, such as PDIV, PDEV, and PD Load, based on historical assessment data, could enhance prediction accuracy. Moreover, incorporating new variables, such as the number of partial discharge points, may further refine the model's effectiveness in assessing cable health.

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