Application of Weighted Degree of Grey Incidence of Optimized Entropy and KFCM for Fault Diagnosis of Circuit Breaker

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Keywords: Weighted degree of grey incidence; KFCM; High-Voltage Circuit Breakers; Fault Diagnosis

Abstract. With the development of power grid, electrical equipment is required to be more and more intelligent. In this paper, a fault diagnostic method combining weighted degree of grey incidence of optimized entropy algorithm and Kernel Fuzzy Cluster Method(KFCM)is proposed. By extractingcharacteristic values of the currentsignals of different main fault types, fault database of the currentsignals can be established. KFCM is utilized to train fault samples of current signals to form the reference sequence.The testing data is regarded as the comparison sequence. Meanwhile, weighted degree of grey incidence of optimized entropy algorithm is utilized to calculate the correlation degree between the two sequences.Finally the fault type of circuit breakers is identified based on the correlation degree. Experiments have proved that this method achieves perfect results in diagnosing main mechanical faults of circuitbreakers.

Introduction

High voltage circuit breakers (HVCBs) are important switchgear of power system and play a key role in the control and protection of the power line. Condition-based maintenance is the development tendency. Online monitoring and fault diagnosis of HVCBs can provide equipment's status information, which is ofgreatguiding significance to enact maintenance plans.Due to the complexity of circuit breakers,status parameters of circuit breakers cannot becomprehensively identified.As an algorithm to handle uncertain problems, degree of grey incidence can be appliedtoanalyze poor information systems.Therefore, weighted degree of grey incidence of optimized entropy algorithm is usedin this paper to recognize faults of circuit breakers,which has achieved good results.

Weighted Degree of Grey Incidence of Optimized Entropy Algorithm

Weighted Degree of Grey Incidence The main idea of grey incidence is to determine whether the relationship betweensequence curves is close according to the similarity of their geometry shape.The aim is to displaythe correlation between the factors quantitatively. Incidence analysis is the basis for grey system analysis and forecast.

A general definition of grey incidence is as follow: assuming a reference sequence named $X_0=(x_0(t)|t=1,2,\ldots,n)$ and m comparison sequencenamed $X_i=(x_i(1)|\ t=1,2,\ldots,n)$, $i=1,2,\ldots,m$, then

$$\gamma\left(x_0(k),\ x_i(k)\right)=\frac{mm+\varepsilon\cdot MM}{|x_0(k)-x_i(k)|+\varepsilon\cdot MM} \tag{1}$$

$$\gamma(X_0,X_i)=\sum_{k=1}^{n}\omega_k\gamma(x_0(k),x_i(k)) \tag{2}$$

is the correlation coefficients of the reference sequence for the comparison sequence at time

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k,where $mm = \min_i \min_k |x_0(k) - x_i(k)|$ is calledthe two-stage minimum differential, $MM = \max_i \max_k |x_0(k) - x_i(k)|$ is called the two-stage maximum differential, $\varepsilon \in [0, +\infty)$ is the resolution factor, ω_k is the weight of the k point and $\sum_{k=1}^{n} \omega_k = 1$.

Determining the Weights In the past,equal weighted factors are used to calculate grey incidence. However, correlation coefficientsof each sequence at different time are of different importance to the system.Therefore, the weighted correlation coefficient optimization model is ought to be established to determine the weight of correlation coefficients. Function (3) is the weighted grey relation entropy for Xi,where p_k is the density value of weighted grey incidence factors.

$$H \otimes (R_i) = -\sum_{k=1}^{n} p_k \ln p_i \tag{3}$$

$$P_k = \frac{\omega_k \gamma(x_0(k), x_i(k))}{\sum_{k=1}^{n} \omega_k \gamma(x_0(k), x_i(k))} \tag{4}$$

