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Comprehensive Detection and Isolation of Fault in Complicated Electrical Engineering

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***Abstract*—In this paper, real time dynamic information of complicated electrical engineering provided by phasor measurement units to analyze and locate the fault is utilized. Based on fuzzy cluster analysis theory and the principle of minimum expected cost of misclassification, we have explored a comprehensive detection and isolation system of fault in complicated electrical engineering. It has been proved by a large number of simulation experiments that the comprehensive fault detection and isolation system can accurately and reliably detect and isolate faults and provide guarantee for the safety and stable operation of electrical power and energy system.**

***Index Terms*—Fault detection and isolation, fuzzy cluster analysis, MECM, wide area protection.**

I. INTRODUCTION

The safe and stable operation of electric power system is of great importance to the national economy and people's livelihood, and it is also the goal pursued by electrical scientists. Relay protection, one of the three defensive lines of electric power system, plays an indispensable role in monitoring the abnormal situations of power grid, clearing fault components and safeguarding system security. In power system, the main protection based on two-terminal electrical measurements, represented by fiber differential, has got to be mature and perfect [1]. However, it fails to be the effective backup of the adjacent electric element while ensuring the absolute selectivity. In the practice of electrical engineering, it is possible for the main protection to be invalid due to the disappearance of DC power supply. Therefore, it is not advisable to completely eliminate the traditional backup protection represented by zone 3 impedance relay which can be the remote backup of adjacent element.

With the increasing complication of power network, the variety of operation modes, and the higher demand of real-time and super real-time, however, many problems lie in the traditional backup protection due to its inherent setting principle, configuration scheme and the choice of information source [2]–[4]:

- It only reflects local information of relay equipment of power grid. To ensure the reliability, the setting has to be made under the most severe and inclement operation conditions, which makes it rather conservative to realize the protection function. Meanwhile, to ensure the selectivity, the rapidity and sensitivity have to be sacrificed, which leads to the extended action time of protection.
- The cooperative relationship of backup protection is quite complex. The configuration and setting are of great difficulty. The emphasis lies in the ineffective adaption to the changes of the system operating condition, which, moreover, can cause unhealthy conditions of protection mismatching and lack of sensitivity.
- The backup protection cannot effectively differentiate the power flow transferring caused by internal faults and external faults. In many blackouts, the cascading trip of backup protection caused by heavy load even accelerates the extension of the range and scope of accidents.

It is the fundamental approach to the current problems of backup protection to get rid of the restraint of partial or local information and to make full use of the multi-point and multivariate wide area information [5]–[7].

The researches in this paper are mainly serving wide area protection system. We will explore a comprehensive detection and isolation scheme of fault in complicated electrical engineering. This paper is organized as follows. In Section II, the theoretical foundation for fault detection and isolation is introduced. Integrated the fuzzy cluster analysis and minimum expected cost of misclassification, a comprehensive fault detection and isolation system will be put forward. In Section III, for general fault modes, the fault detection and isolation in complicated electrical engineering is discussed carefully. Finally, the paper is concluded in Section IV.

II. THE THEORETICAL FOUNDATION FOR FAULT DETECTION AND ISOLATION

A. Fuzzy cluster analysis

In the general form of cluster analysis, each object in dataset will be assigned ultimately to a certain category. In

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other words, it is impossible that an individual exists between categories. But fuzzy cluster analysis use a rather different classification ideas, every observation has partial member relationship in multiple categories, rather than has perfect member relationship in a single category.

The fuzzy cluster analysis is applying the concept of fuzzy set to traditional cluster analysis, and the subjection relation can be determined by membership function. The membership degree that each object belongs to every category is just a value in continuous interval [0, 1]. In fact, an object can belong to multiple categories with different levels of membership degree. One of the major advantages of fuzzy cluster analysis is that it can adapt to those data and categories with poor separation property, which allows the fuzziness of data properties and can offer detailed information for the description of data structures [8], [9].

