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Study on Fault Diagnosis of Circuit-breaker Based on Rough-Set Theory

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Abstract

High voltage circuit-breaker is an important equipment in electric system. The study on fault diagnosis of high voltage circuit-breaker would not only strengthens the security and stability of power system but also increases the economic benefit of it. Obtaining the diagnosis rules is the hardest part in building fault diagnosis expert system. This article analyses the fault samples data of high voltage circuit-breaker by rough set theory, and get diagnosis rules from it. The case shows the method is practical and feasible.

Keywords: *Fault Diagnosis, Circuit-Breaker, Rough Set, Greed Algorithm*

1. Introduction

HVCB (High Voltage Circuit-Breaker) is an important equipment in electric system and play the double task of control and protection on power grid. According to practical requirements of power grid, controllers put into or remove line and electric equipment by HVCB. When line or electric equipment occur faults, it can remove faulty part from power grid to guarantee the normal running of fault-free part. If HVCB can not open and cut line or insulate failure timely, it will make the accident enlargement or cause the dangerous of blackouts and so on. So the performance and reliability of HVCB are directly related to the safety and stability of power system. Studying on the fault diagnosis techniques of HVCB can not only contribute to know the working condition of HVCB and improve the safety and stability of power system, but also avoid the unnecessary maintenance and greatly increase economic benefits of power system [1].

2. The current situation and shortcoming of fault diagnosis of HVCB

The general faulty diagnosis system of HVCB only monitors one or some parameters of specific type of HVCB. On the basis of individual detection, how to judge the whole state of HVCB according to the characteristic parameters of it still lacks an effective method.

The emergence and development of fault diagnosis expert system is one of the most significant achievements of the field of fault diagnosis. In recent years, it is widely used in various fields. We look forward to the fault diagnosis expert system of HVCB should have fault tolerance and adaptive capacity, namely the diagnostic system is not only applicable to different types of HVCB, but also can amend their own knowledge base according to the knowledge gained in the diagnosis to ensure the completeness of knowledge[2] .

Expert system can mimic the decision-making process of expert, so it is ideal for the application of complex system, such as HVCB. However, to obtain a complete knowledge base is the key to build the fault diagnosis expert system. Rough set theory is an effective way to handle incomplete information. It has a strong ability of qualitative analysis. Using it to deal with the failure data of HVCB can easily find out the intrinsic link between its parameter and failure. So this contributes to build the expert system knowledge base of fault diagnosis.

3. Basic knowledge of rough set theory

In 1982, on the basis of relation theory, Z. Pawlak (professor of Warsaw University of Technology) and his collaborators presented a new mathematical theory to deal with imprecise,

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uncertain and incomplete data. This theory extended from traditional set theory. Base on the data, rough set theory can find data's intrinsic relationship and extract useful features to get the most simple expression of knowledge[3].

Generally speaking, knowledge is the summary and refined of practical experience, it has an abstract and universal, it is a general description of state of motion and the variation laws. The ability of category according to the characteristics of things is "knowledge". Let U is a non-empty finite set from the object we are interested. It is called a domain. Any subset of the domain ($X \subseteq U$), called a concept of U. Any subset cluster of U called the abstract knowledge of U, referred to as knowledge. To set a domain U and a cluster of equivalence relation(S), calling the two-tuples of K=(U,S) is a knowledge base or similar space of U. If $P \subseteq U$ and P is not the empty set, the intersection of all equivalence relations of P also is a equivalence relations. It is called indiscernibility relation on P, denoted by IND (P).

3.1 The attributes and decision table

The decision table is a special kind of knowledge representation system. The majority of decision-making problems can be expressed in the form of decision table. It plays an important role in the decision-making application. The role of decision table is classification and object discrimination by using the significant characteristics of knowledge.

General formal calling the four-tuples of DT= (U, $C \cup D$, V, f) is a decision table, including: U: U={x_1, x_2, …, x_n} is the non-empty finite set of object called the domain; $C \cup D$: C={α|α∈C} is called condition attribute set. Any $\alpha_j \in C$ (1≤j≤m) is called a simple attribute of C; D={d|d∈D} is called the decision attribute set and C∩D=Φ, C≠Φ, D≠Φ ; V : V=$\cup V_\alpha (\forall \alpha \in C \bigcup D)$ is the range of the information function of f, and f=$\{f_\alpha \mid f_\alpha : U \to V_\alpha, \forall \alpha \in C \bigcup D\}$ is the information function of decision table , f_α is the information function of property α. That is to say, the knowledge representation system of condition attribute and decision attribute is called decision table.

