A Model-Based Fault Detection Framework for Vacuum Circuit Breaker by Trip Coil Analysis

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***Abstract*—Vacuum circuit breaker becomes more and more complicated, integrated, high-speed and intellectualized. To insure vacuum circuit breaker in its good conditions, the function of fault diagnosis gets more important than before in the process of repairing. This paper is addressed a model-based fault detection framework for vacuum circuit breaker by trip coil analysis. At first, the electromagnetic model of the trip coil is built. Secondly, algorithm of abrupt changes detection and dynamic time warping algorithm is introduced. At last, value comparison between the similarity and the threshold concludes whether a fault has occurred or the trip coil has potentially hazardous effects. The experimental results show that this method is effective.**

***Index Terms*—Vacuum Circuit Breaker (VCB), Fault Diagnosis, Dynamic Time Warping (DTW)**

I. INTRODUCTION

Circuit breakers must be fully operational and available at all times. Now circuit breakers are the important system protection assets which should be in condition assessment and performance monitoring. Therefore, any risk of dangerous situations could be surely reduced. In such complex system of vacuum circuit breaker, fault diagnosis plays a vital role. A fault in a system will lead to economic losses. Therefore, fault diagnosis must be done correctly and efficiently. Fault diagnosis is performed when a vacuum circuit breaker is malfunctioning and is to determine the cause responsible for a set of observed symptom [1-3]. One practical predictive maintenance approach is based on the trip coil current.

The trip coil is an electromagnetic actuator which when energized causes an armature to strike and release the trip latch. It can be seen therefore, that while current flowing through the coil affects a force upon the armature, the movement of the armature through the coil generates an electromagnetic field in the coil, which in turn has an effect upon the current flowing through it [4]. The method identifies the critical time instants in the trip coil current, to be used for diagnostic analysis [6-7]. The shape of the coil current characterizes the operating health of the breaker to a greater extent. The shape is influenced by both the electrical parameters of the control circuit and the mechanical movement of the armature. The characteristic behavior of the trip coil in a circuit breaker must be analyzed and modeled before the trip coil can be predictive maintenance. [8-10]

We address a model-based fault detection framework for vacuum circuit breaker by trip coil analysis in this paper. At first, we build the electromagnetic model of the trip coil. Secondly, we introduce the algorithm of abrupt changes detection to get the key points and the DTW algorithm to compute the similarity value of the trip coil current between the test data and the theoretical results. At last, if the similarity value is larger than the threshold value, comparison concludes that a fault has occurred or the trip coil has some potentially hazardous effects. The results of experiment show the diagnosis methodology is accurate and reliable. Such a model-based fault detection framework helps to increase the reliability and availability of the vacuum circuit breaker by reducing the number of shutdowns that are necessary for systematic maintenance.

II. THE DYNAMIC MODEL OF TRIP COIL

The electrical schematic of the ideal trip coil is given in Fig.1. The trip coil has an inductance $L(x)$ and a resistance R. The voltage u applied to the coil results in a current i governed by the differential equation [3-4]. The trip coil has an inductance $L(x)$ and a resistance R in series. The voltage u is applied to the coil results in a current i governed by the equations (1)-(4). The dynamic model of the trip coil in a vacuum circuit breaker is presented by means of solving these functions. Table 1 is these variables in representation.

Manuscript received May 10, 2013; revised June 15, 2013; accepted July 20, 2013.

doi:10.4304/jsw.9.1.251-257

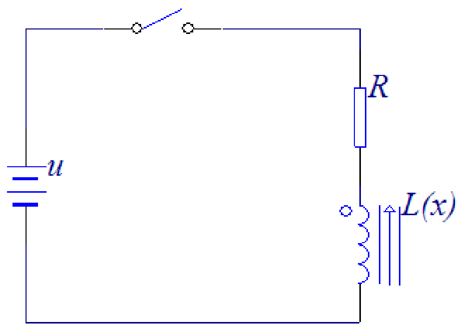


Figure.1 An electrical schematic of the ideal trip coil.

