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Estimation of the Flashover Voltage of Insulator Using Fuzzy Logic (FL)

Abstract. *The aim of this work is to estimate the flashover voltage of a high-voltage insulator that has been deliberately polluted using fuzzy logic (FL). Initially, experimental experiments on a high-voltage insulator were used to collect a data set that was then used to implement the idea of artificial intelligence. These studies were conducted using varying degrees of fake pollution, namely saline distilled water. Each pollution level indicated the quantity of artificial pollution, measured in millilitres, in each section of the insulator. The collecting database provides flashover voltage measurements associated with varying levels of artificial pollution in each insulator zone and its conductivity. Furthermore, we have used fuzzy logic (FL) to forecast the flashover voltage of the high-voltage insulator and assess the insulating condition of simulated pollution. The suggested prediction model, which is based on Federated Learning (FL), is implemented using MATLAB's graphical user interface. Ultimately, a comparison was conducted between the outcomes achieved by FL and real-world ones. The database used in this comparison differs from that used in concepts based on programming language implementation taken from previous literature. The findings demonstrate the superior effectiveness of the FL approach in predicting the flashover voltage of high-voltage insulators when compared to data acquired from practical testing.*

Streszczenie. *Celem pracy jest oszacowanie napięcia przeskoku izolatora wysokiego napięcia, który został celowo zanieczyszczony przy użyciu logiki rozmytej (FL). Początkowo eksperymenty eksperymentalne na izolatorze wysokiego napięcia służyły zebraniu zbioru danych, który następnie wykorzystano do wdrożenia idei sztucznej inteligencji. Badania te przeprowadzono przy użyciu różnego stopnia fałszywych zanieczyszczeń, a mianowicie destylowanej wody solankowej. Każdy poziom zanieczyszczenia wskazywał ilość sztucznych zanieczyszczeń, mierzoną w mililitrach, w każdej sekcji izolatora. Zbierana baza danych zapewnia pomiary napięcia przeskoku związane z różnymi poziomami sztucznych zanieczyszczeń w każdej strefie izolatora i jego przewodnością. Ponadto wykorzystaliśmy logikę rozmytą (FL) do prognozowania napięcia przeskoku izolatora wysokiego napięcia i oceny stanu izolacji symulowanego zanieczyszczenia. Sugerowany model predykcyjny, oparty na Federated Learning (FL), jest implementowany przy użyciu graficznego interfejsu użytkownika MATLAB-a. Ostatecznie przeprowadzono porównanie wyników uzyskanych na platformie FL z wynikami uzyskanymi w świecie rzeczywistym. Baza danych wykorzystana w tym porównaniu różni się od bazy danych stosowanej w koncepcjach opartych na implementacji języka programowania zaczerpniętych z wcześniejszej literatury. Odkrycia wskazują na wyższą skuteczność metody FL w przewidywaniu napięcia przeskoku izolatorów wysokiego napięcia w porównaniu z danymi uzyskanymi z testów praktycznych. (**Oszacowanie napięcia przeskoku izolatora przy użyciu logiki rozmytej (FL)**)*

Keywords: insulator, fuzzy logic, pollution, flashover voltage.
Słowa kluczowe: izolator, logika rozmyta, zanieczyszczenie, napięcie przeskoku

Introduction

An insulator string that serves as insulation depends on the stability and transportability of thenetworks that carry electricity. Therefore, insulator pollution, which is of particular concern when it comes to power quality concerns, is one of the many limitations that transmission lines utilized in the supply of electric power are susceptible to.[1-2]

The phrase "insulator pollution phenomenon" refers to the constant or sporadic build-up of contaminants from different sources. This may be caused by a cloud of smoke from industrial and urban pollution [3], tiny salt particles from marine pollution [4], or fine particles from sandstorms in arid locations. [6]

The examination of the pollution insulator provides the reader with insight on the extent to which pertinent ideas have been explored and what specific areas and subjects need further in-depth inquiry.

Numerous scholars and engineers have produced some excellent studies on the causes of contamination flashover. [7]

Obneuas's mathematical pollution flashover model served as the foundation for the simulation of contaminated insulator flashover [8]. To simulate the moist, contaminated surface of an insulator, an electric circuit model of a partial arc in series with residual resistance was presented in 1958 [8]. Numerous researchers constructed both static and dynamic models, as well as enhanced and refined the pollution flashover model under a variety of scenarios, based on this model [9–10].