The membership function is the basis of fuzzy theory. In fuzzy classification, the object a_i in object collection A is subordinate to a class with a certain membership degree, and all of the objects are subordinate to a certain class with different membership degrees. So, each class can be considered as a fuzzy subset on the object collection A, and the corresponding category of every classification result is just a fuzzy matrix S, namely

$$S=\begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ s_{c1} & s_{c2} & \cdots & s_{cn} \end{bmatrix}. \tag{1}$$

Let Ψ_{FC} be the fuzzy classifying space that the object collection A can be divided into c categories

$$\Psi_{\mathrm{FC}}=\{s_{ij}\in[0,1],\ \sum_{i=1}^{c}s_{ij}=1,\ \sum_{j=1}^{n}s_{ij}<n\}. \tag{2}$$

Suppose the collection of classification objects is $A_1=\{a_1,a_2,\ldots,a_n\}$, every object a_i has m characteristic indexes, which can be expressed as a matrix

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix}. \tag{3}$$

A is also known as a characteristic index matrix of A_1. If one wants to divide the object A_1 into c categories $(2\le c\le n)$, suppose the c clustering center vectors can constitute matrix B

$$B=\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_c \end{bmatrix}=\begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ b_{c1} & b_{c2} & \cdots & b_{cm} \end{bmatrix} \tag{4}$$

In the course of fuzzy cluster analysis, the appropriate fuzzy classification matrix S and clustering centre matrix B will be solved, which will make the objective function $G(S,B)$ reach its minimum value

$$G(S,B)=\sum_{k=1}^{n}\sum_{i=1}^{c}s_{ik}^2 d_{ik}^2,\ S\in\Psi_{\mathrm{FC}}. \tag{5}$$

B. The Rule for Minimum Expected Cost of Misclassification (MECM)

During the course of discriminant analysis, misclassification is unavoidable, and the consequences derive from various types of misclassification might be different. Misclassification cost is just the quantitative exhibition of misclassification consequences [10]. Suppose the probability density functions of group ω_1,ω_2 are respectively $f_1(x), f_2(x)$, and their prior probabilities are respectively p_1, p_2 $(p_1+p_2=1)$. Let $c(j\,|\,i)$ $(i,j=1,2)$ be the cost that sample x $(x\in\omega_i)$ is grouped into ω_j.

For any discrimination rule, the expected cost of misclassification (ECM) is

$$\mathrm{ECM}=E[c(j\,|\,i)]=c(2\,|\,1)P(2\,|\,1)p_1+c(1\,|\,2)P(1\,|\,2)p_2 \tag{6}$$

and the minimum expected cost of misclassification rule is just this kind of discrimination rule that can minimize ECM, namely:

$$\begin{cases} x\in\pi_1, & \text{If } \dfrac{f_1(x)}{f_2(x)}\ge\dfrac{c(1\,|\,2)p_2}{c(2\,|\,1)p_1}, \\ x\in\pi_2, & \text{If } \dfrac{f_1(x)}{f_2(x)}<\dfrac{c(1\,|\,2)p_2}{c(2\,|\,1)p_1}. \end{cases} \tag{7}$$

As can be seen from the former relationship, for a new sample, we only need to know the corresponding ratios, its attribution will be determined provided that the corresponding ratios are known.

Integrating the above research methods, we put forward a comprehensive fault detection and isolation system, see Fig. 1.

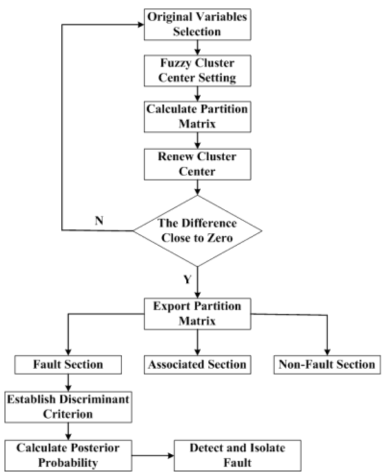

Fig. 1. Comprehensive fault detection and isolation system.