Assuming that the density sequence of weighted grey incidence coefficients is $P = \{p_k \mid \forall k, p_k \geq 0, \sum_{k=1}^{n} p_k = 1\}$ and correlation entropy is $H \otimes (R_i)$, then any change that tends to equalize p_k will increase the incidence entropy. In grey incidence analysis, grey incidence coefficients reflect the impact of each point of comparison sequenceon referencesequence.And inside the grey system comparison sequence, comparison sequence has a constant effect on reference sequence. Therefore, the identification of the weight of incidence coefficients ω_k can make the distribution density value of weighted grey incidence coefficients p_k approach equilibrium. The maximization constraint of weighted grey incidence entropy $H \otimes (R_i)$ is

$$\max\ H \otimes (R_i) = -\sum_{k=1}^{n} p_k \ln p_i \tag{5}$$

$$\text{s.t.}\ \sum_{k=1}^{n} \omega_k = 1, \omega_k \geq 0, k = 1, 2, \cdots, n \tag{6}$$

Construct Lagrangian function is

$$L(p_k, \lambda) = -\sum_{k=1}^{n} p_k \ln p_k + \lambda(\sum_{k=1}^{n} p_k - 1) \tag{7}$$

Then obtain weight vector under the maximization constraint of weighted grey incidence entropy which is,

$$\Omega = \Gamma^{-1} b \tag{8}$$

where

$$\Gamma = \begin{bmatrix} \gamma_1 & -\gamma_2 & & & \\ & \gamma_2 & -\gamma_3 & & \\ & & \ddots & & \\ & & & \gamma_{n-1} & \gamma_n \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}, \quad \Omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_{n-1} \\ \omega_n \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}.$$

Basic Principle of KFCM algorithm

Assuming that $X = \{x_1, x_2, \cdots, x_n\}$ is a set of data sample. At first, through nonlinear mapping $\Phi : \chi \to F$, input space χ is changed to high dimensional feature space F, where the clustering is conducted. The objective function of KFCM algorithm is

$$J_m(U,v)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}\left\|\phi(x_k)-\phi(v_i)\right\|^2 \tag{9}$$

where, $v_i(i=1,2,\cdots,c)$ are the clustering centers of the input space, c is the sort number, $U=\{u_{ik}\in[0,1]\}_{c\times n}$ is fuzzy dividing matrix, u_{ik} is membership degree of the k-th sample for the i-th class and meets $0\le u_{ik}\le 1$,and $0<\sum_{k=1}^{n}u_{ik}<n$ with the constraint $\sum_{i=1}^{c}u_{ik}=1,\forall k=1,2,\cdots,n$, where m is the fuzzy control index, controlling the clustering's fuzzy degree. $\left\|\phi(x_k)-\phi(v_i)\right\|^2$ represents the distance between x_k and the center v_i n the feature space after original data x_k is mapped by ϕ i.

Gaussian function is used as a kernel function:

$$K(x_k,v_i)=\exp[-\left\|x_k-v_i\right\|/(2\sigma^2)] \tag{10}$$

The specific process of KFCM algorithm is as follows:

Initial settings: obtain clustering sort number c; set iterative stop threshold value ε; initiate each clustering center v_i;

Step 1: Classification matrix $U^{(b)}$ is obtained after membership degree is renewed.Formulas are as follows:

$$u_{ik}^{(b)}=\frac{\left[\frac{1}{K(x_k,x_k)+K(v_i^{(b)},v_i^{(b)})-2K(x_k,v_i^{(b)})}\right]^{\frac{1}{m-1}}}{\sum_{j=1}^{c}\left[\frac{1}{K(x_k,x_k)+K(v_i^{(b)},v_i^{(b)})-2K(x_k,v_i^{(b)})}\right]^{\frac{1}{m-1}}} \tag{11}$$