A summary of the valuable contributions made by several scholars on this topic may be found in. [9]

In the presence of high humidity, these particles-which are often composed of a blend of other types of pollution, or "mixed pollution"-carried by the wind and building up on the insulator over time may result in a variety of problems. [14],

Basically, depending on the degree of pollution at the site under consideration, the accumulated pollution creates a notable and sustained leakage current in the insulator. When the critical leakage current is achieved in such a scenario, flashover will happen, and the transmission line would then break.

Predicting the flashover voltage for various kinds of insulators may be made simpler by using Artificial Intelligence (AI) in the field of insulators flashover research. These methods may be divided into four categories: expert systems, fuzzy logic, genetic algorithms, and neural networks [14–16]. We have used the fuzzy logic (FL) methodology, one of the current artificial intelligence methods, to forecast the voltage of the insulator flashover.

Various models and methodologies are used to enhance understanding of the insulator flashover phenomena. We are particularly interested in using fuzzy logic (FL) as an artificial approach to explore the flashover of contaminated insulators among various models and techniques. These methods have previously been used by certain writers in related fields of study. [16-17]

Fuzzy logic is a popular area of study for scientists nowadays. There are already technological spin-offs accessible in the public sphere (such as cameras and washing machines) as well as the industrial sphere (such as robots and machine tools, as well as the regulation and management of complicated energy, transportation, and matter transformation processes).

The challenge of developing a comprehensive mathematical model to investigate the pollution phenomena in the high voltage area has led to the introduction of various analyses, models, and research techniques by various scholars. In the following, we shall forecast the flashover voltage of an actual model of the 1512L high voltage insulator using the artificial intelligence (AI) approach.

This study uses the fuzzy logic approach to forecast the flashover voltage under various electro-geometric parameters, such as conductivity and pollution levels.

The approach of the artificial intelligence technology (Fuzzy Logic (FL)) used to forecast the flashover voltage of a real 1512 L high voltage insulator model will be presented in this paper. As a consequence, the application of the findings from our study will be discussed and evaluated in both standard circumstances and with varying electro-geometric setups.

Prediction of the flashover voltage by the Fuzzy Logic (FL)

Numerous academics have shown interest in fuzzy logic-based flashover modeling [13–17, 19].

A significant issue in each of those studies is defining the quantity and values of the inputs' changeable language words.

The objective of this paper is to present a new methodology for predicting the flashover voltage of polluted insulators based on fuzzy logic.

Here in this section of the study, we employ the Fuzzy Inference System (FIS) to predict the flashover voltage (V) of a high voltage insulator under various pollution constraints, including conductivity (δ (mS/cm)) and the pollution zones Zi (ml), given that 'δ' represents the applied pollution's conductivity and "Zi" and the insulator's areas that were previously mentioned in the reference [18] and shown in figure 1.

The formulation and application of human thinking is the goal of fuzzy logic. Fuzzy logic analysis has shown that the latter method is the most challenging to identify in the literature as it often requires the input of a subject matter expert from a variety of disciplines, particularly when it comes to creating the inference table.

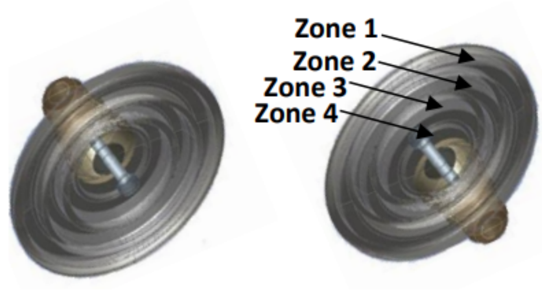


Fig.1. Cap and pin insulator 1512L in two cases clean and polluted.

Uncertain terms like "small," "medium," and "large" are inputted into a fuzzy logic system, which uses them as input to produce judgments on fuzzy output variables [15].

When an observation is hard to represent quantitatively, fuzzy logic has the benefit of incorporating human expert observation and analysis. Figure 2's fuzzy inference system, or "FIS," is the basis of the suggested fuzzy notion.

