FAULT DETECTION ON RADIAL POWER DISTRIBUTION SYSTEMS USING FUZZY LOGIC

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ABSTRACT

Electric power distribution systems are expected to function at all times, even under fault conditions. However, When they operate under fault conditions, the system operator receives information which makes it very difficult to make decisions on whether to restore a tripped feeder to normal operation. To cope with this uncertainty in decision making, a fault diagnosis method based on fuzzy logic is proposed. The proposed method aims to ease the burden of decision making on the part of the system operator by presenting a fast and accurate fault diagnosis method to classify and identify the type of fault which occurs on an overhead radial power distribution network.

Keywords: Radial distribution system, fault diagnosis, and fuzzy logic.

INTRODUCTION

The distribution system is a very important component of an electric power system which also consists of the generation and transmission systems. "The subject of fault location has been of considerable interest to electric power utility engineers and researchers for over twenty years" [1] .Fault occurs due to failure of insulation of the distribution system, bridging of energized phase conductors by objects, accidents e.t.c. These events affect the value of the voltage and current on the distribution system and sometimes the entire power system. Considering the fact that most distribution systems are run overhead and have a radial topology, the need for accurate and reliable fault detection system becomes expedient. In recent times, researchers are more interested in finding solutions to the problem of vagueness, incomplete fault information, error in fault data and information redundancy [2]. "The use of fuzzy logic enables the fault detection system to cope with uncertainties that occur during the location of fault in electrical distribution networks" [3]. In [4], the proposed fault detection technique used fuzzy logic-based algorithm to identify ten types of shunt faults in radial, unbalanced distribution system. The parameters used include fault resistance, fault inception angle, system topology and loading levels.

A hybrid approach of neuro-fuzzy based learning and fault classification approach based on the online learning system was proposed in [5]. In this work, a method of fault location based on the conventional offline neuro controller approach is compared with the suggested hybrid approach for learning and convergent time evaluation for distributed systems.

[6] presents an intelligent fault location and diagnosis system. This system performs fault type identification using a two-step procedure. The first step identifies candidate fault location using an iterative calculation of the load current and the fault current. The second step diagnosed the actual location of the fault by comparing the current waveform pattern with the expected

operation of the protective devices and comparing the interrupted load with the real load. They performed various simulations to obtain a satisfactory result. [7], presents a method for fault diagnosis based on a hierarchy of five agents that cooperate with each other to diagnose a fault. In [8], an extended impedance-based fault-location formulation for generalized distribution systems was proposed. This method uses only local voltages and currents as input data. The formulation considers load variation effects and different fault types. [9], provides a comprehensive review of the conceptual aspects as well as recent algorithmic developments for fault location on distribution system. Several fundamentally different approaches were discussed together with the factors affecting the assumptions of the underlying concepts and the various criteria used in the different approaches were further reviewed. [10], presents a method of fault detection based on Takagi-Sugeno fuzzy models. This model was employed to generate residuals in order to make a decision about the state of the process. The paper focuses on a fuzzy model design procedure. A bounded error approach was applied in generating the rules for the model using available measurements.

FUZZY LOGIC- A REVIEW

To successfully design a fault detection system using fuzzy logic, an understanding of the basic components of a fuzzy decision system is important. These include fuzzy logic concepts such as fuzzy sets and their properties, fuzzy rule base, and fuzzy inference system.

Fuzzy Sets and Membership Functions

The mathematics behind the concept of fuzzy logic is termed fuzzy sets. Fuzzy set theory was first introduced by Prof LoftiZadeh [11]. Fuzzy logic enables the modeling of system conditions with imprecision. Fuzzy logic technique is seen as a form of approximate reasoning which provide decision support and expert systems with powerful ability to make decisions from uncertainty.

