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APPLICATION OF A FUZZY EXPERT MODEL FOR POWER SYSTEM PROTECTION

Proposal for a synergetic detection of low current faults

C. J. Kim and B. Don Russell

Department of Electrical Engineering, Texas A&M University, College Station, TX 77843, USA

ABSTRACT-The objective of this paper is to develop a fuzzy logic based decision-making system to detect low current faults using multiple detection algorithms. This fuzzy system utilizes a fuzzy expert model which executes an operation without complicated mathematical models. This fuzzy system decides the performance weights of the detection algorithms. The weights and the turnouts of the detection algorithms discriminate faults from normal events. This system can also be a generic group decision-making tool for other areas of power system protection.

I. Power System Protection and Low Current Faults

Power system protection is an area of electric power system engineering involving the protection of equipment, crew members, and the public. Overcurrent relaying is a protection scheme that focuses on the level of current or voltage to decide system status, "normal" or "fault." When the current level is above a certain threshold, the simple logic in the protective device separates the endangered portion from the healthy area of power network. While the function of overcurrent relaying is essential, it has significant limitations.

Overcurrent relaying cannot detect a fault which draws fault currents below the threshold of protective devices. Such low current faults may be caused by a downed conductor on the ground or in contact with a grounded object. Arcing is often associated with these low current faults, which may result in a fire hazard and personal injury. The fault current characterized by an arc is variable, transitory, and random in its behavior. The amplitude of harmonic component of the arc currents is large in some faults, but sometimes it is very low, similar to the level of the normal state[1]. On surfaces such as grass, asphalt, and concrete, the behavior of faults can be very similar to the phenomenon of switching events. Hence, the detection and discrimination of the low current faults from switching events and the normal states is a complex problem [2].

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II. Discrimination of Low Current Faults

The discrimination of faults from these normal events determines to a large extent the balance between security and sensitivity for a distribution protection system. Utilities representatives have stressed that one of their main concerns is the minimization of false detection. The reason for this position is that, while energized downed conductors are a public safety hazard, frequent unnecessary service interruptions can pose safety problems of their own.

Many detection algorithms have been proposed for dealing with the low current faults[3 - 5], however, a complete solution has not been found. The performance of each algorithm is very much affected by the surrounding conditions such as ground surface types and unbalance of the three phase currents. However, determining the surrounding environment cannot be done by any exact method.

In the last few years research intensified on this discrimination problem[6, 7]. The present conclusion is that no single detection algorithm can detect the majority of low current faults and discriminate them from the normal switching events. However, a combination of several algorithms may be used to discriminate and detect a significant percentage of the faults.

This paper provides a formal method to implement a combined set of detection algorithms, while including not well defined affecting factors to the detection algorithms, as a synergetic detection using fuzzy expert model[8].

III. A Fuzzy Expert Model

A fuzzy expert model assigns performance weights to the detection algorithms based upon their responses to different environments. Then it combines the performance weights and turnouts of the algorithms. This combined property is the element to decide the status of the power line. The development step and the operation of the fuzzy expert model follow.

A. Algorithm Analysis

The first work for the development of the fuzzy expert model is to select reliable detection algorithms which can be programmed into a microcomputer system. The next work is to define the environmental influences. These influences increase or decrease the fault current and suppress some harmonic components. The authors hold vast amount of the staged fault test data performed in different areas of this country over a decade. This data tells general tendency of the performance of the detection algorithms in the various situations.

B. Rule Formation

The initial analysis on the detection algorithms and the environmental influences will provide a relationship between the environmental inputs and the performance of the detection algorithms. This information will result in the rules on the performance weights of the detection algorithm. In this step, membership functions must be defined, too. The next step of work is to combine the detection algorithms' turnouts and the performance weights. Each turnout is multiplied to a corresponding performance weight. Then, is the formation of a textual rules to move up or down the Scale with combed properties of the current time and the next.

C. Rule Tuning

Once fuzzy expert model is developed after checking and debugging, it is necessary to tune it to meet the discrimination purpose. The tuning efforts focus on the minimization of the false identification and the maximization of the correct identification. The staged fault test data can be used in the tuning process. If there is contradictory in the changes of the rules for the fuzzy systems execution, the security issue has higher priority than the sensitivity issue.

D. Operation of the Fuzzy Expert Model

The operation of the fuzzy expert model is designed with two stages of rule execution: the weight derivation rule and the decision rule. The output is the Scale indicating the power line status. Figure 1 is the illustration of the two-stage operation of the fuzzy expert model. The detailed explanation on two stages of the fuzzy expert model follows in the next two chapter.

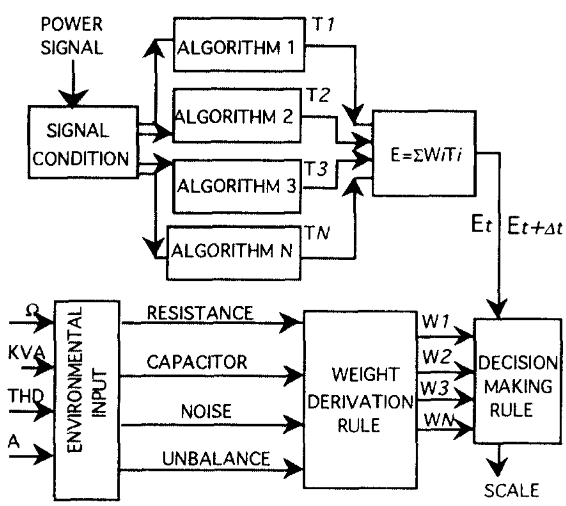

Figure 1. The two-stage operation of the fuzzy expert model.