We have observed that testing reveal that an increase in applied voltage causes an electrical discharge to occur. At the start of its growth, it takes up a certain proportion of the insulator surface.

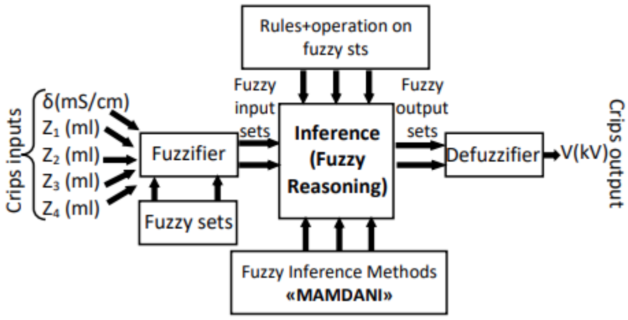


Fig.2. Architecture of a fuzzy inference system (FIS) studied.

Definitions of the following are necessary for our fuzzy logic issue formulation:

The fuzzy inference system's (FIS) inputs and outputs The study's selected inputs and outcomes are shown in a table.1.

Table1. Variable of inputs and output.

Input		Output	
Symbol	Designation	Symbol	Designation
δ(mS/cm)	Conductivities	V(kV)	Flashover voltage
Z_i (Z_1, Z_2, Z_3, and Z_4) (ml)	Pollution zones in the HV insulator		

The fuzzy characteristics

The truth values are shown in Table 2 below. The final discourse universes, or intervals of these values, are shown in the findings (Figure 4).

Together with the input and output variables' discourse universes, or intervals of these truth values, as described in the figures.

All values that may suggest one of the flashover stages are included in the fuzzy intervals for each language variable in the preceding table.

Any voltage values "V" less than "20 kV" indicate that no step has been achieved.

The fuzzy inference rules

The fuzzy rules which connect the subsets of inputs and outputs have been entered in this section. This step involves determining the relationships between the input and output sets in light of the practical outcomes that have been attained. The linguistic links between inputs and outputs are shown in the following table. (table4).

Cases marked with a "X" are those that cannot be produced in a lab. (Illogical combination) that is false.

Fuzzification

The task at hand involves computing the membership degrees of the fuzzy sets established and connected with each numerical input value in the fuzzy system database. The digital inputs are transformed into fuzzy symbolic information by this block so that the inference mechanism may utilize it. The experimental database used is the one from our lab, which is a real insulator and was mentioned in [18].

The database processing, which takes into account all the results and observations throughout the testing, helps determine the influence of each input on the flashover voltage.

- It is implied that the insulator is stiff and the flashover voltage is high by the low conductivity and low pollution levels.

Table 2. Decomposition of input and output variables.

Linguistic Variable of Inputs and Outputs											
Input										Output	
Conductivities δ(mS/cm) [0-94]		Zone Z_1(ml) [0-150]		Zone Z_2(ml) [0-120]		Zone Z_3(ml) [0-270]		Zone Z_4(ml) [0-270]		Flashover voltage [20-80]	
TL	S	TL	S	TL	S	TL	S	TL	S	TL	S
VSC	Very small conductivity [0-2]	SQ1	Small quantity [0-57]	SQ2	Small quantity [0-39]	SQ3	Small quantity [0-20]	SQ4	Small quantity [0-30]	VSV	Very small voltage [20-44]
SC	Small conductivity [2-15]	AQ1	Average quantity [40-101]	AQ2	Average quantity [27-75]	AQ3	Average quantity [14-215]	AQ4	Average quantity [18-228]	SV	Small voltage [39-49]
AC	Average conductivity [13-29]	HQ1	high quantity [84-150]	HQ2	high quantity [64-120]	HQ3	high quantity [196-270]	HQ4	high quantity [211-270]	AV	Average voltage [47-67]
HC	High conductivity [27-59]	TL: Language Term S: Meaning								HV	High voltage [51-78]
VHC	Very high conductivity [60-94]									VHV	Very high voltage [56-80]