A fuzzy set is an extension of the conventional crisp set. A crisp set allows only full membership or no membership of an element of a set, whereas fuzzy sets permit a gradual or smooth transition from no membership to full membership. A fuzzy set A in X as described by Zadeh in [11] is characterized by a membership (characteristic) function $f_A(x)$ which assigns a real number in the interval (0,1),with the value of $f_A(x)$ at x representing the "grade of membership" of element x in set A. As the value of $f_A(x)$ approach unity, the grade of membership of element x in set A rises to a maximum. In the conventional or crisp set, the membership of an element such as x in a set A takes only two values: 0 and 1. $f_A(x) = 1$, if x is member of set A and $f_A(x) = 0$, if x is not a member of set A.

Fuzzy Rule Base

To design a fuzzy inference system (FIS), it is necessary to extract rules from sample data points which define the fuzzy logic based system. According to [12], these fuzzy rules are obtained from expert knowledge of the system behavior. On most occasions, these rules are not known due to the uncertainties associated with human reasoning. Sample data points or training samples may be available in the input /output space. To solve the problem of uncertainty in human reasoning, fuzzy rules are generated which define the mapping surface. The rules generated are used to develop an FIS that performs the desired mapping of the input data points.

Fuzzy Inference System and Logic Set Operations

A Fuzzy inference system (FIS) defines a nonlinear mapping of the input data vector into a scalar output using fuzzy rules. The mapping process involves input/output membership functions, fuzzy logic operators, fuzzy if – then rules, aggregation of the output sets, and defuzzification. Figure 1 shows a block diagram which illustrates the components of a fuzzy inference system as described in [12].

Fuzzy set operations are similar to the conventional set operations. The most elementary set operations are union, intersection, and complement, which are denoted by OR, AND, and NOT operators, respectively. The union of set A and B is AUB, contains all elements in either A or B; that is, $\mu_{AUB} = 1$ if $x \in A$ or $x \in B$. The intersection of A and B, denoted A n B, contains all elements that are both members of set A and set B; that is $\mu_{AnB}(x) = 1$ if $x \in A$ and $x \in B$. The complement of set A is denoted by \hat{A} , and it contains all elements that are not members of set A; that is $\mu_{\hat{A}}(x) = 1$ if x is not an element of set A, and $\mu_{\hat{A}}(x) = 0$ if $x \in A$. This is further illustrated in the table given in [12].

The Algorithm for the Design of the FuzzyInference System

It includes the following:



Figure 1.Algorithm for the fuzzy inference system

Fuzzifying inputs

The first step is to take inputs and determine the degree to which they belong to each of the fuzzy set designed through membership functions. The membership function to be used includes the trapezoidal, bell, Gaussian e.t.c [11]. These membership functions are in built in the fuzzy logic tool box in MATLAB computer software.

Application of fuzzy operators

If a given rule base has more than one part, the fuzzy logical operators are applied to evaluate the strength of the rules formulated for the fuzzy system.

Application of fuzzy expert system

Mamdani and Takagi – Sugeno expert systems are the two types of expert systems used in the fuzzy inference system. The Mamdani type of expert system was developed by EbrahimMamdani. It is the most commonly used of the two types of expert systems mentioned. The expert system is described as an implication method and is defined in [14] as the shaping of the output membership function on the basis of the firing strength of the fuzzy rules. The two most commonly used methods of implication are the minimum and the product. Generally, Takagi-Sugeno system is used if the knowledge can be extracted from raw data, and Mamdani systems are preferred when the knowledge is developed by human experts in the form of linguistic rather than numerical values. The Mamdani system is used in this work.

Aggregation of all outputs

Aggregation is a process whereby the outputs of each rule are combined. Aggregation is performed once for each output variable. The input to the aggregation process is the truncated output fuzzy sets returned by the implication process for each rule formulated. The output of the aggregation process is the combined output fuzzy set.

Defuzzification of all outputs

The aggregated output fuzzy set serves as input to the defuzzifier. The defuzzifier combines the information in the fuzzy inputs to obtain a single crisp (non-fuzzy) output variable. The simplest and most widely used centre of gravity method is used for the defuzzification process. For example, if fuzzy levels low (L), normal (N) and high (H) have membership values that are labeled μ_1 , μ_2 , and μ_3 , then the crisp output signal y is defined as

PROPOSED METHODOLOGY

This method of fault detection applies the three phase (A, B, and C) feeder currents and phase voltages as the inputs to the fuzzy inference system (FIS).