TABLE I. THE CATEGORY COEFFICIENTS AND RESULTS OF NODE POSITIVE SEQUENCE VOLTAGES.

Node	No.	Non-Fault Section	Associated Section	Fault Section	Classification Results
BUS-1	1	0.828831	0.110253	0.060916	Non-fault section
BUS-2	2	0.154242	0.615218	0.23054	Associated section
BUS-3	3	0.134873	0.213928	0.651198	Fault section
BUS-4	4	0.096791	0.25109	0.652119	Fault section
BUS-5	5	0.080147	0.805871	0.113983	Associated section
BUS-6	6	0.07042	0.851757	0.077823	Associated section
BUS-7	7	0.096316	0.781219	0.122465	Associated section
BUS-8	8	0.100664	0.776817	0.122519	Associated section
BUS-9	9	0.79392	0.133613	0.072467	Non-fault section
BUS-10	10	0.104813	0.804564	0.090624	Associated section
BUS-11	11	0.08117	0.840198	0.078633	Associated section
BUS-12	12	0.070639	0.835004	0.094357	Associated section
BUS-13	13	0.072216	0.833759	0.094025	Associated section
BUS-14	14	0.122264	0.444929	0.432807	Associated section
BUS-15	15	0.069799	0.160232	0.769969	Fault section
BUS-16	16	0.064726	0.139092	0.796181	Fault section
BUS-17	17	0.168569	0.246835	0.584596	Fault section
BUS-18	18	0.236487	0.298819	0.464693	Fault section
BUS-19	19	0.258415	0.604924	0.136661	Associated section
BUS-20	20	0.155685	0.71402	0.130295	Associated section
BUS-21	21	0.126496	0.516013	0.357491	Associated section
BUS-22	22	0.372331	0.48425	0.143419	Associated section
BUS-23	23	0.366644	0.491284	0.142072	Associated section
BUS-24	24	0.081594	0.201896	0.71651	Fault section
BUS-25	25	0.209259	0.613532	0.177209	Associated section
BUS-26	26	0.133115	0.365924	0.500961	Fault section
BUS-27	27	0.095209	0.169991	0.734799	Fault section
BUS-28	28	0.285518	0.554364	0.160118	Associated section
BUS-29	29	0.495217	0.368647	0.136136	Non-fault section
BUS-30	30	0.848888	0.100184	0.050928	Non-fault section
BUS-31	31	0.83361	0.112762	0.053628	Non-fault section
BUS-32	32	0.821852	0.121822	0.056327	Non-fault section
BUS-33	33	0.833265	0.11448	0.052255	Non-fault section
BUS-34	34	0.885527	0.075604	0.038869	Non-fault section
BUS-35	35	0.845144	0.100644	0.054212	Non-fault section
BUS-36	36	0.709772	0.18093	0.109298	Non-fault section
BUS-37	37	0.772739	0.156801	0.070461	Non-fault section
BUS-38	38	0.886062	0.076245	0.037693	Non-fault section
BUS-39	39	0.572836	0.255542	0.171622	Non-fault section

III. FAULT DETECTION AND ISOLATION IN COMPLICATED ELECTRICAL ENGINEERING

According to different kinds of short circuit faults, we have carried through large numbers of simulation experiments, and the results have demonstrated that the comprehensive fault detection and isolation system in this paper is successful. Let's take a symmetrical short circuit fault in IEEE 39-bus system as an example, the electric diagram of IEEE 39-bus system can refer to [5]. In the system structure, Bus18 is the actual fault position. By BPA simulation and program calculation with MATLAB, firstly, we study the partition of fault section and non-fault section based on fuzzy cluster analysis theory. By node positive sequence voltage, the category coefficients can be calculated. Here let's specify the number of categories as three: fault category, associated category and non-fault category. The category coefficient reflects the possibility that corresponding measurement value will be assigned into an appropriate category. The concrete category coefficients and results of node positive sequence voltage have been listed in Table I. And we have also obtained classification diagram.