Tablw 3. Inference matrix

			VSC			SC			AC			HC			VHC		
			SQ1	**AQ1**	**HQ1**	**SQ1**	**AQ1**	**HQ1**	**SQ1**	**AQ1**	**HQ1**	**SQ1**	**AQ1**	**HQ1**	**SQ1**	**AQ1**	**HQ1**
SQ4	SQ3	SQ2	VHV	HV	HV	HV	HV	AV	HV	HV	AV	AV	AV	AV	SV	SV	SV
		AQ2	HV	HV	HV	HV	HV	AV	HV	AV	AV	AV	AV	AV	SV	SV	SV
		HQ2	HV	HV	HV	HV	AV	AV	HV	AV	AV	AV	AV	AV	SV	SV	SV
	AQ3	SQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		AQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		HQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	HQ3	SQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		AQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		HQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
AQ4	SQ3	SQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		AQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		HQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	AQ3	SQ2	AV	AV	AV	AV	AV	AV	AV	AV	AV	AV	AV	SV	SV	SV	VSV
		AQ2	AV	AV	AV	AV	AV	AV	AV	AV	SV	AV	SV	SV	SV	VSV	VSV
		HQ2	AV	AV	AV	AV	AV	SV	AV	AV	SV	SV	SV	SV	SV	VSV	VSV
	HQ3	SQ2	AV	AV	AV	AV	AV	AV	AV	AV	SV	AV	AV	SV	SV	SV	VSV
		AQ2	AV	AV	AV	AV	AV	AV	AV	AV	AV	AV	SV	SV	SV	VSV	VSV
		HQ2	AV	AV	AV	AV	AV	SV	AV	AV	SV	SV	SV	SV	SV	VSV	VSV
HQ4	SQ3	SQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		AQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
		HQ2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	AQ3	SQ2	AV	AV	AV	AV	AV	AV	AV	SV	SV	SV	SV	SV	SV	SV	SV
		AQ2	AV	SV	SV	AV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
		HQ2	SV	SV	SV	SV	SV	SV	SV	SV	VSV	VSV	VSV	VSV	VSV	VSV	VSV
	HQ3	SQ2	AV	AV	AV	AV	AV	AV	AV	SV	SV	SV	SV	SV	SV	SV	SV
		AQ2	AV	SV	SV	AV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV	SV
		HQ2	SV	SV	SV	SV	SV	SV	SV	SV	VSV	VSV	VSV	VSV	VSV	VSV	VSV

- When there is little noise and average conductivity, the flashover voltage is average, which makes the system not as rigid.
- The conductivity and pollution level both affect the flashover voltage.
- Our understanding of the development of the electric arc under various pollution situations under an AC voltage was largely aided by our expertise in the high voltage laboratory. As a result, we proposed the discourse universes and fuzzy intervals for each input and output variable.
- Every language variable may indicate a step, which is why the input discourse universe was selected.
- The output discourse universe is chosen based on the knowledge that, as previously discussed in detail in the preceding chapter, each "V" value may represent a flashover stage and that, using various values, the development of the flashover voltage can be shown.
- A review of the literature revealed that the membership function is chosen at random. Since the triangle and trapezoidal membership functions in our instance display a stable value of the variable throughout a specified interval, they may be initially appropriate to represent the fuzzy variables of the input and output of the FIS. This form is the best option that yields the best result since it may be changed to enhance the outcomes that are obtained.

a. The linguistic variable and the fuzzy interval

Actually, table 3 already mentions the input and output fuzzy variables together with associated discourse universes (fuzzy intervals). To clarify the idea, a random selection of input and output language phrases is produced.

b. The membership function

A fuzzy set's corresponding membership function defines it. The following titles will provide an overview of the inputs and outputs associated with each membership function.

Our experience has guided the selection of the membership function type. The fuzzy intervals, variables, and discourse universe should be selected at the outset before adding the membership function types that we have selected.

Table 5 lists the quantity of functions and fuzzy intervals used for the inputs and outputs, along with the number of variables and kind of membership function selected. The efficiency and dependability of our suggested model can only be determined by analyzing the outcomes of the prediction of the flashover voltage of the actual insulator obtained for each choice. In actuality, there is no rule that should be followed when determining the number of variables, intervals, or even the form of the membership function.

Table 4. Number of fuzzy intervals, number and type of membership function of the inputs and the output.