Membership Functions

Different levels of the fault currents and voltages for different fault conditions on the distribution lines are classified into various degrees of membership functions- Low, Normal, and High.



Figure 2. Input Membership function for the Line currents and voltages for the FIS



Figure 3.Output membership functions for the FIS

These membership functions are used in forming the rule base for the fuzzy logic fault detection system. Table 1 below shows the rule base formulation for the fuzzy based fault detection system.

Rule No	I _A	I _B	I _C	I _N	V _A	V _B	V _C	Type of Fault
R1	Н	Ν	Ν	Η	L	Ν	Ν	SLG- A
R2	Ν	Н	Ν	Н	Ν	L	Ν	SLG- B
R3	Ν	Ν	Н	Н	Ν	Ν	L	SLG- C
R4	Н	Н	Ν	Ν	L	L	Ν	DL-AB
R5	Ν	Н	Н	Ν	Ν	L	L	DL-BC
R6	Н	Ν	Н	Ν	L	Ν	L	DL-AC
R7	Н	Н	Ν	Н	L	L	Ν	DLG-AB
R8	Ν	Н	Н	Н	Ν	L	L	DLG-BC
R9	Н	Ν	Н	Н	L	Ν	L	DLG-AC
R10	Н	Н	Н	Ν	L	L	L	3Ø-Fault

Table 1 Fuzzy Rule base Formulation

(H): High (N): Normal (L): Low

The rule base formulation as shown in table 1 are extracted from the fault simulations performed using more than fifty electromagnetic transient program (EMTP) simulation runs using NEPLAN software. The rules are structured as follows:

IF I_A = High, I_B = Normal, I_C = Normal, I_N = High,

THEN fault type = SLG - A

(Single Line- to- Ground fault at phase A)

SIMULATION AND RESULTS

Line Model for the Simulation

The relatively short lengths of the medium voltage (MV) and low voltage (LV) distribution circuits enable simple modeling techniques to be used for lines. The radial network configuration is used to make to simplify the network model, hence large matrix model are seldom necessary. It is usually sufficient to represent a distribution circuit by a series impedance and ignore its capacitance, except when carrying out voltage calculations on a long cable for example, when a π or T equivalent circuit with capacitance shunt branches should be used. Figure 4 represents a line model for power distribution systems.



Figure 4. Radial distribution line model

Where, Vs = the sending end voltage. Vr = the receiving end current, R = line resistance, and L = line inductance

Test System

In this section, we validate the accuracy and performance of the fuzzy logic based fault diagnostic system as described in this work based on the test radial distribution system on which the fault simulation was performed.

The model is tested on the radial distribution system 33/11kv network of Power Holding Company of Nigeria (PHCN) Plc. The distribution system consists of 132/33/11kv 45 MVA, 132/33kv 40 MVA, and 132/33kv 60 MVA power transformers in the transmission control center (TCN). The TCN feeds three injection substations: GTC, Onitsha Rd, and Egbu injection substations. Each has 2 X 15MVA power transformers as shown in table 2(a).

No of windings	Nominal Voltage (RMS)	Base MVA
3	132/33/11kv	45
2	132/33kv	40
2	132/33kv	60
2	33/11kv	15

 Table 2(a). Transformer parameters [13]

Table 2(b) shows the sequence components required in building the logical model of the radial distribution system for simulation

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	sitti e, negati e an	a zero sequence	i itesistunce,	maacuncey	and capacitance	

R+ = R-	0.157 Ω/km
L+ = L-	0.011 H/km
C+ = C-	5.7 F/km



Figure 5. Single line representation of the radial distribution system

Simulation Model

The system model was performed using the Matlab/Simulink software version 7.7. Simulink is an environment for multi domain simulation and model-based design for dynamic and embedded systems [14]. It provides an interactive graphical environment and a customizable set ofblock libraries that let you design, simulate, implement and test a variety of time-varying systems including power, communications, controls, signal processing, e.t.c.