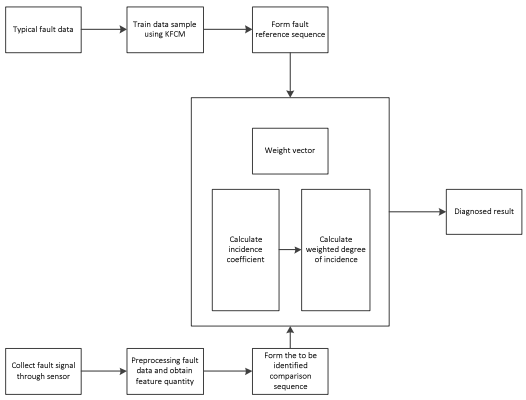
Step 2: The clustering center matrix $V^{(b+1)}$ is obtained after each clustering center is renewed.Formulas are as follows:

$$V_i^{(b+1)}=\frac{\sum_{k=1}^{n}(u_{ik}^{(b)})^m K(x_k,v_i^{(b)})x_k}{\sum_{k=1}^{n}(u_{ik}^{(b)})^m K(x_k,v_i^{(b)})} \tag{12}$$

Step 3: If $\left\|V^{(b)}-V^{(b+1)}\right\|<\varepsilon$, the algorithm comes to the end, with classification matrix U and clustering center V as a result. Otherwise, let b=b+1, and turn to step 1.

Fault Diagnosis Algorithm Based on Weighted Degree of Grey Incidence of Optimized Entropy

In order to use this model to diagnose circuit breakers' fault, the corresponding fault diagnosis system is designed, shown in Figure 1. The system consists of data acquisition and processing module, reference sample training moduleand fault diagnosis module.The system can be directly connected tothe circuit breakers' sensors for online real-time monitoring and fault diagnosis of circuit breakers. Data acquisition and processing module aremainly responsible in collecting data byusing sensors, and preprocessing the data by filtering, de-noising and so on. After that, the reference sequence is formed by obtaining signal's characteristic value. Reference sample training module mainly uses KFCM algorithm to train various typical fault data in the database of circuit breakers, thereby a comparison sequence is composed by the various types of fault.Fault diagnosis module uses mode based on weighted degree of grey incidence l to make the circuit breakers' status data collected asthe reference sequence. Also, it makes the set of fault samples gained by training as the comparison sequence. The correlation degree can be gained and sorted after calculation of weighted degree of grey incidence between the reference and comparisonsequence. Finally, the fault type of the greatest correlation degree can be considered as the diagnosis fault.This system features advantages such aslow module coupling degree and high calculation speed, etc.



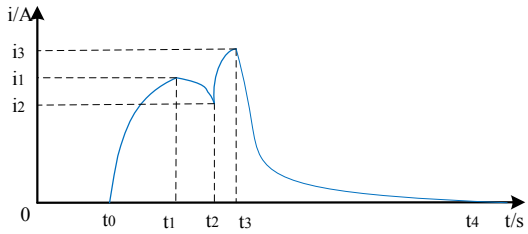


Fig.1 Frame map of fault diagnosisFig.2 waveform of opening current signal

Open Fault Case Analysis

HVCBs produce obviouswaveformof closing coil current and charging motor current during opening and closing process, which can show the operating state of circuit breakers' operating mechanism.Choosing the characteristic parameters lays a foundation for fault identification. A typical opening current curve is shown in Figure 2.To divide the curve into four stages, $t_0$is used as a starting point. There are three current extreme points and seven feature parameters in total $\{t_1,t_2,t_3,t_4,i_1,i_2,i_3,\}$.

In order to verify the effectiveness of weighted degree of grey incidence of optimized entropy algorithm, MATLAB is used to analyze a specific problem. Processes are: a) According to different fault types with KFCM algorithm, typical opening fault data is classified and the clustering centers are calculated; b) The reference sequenceis formedby the clustering centers of different fault types and the comparison sequence is formed by the data to be diagnosed, after which, the weighed degree of grey incidence between these two sequences is calculated; c)According to the degree calculated above, the fault type of data is identified.