In view of the symmetrical short circuit fault in IEEE 39-bus system, based on the results of fuzzy cluster analysis, 39 nodes in this actual system have been quickly classified. In the three categories obtained, Bus3, Bus4, Bus15, Bus16, Bus17, Bus18, Bus24, Bus26 and Bus27 are assigned into fault category; Bus2, Bus5, Bus6, Bus7, Bus8, Bus10, Bus11, Bus12, Bus13, Bus14, Bus19, Bus20, Bus21, Bus22, Bus23, Bus25 and Bus28 are assigned into associated category; Bus1, Bus9, Bus29, Bus30, Bus31, Bus32, Bus33, Bus34, Bus35, Bus36, Bus37, Bus38 and Bus39 are assigned into non-fault category. So, the fault section in this actual system has been clearly separated. The nodes near Bus18 have been assigned into a single category. In subsequent researches, we will utilize the rule for minimum expected cost of misclassification (MECM) to realize more refined fault detection and isolation.

By the principle of MECM, the classification function coefficients have been calculated and the linear discriminant model can be expressed as:

$$F_1(x) = -431.652 + 919.281x_1 - 28.585x_2, \tag{7}$$

$$F_2(x) = -439.379 + 916.616x_1 + 15.817x_2. \tag{8}$$

Thereupon, the ultimate posterior probabilities and MECM classification results based on node positive sequence voltages are listed in Table II.

According to the above MECM classification results, the misjudgement ratio is zero, and the accuracy of classification has reached 100 %.

TABLE II. THE POSTERIOR PROBABILITIES AND MECM CLASSIFICATION IN IEEE 39-BUS SYSTEM.

Node	**Classification**	**Posterior Probability (Fault Population)**	**Posterior Probability (Normal Population)**	**MECM Classification**
BUS-3	Normal	0.004979	0.995021	Normal
BUS-4	Normal	0.000001	0.999999	Normal
BUS-15	Normal	0.000004	0.999996	Normal
BUS-16	Normal	0.000009	0.999991	Normal
BUS-17	Normal	0.122668	0.877332	Normal
BUS-18	Fault	0.999964	0.000036	Fault
BUS-24	Normal	0.000002	0.999998	Normal
BUS-26	Normal	0.000000	1.000000	Normal
BUS-27	Normal	0.000159	0.999841	Normal

So, for the symmetrical short circuit fault in IEEE 39-bus system, the system fault has been accurately determined by the comprehensive fault detection and isolation system in this paper.

It is crucial to stress that this comprehensive fault detection and isolation system presented in this paper has remarkable anti-interference capability.

IV. CONCLUSIONS

In this paper, one utilizes real time dynamic information of complicated electrical engineering provided by PMU to analyse and locate fault. Under traditional monitoring condition, the online rapid diagnosis of power grid fault is mainly based on relay protection and circuit breaker action provided by supervisory control and data acquisition system, and this greatly depends on the correct action of relay protection and circuit breaker. The fault detection and isolation that we are providing is based on fuzzy cluster analysis theory and the principle of MECM, which can reduce the influence of relay protection’s wrong action device on fault detection. Using variables that describe the state of power system, such as voltage phasor, current phasor, frequency and phase angle et al, to carry global analysis, it extended the styles of information that can be used to analyse and diagnose the fault. Meanwhile, the utilized information is analog quantity with high fault tolerance rate. This makes the analysis results more reliable, and makes the fault detection more accurate. It has been proved by a large number of simulation experiments, that the comprehensive fault detection and isolation system proposed in this paper can accurately and reliably detect and isolate faults and provide guarantee for the safety and stable operation of complicated electrical engineering.

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