The simulations for the various types of faults were carried performed and the various values for both faulted and non-faulted current were taken and recorded. The following blocks were used in building the logical model for fault detection.

Block Parameters: EGBU	
Three-Phase Transformer (Two Windings) (mask) (link)	*
This block implements a three-phase transformer by using three single-phase transformers. Set the winding connection to 'Yn' when you want to access the neutral point of the Wye. Click the Apply or the OK button after a change to the Units popup to confirm the conversion of parameters.	
Configuration Parameters Advanced	
Units pu	
Nominal power and frequency [Pn(VA) , fn(Hz)]	=
[60e6 , 50]	
Winding 1 parameters [V1 Ph-Ph(Vrms) , R1(pu) , L1(pu)]	
[1.32e+005 0.00125 0.08]	
Winding 2 parameters [V2 Ph-Ph(Vrms) , R2(pu) , L2(pu)]	
[33000 7.1504 28.041]	
Magnetization resistance Rm (pu)	
0.41667	
Magnetization reactance Lm (pu)	
500	
Saturation characteristic [i1, phi1; i2, phi2;] (pu)	-
< >	
OK Cancel Help Apply	

Figure 6(a). The Transformer block

In the transformer block, we specify the required parameters of the two winding transformer. This block represents a real step down transformer on the distribution network. The values are set to the per unit system.



Figure 6(b). Fuzzy Fault detection block (Subsystem)

The fuzzy fault system block in the figure above, houses the simulation of the fuzzy logic fault detection system.

Block Parameters: TCN	
Three-Phase Transformer (Two Windings) (mask) (link)	
This block implements a three-phase transformer by using three single-phase transformers. Set the winding connection to 'Yn' when you want to access the neutral point of the Wye. Click the Apply or the OK button after a change to the Units popup to confirm the conversion of parameters.	
Configuration Parameters Advanced	
Units pu	
Nominal power and frequency [Pn(VA) , fn(Hz)]	=
[40e6 , 50]	
Winding 1 parameters [V1 Ph-Ph(Vrms) , R1(pu) , L1(pu)]	
[33e3 , 0.002 , 0.08]	
Winding 2 parameters [V2 Ph-Ph(Vrms) , R2(pu) , L2(pu)]	
[11e3 , 0.002 , 0.08]	
Magnetization resistance Rm (pu)	
500	
Magnetization reactance Lm (pu)	
500	
Saturation characteristic [i1 , phi1 ; i2 , phi2 ;] (pu)	
4 III I	-
OK Cancel Help Apply	

Figure6(c). Three phase block

Figure 6(c) implements a three phase source for the distribution system.

Block Parameters: T-P L
Three-Phase Series RLC Load (mask) (link)
Implements a three-phase series RLC load.
Parameters
Configuration Y (grounded)
Nominal phase-to-phase voltage Vn (Vrms)
11e3
Nominal frequency fn (Hz):
50
Active power P (W):
5e9
Inductive reactive power QL (positive var):
0
Capacitive reactive power Oc (negative var):
0
Measurements None
OK Cancel Help Apply

Figure 6(d) Three phase load block

The three phase load block implements a three phase load, which is either purely resistive or inductive.

Other blocks such as the display block, scope, circuit breakers and measurement blocks were also used in building the logical model for simulation [14].



Figure 6(e) Logical model for the simulation

Simulation Results

Fault condition	Line A	Line B	Line C
No Fault	0.5239	0.5913	0.6026
Line A–G Fault	-0.0099	0.5017	0.4429
Line B-G Fault	0.5407	-0.0042	0.5159
Line C-G Fault	0.5317	0.5977	-0.0844
Line AB Fault	0.9339	0.95467	0.4267
Line AC Fault	0.9129	0.5507	0.98146
Line BC Fault	0.4344	0.9524	0.97432
Line AB-G	-0.0344	-0.0344	0.5344
Line BC-G	0.55344	-0.0044	-0.0044
Line AC-G	-0.044	0.55344	-0.05344
3Ø- Fault -G	-0.0004	-0.0008	-0.0005

 Table 3. Output crisp Values from the fuzzy fault detection system.