		Number of intervals	Number of functions	Type of functions
Inputs	Conductivities δ(mS/cm)	5	5	Trapezoidal & Triangular
	Zone 1 Z_1(ml)	3	3	
	Zone 2 Z_2(ml)	3	3	
	Zone 3 Z_3(ml)	3	3	
	Zone 4 Z_4(ml)	3	3	
Output	Flashover voltge (kV)	5	5	

The fuzzy rules

The fuzzy rules that link the input and output at this point, the fuzzy rules that link the input and output subsets have been implemented at this point. Based on the findings from the practice (the experiment) in the first chapter, this stage establishes the link between the input and output sets. One of the most popular techniques is that the regulations are always established by a trained specialist or operator.

We validated our FL-based prediction system and exploited and extended the set of fuzzy rules of our employed FIS using the experimental results.

An inference matrix (table 4) has been used to account for all instances and intermediate stages. It has the best fuzzy rules that produced the best results with the least amount of mistake. This matrix assisted in illuminating 405 instances (5*3*3*3*3), of which 180 cases were found in table "X"; these cases are cases that, due to their incorrect combinations, cannot be realized in actuality; as a result, 225 rules are needed to compute the "V" output.

It was shown by other studies that competence has the right to minimize the number of rules while maintaining the same outcomes. After much effort, we were able to cut the number of rules to only 25 while maintaining the same final outcomes.

In reality, we suggested the first set of accepted guidelines. Then, in order to enhance the outcomes in accordance with the gathered experimental data, we modified both these rules and the membership functions. The best fuzzy rules with the best outputs are shown in inference table 4. The process of gathering these rules is a component of the fuzzy rules' natural extraction techniques, which make use of an expert's abilities. This section will go into depth on the membership functions adjustment.

Listed below are a few recommended rules:

- If (Conductivities (mS/cm)is VSC) and (Z1(ml) is SQ1) and (Z2(ml) is SQ2) and (Z3(ml) is SQ3) and (Z4(ml) is SQ4) then (flashover (kV) is VHV)
- If (Conductivties (mS/cm)is SC) and (Z1(ml) is SQ1) and (Z2(ml) is SQ2) and (Z3(ml) is SQ3) and (Z4(ml) is SQ4) then (flashover (kV)is HV)
- If (Conductivties (mS/cm)is AC) and (Z1(ml) is SQ1) and (Z2(ml) is SQ2) and (Z3(ml) is SQ3) and (Z4(ml) is SQ4) then (flashover (kV)is HV)

⋮

etc.

Operators of the Min-max type "Mamdani" are used in this instance to determine the output of every rule that has been activated and to forecast the numerical value of the "V" output using the gravity center approach of the "response surface".

Implementation of the fuzzy inference system

Our goal is to increase the number of inputs in order to account for any limitation that influences the flashover voltage.

This section of the present chapter will use the Matlab graphical interface "Fuzzy logic" to create the fuzzy inference system (FIS) and estimate the flashover voltage under different pollution situations and an AC voltage. The next section provides a thorough explanation of how our fuzzy inference system, or "FIS," was put into practice.

Implementation of the Fuzzy Inference System "FIS" under MATLAB

The employed FIS is shown in Figure 3. The degree to which the output variable belongs to its fuzzy sub-sets may be defined in a number of ways. The manner that the "and and or" operators used in the inference rules will be applied is basically different between both strategies.

The "Mamdani" analysis, which is the most popular in prediction research, is the foundation of our present work. The input and output variables, as well as the foundation of the rules that are often joined together to build the knowledge base, are shown in the accompanying figure together with its many selected features (MIN for the "and" operator, Max for "or," and MAX for the aggregation and defuzzification per gravity center).