IV. Performance Weight Derivation

A. Environmental Influence

A well-known fact is that the amount of fault current induced in contact with any material is negative proportional to the resistance of the material. The environmental influences also include the following variables: the degree of power system unbalance; harmonic noise generated by devices like arc welders; capacitor bank connected to a power feeder for power factor compensation.

Therefore, four environmental influences as inputs to the system are: Ground, Phase, Noise, Capacitor. The sensing parameters for the four influences are resistance [W], sum of 3-phase currents [A], total harmonic distortion [THD%], and size [KVA] of capacitor bank, respectively.

Then the input ranges are divided into linguistic variables. Typical five ranges to describe the expected values are: PB(Positive Big), PS(Positive Small), Z(Zero), NS(Negative Small), and NB(Negative Big). Because there are four inputs with different sensing variables, these typical five ranges should be interpreted accordingly. Table I interprets each range of the different inputs. To get a fuzzified value of the five ranges, triangular shape membership function is selected for simplicity purpose. Membership functions are generally grouped together overlapping each other.

Table I. Derivation of the Environmental Input Range

	GROUND (Ω)	CAPACITOR (KVA)	NOISE (THD%)	PHASE (A)
PB	Extremely Resistive	Very Big	Extremely Noisy	Extremely Unbalanced
PS	Greatly Resistive	Big	Greatly Noisy	Greatly Unbalanced
Z	Significantly Resistive	Medium	Moderately Noisy	Moderately Unbalanced
NS	Moderately Resistive	Small	Slightly Noisy	Slightly Unbalanced
NB	Slightly Resistive	Very Small	Rarely Noisy	Rarely Unbalanced

B. Weight Derivation Rule

Next, the output should be decided. The output indicates the amount of increase or decrease to the performance weights. Again, the same five ranges can be used. They are NB(Large Decrease), NS(Small Decrease), Z(No Change), PS(Small Increase), and PB(Large Increase).

As inputs and outputs are determined, the final step is to develop the weight derivation rule. This rule generally is quite simple and, in many cases, intuitive. Each detection algorithm has a set of rules determining the amount of increase or decrease of the performance weights with the environmental inputs.

For each algorithm, four mutually independent sets of rules are needed. And they are to be checked one at a time to match and decide the final increase or decrease amount. As passing through all the rules on all four inputs, the temporary output varies with the amount of increase and decrease, and finally reaches a point. Derived performance weights should be adjusted so that the sum of all them is 1.0.

V. Decision-Making

A. Combined Property as Input

The performance weight is not a direct input to the decision-making stage. Instead, the input to the decision-making is obtained from the combination of the performance weights and real-time information of the detection algorithms' turnouts of "fault" or "normal." One of the possible measures which decide the combined property, E, may be expressed by the following equation:

$$E = \sum_{i=1}^{n} w_i T_i \quad \text{for } i = 1, n.$$

where, w_i and T_i indicate the performance weight and turnout of the algorithm i, respectively, and n indicates the number of detection algorithms to be combined.

The power system has many cases of short and self-ceasing transients which may look like low current faults, therefore, an instantaneous decision based upon input at a time may be resulted in false identification. Therefore, two inputs to the decision-making are the two consecutive combined properties, E_c and E_n: E_c is the combined property at the current time, say t, and E_n is the combined property at the next time, t+Δt (See Figure 1). The time interval, Δt, may be a second or a few seconds. As time goes by the amount of Δt, E_c is replace by E_n and new E_n is calculated at the next time in a manner of moving window process.

The combined property input may be divided, similarly, into five ranges. They are PB (Definitely Fault), PS(Maybe Fault), Z(Not Known), NS(Maybe Not-Fault), and NB(Definitely Not-Fault).

B. Decision Rule

If two inputs, E_c and E_n, are same, the output Scale would stay where it was. If E_n moves positive direction (which means to fault direction) from E_c, then the Scale moves up to indicate the system status of abnormality. A typical rule matrix for decision may be formed as shown in Table II.

In the inference process, because of the overlapped membership functions, one set of the combined property can decide multiple output ranges. The center of gravity of the overlapped outputs, or a centroid, is used to calculate crisp output status[9]. If the defuzzified output reaches a certain threshold level, then a corresponding signal will be generated to indicate the power line status and, if desirable, it will directly activate protective device or alarm.

Table II. A Typical Rule Matrix for Decision

En \ Ec	NB	NS	Z	PS	PB
NB	Z	NS	NS	NS	NB
NS	PS	Z	NS	NS	NB
Z	PS	PS	Z	NS	NB
PS	PB	PS	PS	Z	NS
PB	PB	PB	PB	PS	Z

VI. Discussion and Conclusions

A fuzzy expert model application for power system protection, particularly for the detection of low current faults, is proposed. This proposed model has three major contributions to the detection of the low current faults and other areas of the power system protection. The first is that this research provides a formal methodology, not in a formula but in a hands-on linguistic form, to measure the environmental influences to the detection algorithm. The second significance is that it provides a synergetic detection method with a fuzzy expert model using multiple detection algorithms. The third one is that the decision-making stage is based upon the time-moving fuzzy inputs in real-time base. This model can also be a generic tool for other areas of power system protection such as an adaptive computer relaying.

VII. Bibliography

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