3.2 The knowledge reduction of decision table

A decision table contains a large number of sample information. The key step of intelligent information processing for the decision table is knowledge reduction. The so-called knowledge reduction is to remove unrelated or unimportant knowledge under the premise of maintaining the classification capabilities of the knowledge base does not change. For the decision tables, knowledge reduction is the process to remove the redundant attributes and attribute values and to obtain the minimal decision table and the minimum rules under the premise of maintaining the dependency between condition attributes and decision attributes of the original decision table does not change. After knowledge reduction, we will be able to reduce the computation and storage of information processing under the premise of not affecting the classification ability of decision table.

3.2.1 Discretization of continuous attributes

When using of rough set theory to deal with the decision table, the value of decision must be the form of discrete data. If the range of some condition and decision attribute is continuous values, we must make discretization at first. For discrete data, sometimes we also need to merge the discrete value and obtain the discrete value of the higher abstraction. Typically, discretization is that selecting number of split points on range of continuous property to divide the entire property into several sub-intervals and a symbol replace each sub-interval. Discretization of continuous attributes not only can reduce the computational complexity, but also suppress noise to some extent.

3.2.2 Attribute Reduction

A decision table is a decision-making information system. The table contains a large number of field samples, each sample represents a basic decision-making rules. We will get a set of decision rules, if setting out all decision-making rules. However, this decision rule is only mechanically recorded on each sample, adaptability, and can not meet the new situation. So this decision set is useless. In order to extract the rules of more fitness from the decision table, we need to reduce the decision table to make each record in the decision table represent a class sample with the same regularity properties. This decision rule only has adaptive.

3.3 Based on Greedy Algorithm for Knowledge Reduction

The core idea of greedy algorithm is that making the best choice in the current opinion when solving the problem. This algorithm obtains the optimum solution through the initial state and after a number of greedy selection. Each choice of Greedy algorithm is the optimal selection of each step. Its main method is top-down and iterative to make successive greedy choice. After each greedy selection, the original problem can simplified as smaller similar sub-problems comparing to the previous scale. The basic idea of using the greedy algorithm for solving as follows:
1. A mathematical to describe the problem;
2. Solving the problem into several sub-problems;
3. Solving each sub-problem in turn to get the local optimal solution of sub-problems.
4. Synthesizing the local optimal solution of sub-problem into a solution of the original question.

The advantages of the greedy algorithm is that the data discretization method based on the greedy algorithm can identify the property breakpoints under the premise of ensuring the no-distinguish relationship of system does not change. Attributes reduction method based on the greedy algorithm also can extract the important condition attributes from the sample set to achieve the attributes reduction of decision-making table. The idea of the algorithm is clear and easy to describe by using computer language.

4. Algorithm Simulation

Taking ZN42-27.5kV indoor vacuum circuit breaker fault samples for example, this paper will introduce the method of establishing fault diagnosis rules by Rough Sets Theory [4]. High voltage circuit breaker uses operating actuator's control contact to break or close the circuit. An action includes three stages-energy storage, closing operation and opening operation. We monitor it's current signal of opening and closing operating coil with Hall sensor. The current waveform of typical opening/closing operating coil is illustrated in Figure 1.

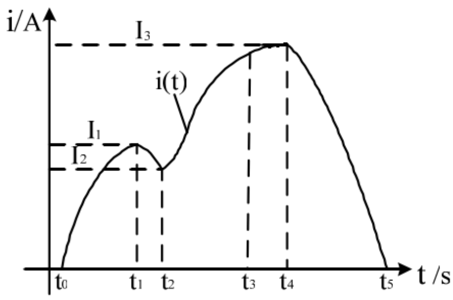

Figure 1. The current waveform of opening/closing operating coil

Table 1. The original decision table

U	I_1	I_2	I_3	D
X_1	1.61	1.11	2.23	1
X_2	1.62	1.17	2.18	0
X_3	1.61	1.21	2.28	0
X_4	1.62	1.13	2.21	0
X_5	1.62	1.09	2.26	1
X_6	1.61	1.13	2.26	1
X_7	1.63	1.15	2.21	0

Taking t0 as time zero, we measured three characteristic parameters of I1、I2 and I3. These three values can respectively reflect the information of supply voltage and coil resistant, as well as electromagnet core's movement. So, we chose these three values as condition attribute and took it that whether has "closed core jamming at the beginning（HKS）"fault as decision attribute. To select seven groups of data to build the original decision table, while D represents that the sample whether has any fault. If 1 means yes, while 0 means no. The original decision table is shown in Table 1.