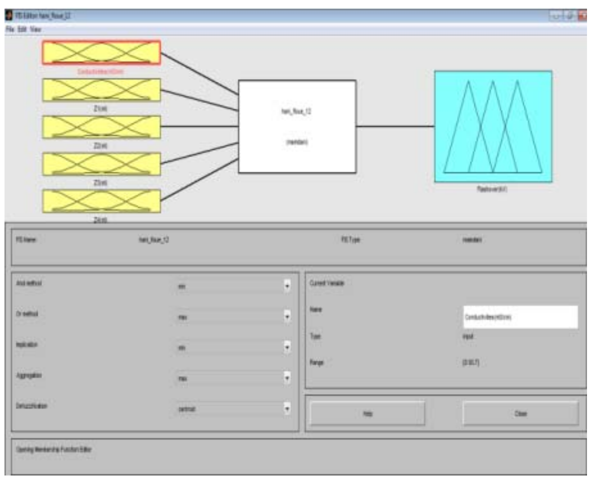


Fig.3. Principal window of fuzzy inference system "FIS Editor" under MATLAB

a. Fuzzification of the input and output variables

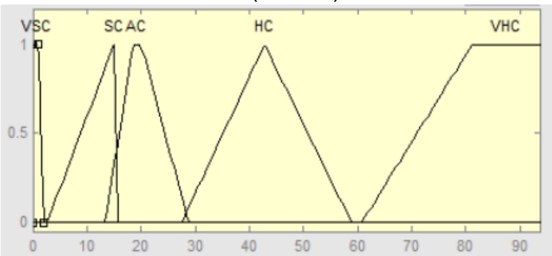
The zones (areas) "Zi (Z1, Z2, Z3, Z4)" and "δ" conductivity were our choices for input and output, respectively.

The "V" flashover voltage is the only output. Our decision has been based on our experiences as well as evaluations of the outcomes of the trial. Still, different tests can need different inputs and results.

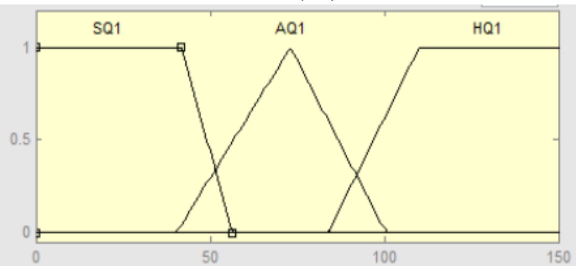
The input and output generation utilizing the FIS under MATLAB is shown in the accompanying image. We made a number of changes to enhance the outcomes. In actuality, we retained the membership function forms (shapes) that, when compared to the experimental data in the reference [18], provide a minimal average error with accurate predictions.

The input and output membership functions of the FIS that were built using fuzzy logic in Matlab during the final phase are shown in Figure 4.

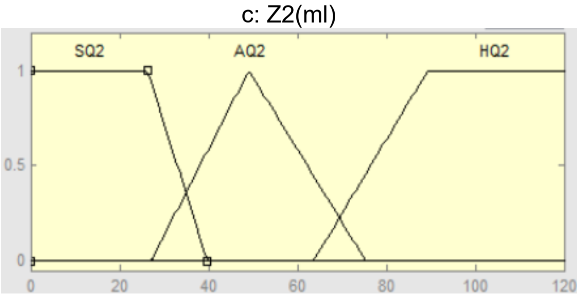
a: δ(mS/cm)



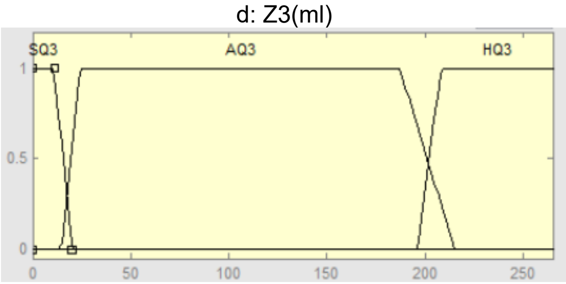
b: Z1(ml)



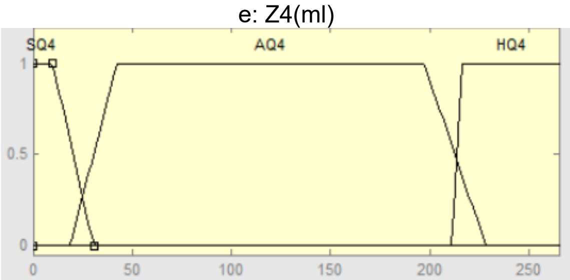
c: Z2(ml)



d: Z3(ml)



e: Z4(ml)



f:V (kV)