Figure 7(a). Single line- ground fault (C-G)



Figure 7(b). Double line- fault (A-B)



Figure 7(c). Double line -ground fault (AB-G)



Figure 7(d). 3 phase fault to ground (ABC-G)

CONCLUSION

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A fault detection system based on fuzzy logic has been designed in this work. This design was tested on a real radial power distribution network using real data and Matlab/Simulink software. It was able to detect single line to ground fault, phase to phase fault, double line to ground fault, and three phase fault. It has been shown that faults could occur in radial distribution systems with all possible combinations; hence the importance of the fuzzy membership functions in capturing the various combinations. The simplicity of this design based on fuzzy logic, means a drastic reduction in load loss and energy loss on distribution systems due to prolonged outages leading to longer feeder downtime during faulted conditions

REFERENCES

[1] D. Biswarup, (2006), "Fuzzy logic-based fault-type identification in unbalanced radial power distribution system", *IEEE Transactions on Power Delivery*, Vol 21 No 1. January, IEEE press.

[2] D. Jalali& N. Moslemi, (2005), "Fault location for Radial Distribution Systems using fault generated High-Frequency Transients and Wavelet Analysis", *18th International Conference on Electricity Distribution*, Turin, 6-9 June, pp 1-4, date of current version:11 March 2010, IEEE Publisher.

[4] H.S Naveh, H.K Zadeh, B.T Hosseini& A.S Zadeh, (2010), A Novel Approach to Detection High Impedance Faults Using Fuzzy Logic

[3] E.H. Mamdani, "Application of Fuzzy Logic to Approximate Reasoning Using Linguistic Synthesis", <u>www.google.com</u>, Viewed date: March 17, 2008.

[5] J. Yang, M. Montakhab, A.G. Pipe, B. Carse, T.S. Davies, (2004), "Application of multi-Agent technology to Fault Diagnosis of Power Distribution Systems", *Proceedings of engineering of Intelligent systems (EIS 2004)*, February 29- March 2, Island of Madeira, Portugal, EIS Press.

[6] L.A. Zadeh, (1965), "Fuzzy Sets", Journal of Information and Control, Vol 8, pp 338-353, USA.

[7] M. Mirzaei, M.Z AbKadir, E. Moazami, H. Hizam, (2009), Review of Fault Location Methods for distribution Power system. *Australian Journal of Basic and Applied Sciences*, 3(3): 2670-2676, INSI net Publication.

[8] M.M Saha, D. Das, P. Verho& D. Novosel, (2002), Review of Fault Location Techniques for Distribution Systems, "Power Systems and Communications Infrastructures for the Future", Beijing, September

[9] P. C. Sekhar, B.V Sanker Ram, K.S. Sarma. (2005), "Neuro-Fuzzy Approach for Fault location and Diagnosis Using Online learning system", *Journal of Theoretical and Applied Information Technology*, <u>www.jatit.org</u>

[10] Q.F Zeng, Z.Y He, J.W Yang & W. Gao, (2009) Fault section Estimation of Electric Power systems based on Adaptive Fuzzy Petri Nets, The International conference in Electrical Engineering, ICEE

[11]R.H. Salim, M. Resener, A.D. Filomena, K.R. Caino De Oliviera, A.S. Bretas, (2009), "Extended Fault-Location Formulation for Power Distribution Systems", *IEEE Transactions on Power Delivery*, Vol 24, No 2.April pp 508-516. IEEE Press.

[12]R. Machatra, N. Singh, Y. Singh. (2010). Fuzzy Logic Modeling, Simulation and Control: A review, *IJCST Vol 1. Issue 2*, December, IJCST Publication.

[13]PHCN PlcOwerri Business unit, 2011, Control room data for the injection substations

[14] Math Works, Matlab/Simulink R2008 (B) software, <u>www.mathworks.com</u>