4.1 Data Discretization

We are tend to seek out the minimum number of breakpoint-sets if do. With adopting discretization method based on the Greedy Algorithm to find the minimum number of breakpoint-sets, the concrete steps are as follows:

Step 1: According the original information table S to construct a new one S*=<U*, R*, V*, F*> ;

S* is such an information table, in which U*={ (x_i, x_j) $\in$U* U|d(x_i)≠d(x_j)}, and (x_i,x_j) is a new element generated by two samples which have different decision attribute. R*={ p_r^a |a $\in$C}, p_r^a is the r-th breakpoint of attribute a, that is to say, p_r^a is the mid-point of any two adjacent attribute points. For any p_r^a ,if $p_r^a \subseteq$[min(a(xi), a(xj)), max(a(xi), a(xj))], then p_r^a (a(x_i), a(x_j))=1, else p_r^a(a(x_i), a(x_j))=0.

Step 2: To initialize the best breakpoint set CUT=Φ ;

Step 3: To select the breakpoint which has the most number of 1 on all the columns from the information table and add it into CUT, then remove the column the breakpoint in, as well as all rows whose value is 1 of the breakpoint; If there is one more breakpoint's column that has the same number of 1,we compute the sum of the number of 1 exited in all rows whose value is 1 in the breakpoint column and chose the minimum one to add into CUT.

Step 4: If the information table S* is not empty, then go to Step 3, else stop. Now, CUT is the breakpoint-set we want. For the original decision table, we can get P_1^{I1}=1.615, P_2^{I1}=1.625, P_1^{I2}=1.10, P_2^{I2}=1.12, P_3^{I2}=1.14, P_4^{I2}=1.16, P_5^{I2}=1.19, P_1^{I3}=2.195, P_2^{I3}=2.22, P_3^{I3}=2.245, P_4^{I3}=2.27 according to this algorithm.

After discretization, we can get a decision table shown in table 2.

Table 2. The information table after discretization

U	I_1	I_2	I_3	D
X_1	1	0	1	1
X_2	1	1	0	0
X_3	1	1	1	0
X_4	1	0	0	0
X_5	1	0	1	1
X_6	1	0	1	1
X_7	1	1	0	0

4.2 Attribute Reduction

Attribute reduction based Greedy Algorithm has the similar steps to the discretization above, except for that there are some differences on the method of constructing information table S*, and the concrete steps are as follows:

Step 1: According the original information table S to construct a new one S*=<U*, R*, V*, F*> ; where U*={(x_i, x_j)∈U*U|d(x_i)≠d(x_j)} ; R*={ p_r^a |a $\in$C}, if a(x_i)≠a(x_j) , then a(x_i, x_j)=1, else a(x_i, x_j)=0.

Step 2: To initialize the best condition attribute set CUT;

Step 3: To select the condition attribute which has the most number of 1 on all the columns from the information table and add it into CUT, then remove the column the condition attribute in, as well as all rows whose value is 1 of the condition attribute; If there is one more condition attribute's column that has the same number of 1, we compute the sum of the number of 1 exited in all rows whose value is 1 in the condition attribute column and chose the minimum one.

Step 4: If the information table S* is not empty, then go to Step 3, else stop. Now, CUT is the condition attribute-set we want.

After discretization, we can get a new information table shown in table 3.

Table 3. Attribute reduction information table

U	I_1	I_2	I_3	SUM
(x_1,x_2)	0	1	1	2
(x_1,x_3)	0	1	0	1
(x_1,x_4)	0	0	1	1
(x_1,x_7)	0	1	1	2
(x_2,x_5)	0	1	1	2
(x_2,x_6)	0	1	1	2
(x_3,x_5)	0	1	0	1
(x_3,x_6)	0	1	0	1
(x_4,x_5)	0	0	1	1
(x_4,x_6)	0	0	1	1
(x_5,x_7)	0	1	1	2
(x_6,x_7)	0	1	1	2
SUM	0	9	9	

Applying the above method to complete the mathematical reduction, we can get the simplest decision-making information table shown in table 4:

Table 4. The decision-making information table after attribute reduction

U	I_2	I_3	D
X_1, X_5, X_6	0	1	1
X_2, X_7	1	0	0
X_3	1	1	0
X_4	0	0	0

5. Conclusion

We get the diagnostic rules from using Rough Set Theory to process the fault sample data, then just according to the two attributes, I_2 and I_3, detect the high voltage circuit breaker and check it whether has any fault of “closed core jamming at the beginning”. This paper using Rough Set Theory on building the diagnostic knowledge base is an attempt. The attribute reduction method based on the greedy algorithm has clear thinking and clear steps. So, it can be easily described by computer language. If it can be implemented by using a computer program that can process a large number of data, which is convenient for us to pick up the diagnostic rules and all the above is helpful to build the fault diagnose expert system knowledge base. It has a good promotion and application value that using the method based fault samples builds the diagnostic rules.

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