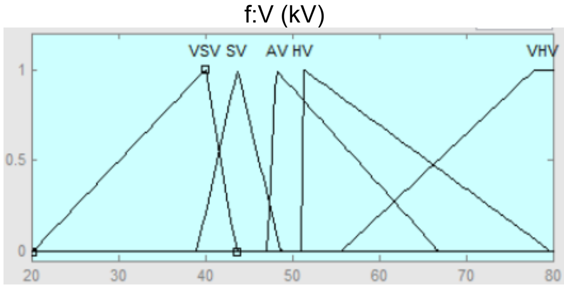


Fig. 4. Inputs and output under the interface FIS a,b,c,d,e: Inputs, f: Output.

b. Inference rules

Figure 5 shows the window used to introduce the fuzzy rules applied in our FIS.

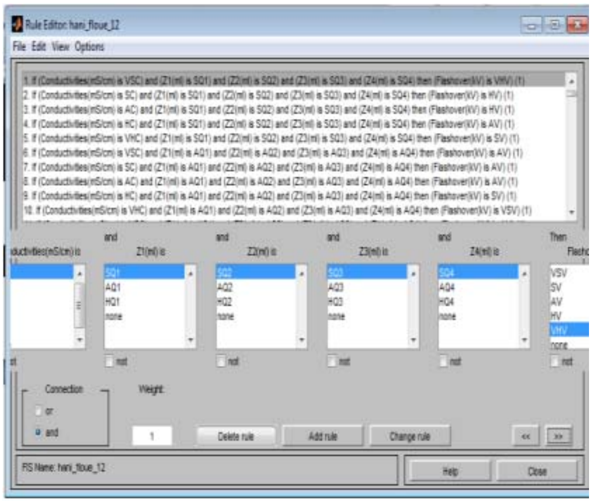


Fig. 5. Window for visualization fuzzy rules.

- Table 2 illustrates the fuzzification of the five input variables.
- It is possible to build the appearance functions that lead to 135 inference rules.
- The "FIS" graphical interface allows adding and modifying rules without going over the allotted number. The greatest number of rules that our study produced was 405 (5*3*3*3*3). Experience gains in the unfavorable situation are overlooked, resulting in a maximum of 135 rules.
- The membership functions, which are determined by the linguistic words connected with the inputs, define the output that is impacted by this rule. The related linguistic term also defines the output.
  Table 3 groups the collection of regulations that are in use.

c. Defuzzification

Finding the gravity center of the resultant membership function is the most popular technique for defuzzification, the last stage in creating a fuzzy operational system. It's among the most popular techniques.

There are two phases in the defuzzification stage:

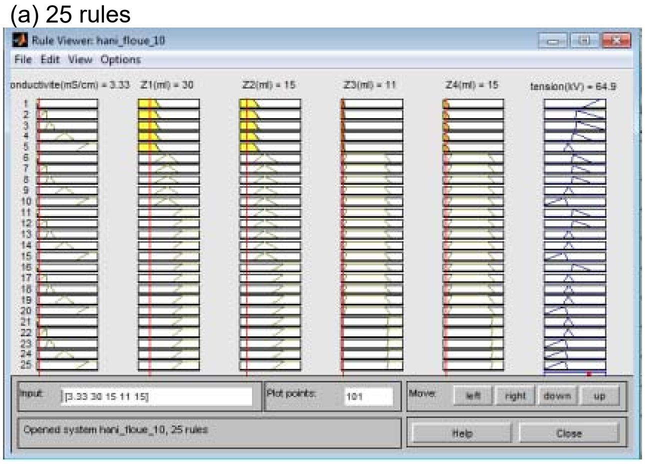
- The system designer should choose a fuzzy logic operator to combine the common language variables. Consequently, it is a crucial stage in the inference system because it allows the value of the final fuzzy output variable to be determined using an inference approach based on the fuzzy inputs resulting from fuzzification and on all of the fundamental rules.

• We can really start the delicate process of defuzzification in a second stage. The distinct and identical material is characterized by a number of linguistic factors.

An illustration of the Matlab defuzzification processes may be seen in Figure 6. It displays (a) a sample of a Matlab defuzzification phase with 25 rules, and (b) the same example with 135 rules that produced identical outcomes.