Select 40 sets of typical fault data samples from the substation fingerprint database, which contains normal data and common types of fault such as core jam, too low coil voltage, too long core idle stroke and so on. These samples are used as training samples;the data is shown in Table 1. Aftercalculated by KFCM algorithm, the data are accurately classified into 4 types, which is consistent with the actual situation. And 4 clustering centers are obtained, shown in Table 2, corresponding to normal state, the core jam, too low coil voltage and too long core idle stroke.These 4 clustering centers are used as reference sequence and a set of state data are obtained: 12.36, 23.72, 28.44, 72.72, 1.74, 1.45, 2.06, which is used as comparison sequence to calculate and to diagnose fault. The obtained incidence coefficients are shown in Table 3 while the weighted vectors are in Table 4.Finally, according to weighted degree of grey incidence of optimized entropy algorithm, the weight incidence degree are $\gamma(X0,X1)= 0.5504$, $\gamma(X0,X2)= 0.5787$, $\gamma(X0,X3)= 0.7171$, $\gamma(X0,X4)=0.5757$. It can be observed that weight incidence degree of X0 and X3 are the largest and are diagnosed as the third state, which is too low coil voltage. At the same time, it is in full compliance with the real data collected.

Tab.1 Forty sets of fault data

NO.	t1	t2	t3	t4	i1	i2	i3
1	11.88	18.24	22.36	67.36	1.71	1.43	2.08
2	11.8	18.04	22.42	67.04	1.7	1.43	2.06
3	11.92	18.2	22.36	66.96	1.71	1.41	2.07
4	12.16	18.12	22.42	67.28	1.7	1.44	2.05
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
39	11.8	18.24	22.2	66.32	1.43	1.1	1.61
40	11.72	18.2	22.16	66.04	1.44	1.12	1.59

Tab.2 The clustering centers of fault data

NO.	t1	t2	t3	t4	i1	i2	i3
1	11.95	18.14	22.31	67.24	1.70	1.43	2.07
2	11.70	18.20	22.23	66.23	1.46	1.12	1.61
3	12.32	23.73	28.54	72.71	1.71	1.44	2.08
4	11.72	20.21	22.95	68.20	1.72	1.45	2.09

Tab.3 Conjunction coefficient

γ(x0,x1)	γ(x0,x2)	γ(x0,x3)	γ(x0,x4)
0.8867	0.9023	0.6350	0.8130
0.3559	0.4026	1.0000	0.4392
0.3347	0.3732	0.3883	0.3338
0.3600	0.3623	0.9347	0.3785
0.9909	1.0000	0.7555	0.9956
0.9959	0.9858	0.9641	1.0000
1.0000	0.9536	0.8473	0.9899

Tab.4 Weighted vector

ω(x0,x1)	ω(x0,x2)	ω(x0,x3)	ω(x0,x4)
0.0887	0.0916	0.1613	0.1012
0.2210	0.2054	0.1025	0.1872
0.2350	0.2216	0.2638	0.2464
0.2184	0.2282	0.1096	0.2173
0.0794	0.0827	0.1356	0.0826
0.0790	0.0839	0.1063	0.0822
0.0786	0.0867	0.1209	0.0831

To further verify the accuracy of diagnostic system, we select 50 sets of fault samples belonging to 4 states, which contain 9 sets of normal state, 23 sets of too low core jam, 10 sets of too low coil voltage and 8 sets of too long idle stroke.According to the proposed method, the simulation results are shown in Table 5, from which it can be found out that the faultdiagnosis rate accuracy is more than 96%. Thus, the method proposed in this paper can accurately identify the type of fault, with high reliability and stability.

Tab.5 Diagnostic results

State ID	Actual fault	Diagnostic results	Misdiagnosis number	Number missed
F1	9	10	1	0
F2	23	21	0	2
F3	10	11	1	0
F4	8	8	0	0

Conclusion

Aiming at the shortages of traditional grey incidence analysis method, weighted degree of grey incidence of optimized entropy algorithmis applied to identify circuit breakers' fault, achieving good results. Experiments show that the model is simple, reliable, high stabilityand suitable for fault diagnosis with insufficient training samples.This fault diagnosis method canbe used not only in online diagnostic system and offline fault analysis of breakers, but also in providing decision basis for breakers' condition-based maintenance.in the future, the algorithm proposed can be improved by multi-parameter mix or combination with other diagnostic methods.

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