Additionally, Figure 6 provides an example of how our FIS is applied to the following inputs: Z1 = 30 ml, Z2 = 11 ml, Z3 = 15 ml, Z4 = 15 ml, and δ = 3.33 mS / cm. For both circumstances, the vector [3,33 30 11 15 15] consists of (a) 25 rules and (b) 135 rules. The flashover voltage is shown in the value of the computed (predicted) output after defuzzification. The output voltage was equal in both scenarios.

(a) 25 rules



(b) 135 rules

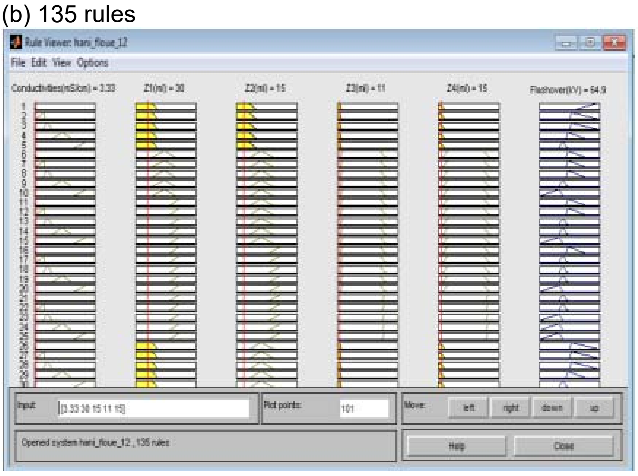


Fig. 6. Window for visualization fuzzy rules, (a) 25 Rules, (b) 135 Rules.

I apply another example now the clean case; the vector [0 0 0 0 0] or δ=0 mS/cm, Z1=0 ml, Z2=0 ml, Z3=0 ml, Z4=0 ml. The output voltage is 72 kV (predicted) for both cases (a) and (b).

Tests and validation

We will compare the prediction results from the FIS for the different input values [δ, Z1, Z2, Z3, and Z4] with the simulation results and with the practices gathered from the literature.

• The input and output membership functions have a trapezoidal and triangular shape (form), according to the prediction findings produced by the FIS system running on MATLAB.

• The following tables show that the average inaccuracy is around 6% (6.426%).

• The findings of this study allow us to conclude that the fuzzy system is a viable, efficient, and trustworthy method for forecasting the flashover voltage tests of the HV 1512L insulator, which were conducted in the laboratory and examined in our work [21]. As a consequence, we proposed using the simulated fuzzy system to forecast outcomes for additional input values that are not accessible in the laboratory.

• The findings obtained indicate that fuzzy logic has significant potential for studying flashover voltage prediction.

• Better results are obtained when the parameters of the fuzzy inference system the number, type, and form of the membership functions, the inference rules, and the defuzzification technique are correctly chosen.

• Any adjustments made to the FIS parameters might affect the outcome. The outcomes of our investigation were improved by altering the gates of the various input and output functions while maintaining their trapezoidal and triangular shapes.

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Conclusion

One benefit of fuzzy logic is that it may be easily interpreted and used without the requirement for an extra mathematical model. This study presents an artificial intelligence method based on fuzzy logic and the MAMDANI type that was created to anticipate the flashover voltage. In actuality, this article provides the background information required to comprehend the methodology. Therefore, we first described the main components of a fuzzy system and their application, as well as the fuzzy inference system (FIS) and the idea of the linguistic variable.

The FL is used to symbolize hazy and inaccurate information, allowing us to state that the FL needs professional assistance, which is crucial when creating a fuzzy system. A sound selection of the system's many parameters is the most crucial stage in using fuzzy logic, the parameters of which are applied based on the various phases that are required.

The outcomes achieved with the FL demonstrate its efficacy in terms of a high accuracy prediction rate and a very low computation time. The choosing of the fuzzy logic's parameters is where the challenge in employing it is found. Actually, the true challenges lie in fuzzifying the input and output variables (i.e., the membership function form, and the number of fuzzy sets assigned to each variable), as well as in developing the fuzzy rules that map the inputs to the outputs. It may be said that while selecting the parameters for the fuzzy inference system, there are no set norms to adhere to.

Simplified in its implementation, the fuzzy inference system "FIS" in the MATLAB environment makes use of the "Fuzzy Logic" interface. The accuracy of our suggested model to forecast the flashover voltage is shown in this study.

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