TABLE I.
VARIABLES REPRESENTATION IN THE DYNAMIC MODEL OF TRIP COIL

Variables	Variables Representation
x	an effective displacement of the armature
$L(x)$	inductance of the trip coil with the armature displacement x
R	resistance of the trip coil
i	the trip coil current
u	supply voltage of the trip coil current
m	mass of the armature
k	coefficient of the spring rigidity
F_e	electrodynamic force of the trip coil
v	the armature velocity
a	the armature acceleration
f_0	the friction force of the armature movement
t_0	the time when supply voltage u being applied
t_1	the time when the coil current starts rising
t_2	The time that end of armature movement

$$u = Ri + L(x)\frac{di}{dt} + vi\frac{dL(x)}{dx} \quad (1)$$

The balance equation of forces acting on the armature of a mass *m* is as follows:

$$F_e - kx - f_0 = m\frac{dv}{dt} \quad (2)$$

$$F_e = \frac{1}{2}i^2\frac{dL(x)}{dx} \quad (3)$$

$$\frac{dx}{dt} = v \quad (4)$$

The simulation of the close coil is performed by means of the Matlab 2012 with Simulink(Fig. 2). A simulation model is made in Simulink basing on Equ.1-Equ.4. This model is used to simulate the mathematical model of the close coil. The simulation results in obtaining time curves of the coil current *i*. The course of current *i* changes over time displays the way in which the electromagnetic force of the coil is controlled. The simulation curve is shown in Fig.3.

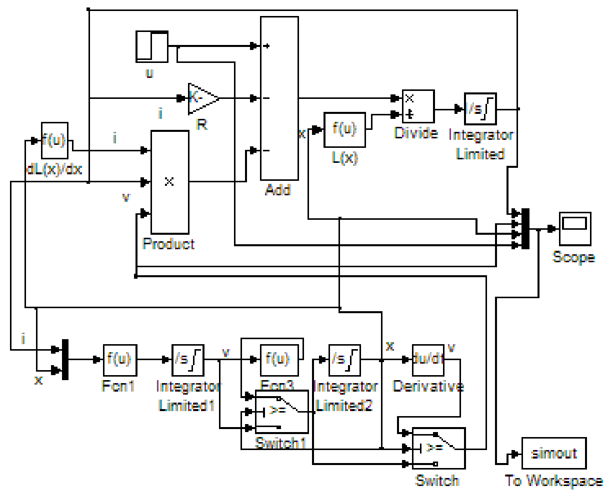


Figure.2 Simulation model

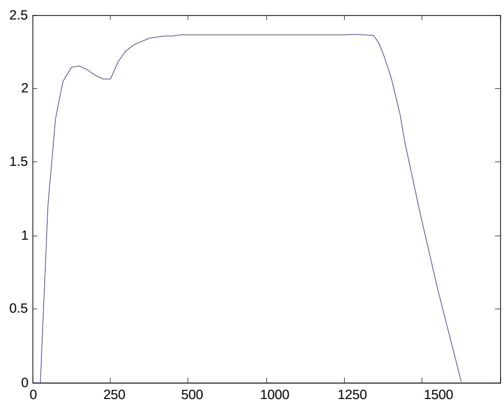


Figure.3 Result of simulation

III. A MODEL-BASED FAULT DETECTION FRAMEWORK

The problem of fault detection for a trip coil in VCB involves two aspects. Firstly, the detection of failures should be achieved. Secondly, the detection of smaller faults, which affect a trip coil without causing it to stop. And this is also required to prevent the subsequent faults. Both faults and failures in a trip coil can be approached in the abrupt change detection [11-12]. Algorithm of abrupt changes detection is the core of the fault detection framework.

Algorithm of abrupt changes detection is a powerful new tool for determining whether a change has taken place. It is capable of detecting subtle changes by three steps, which are data smoothing, change-point detection, and potential hazards detection. Data smoothing is used to eliminate "noise" and extract real trends and patterns of the trip coil current. Change-point detection is to discover time points at which properties of the trip coil current change. Finally, potential hazards detection is to scan for potential hazards of the trip coil and accidents in a vacuum circuit breaker can be avoided.

A. Data Smoothing

An input sampling sequence of the trip coil current with a fixed sampling rate is $i = \{i_1, i_2, \ldots, i_t\}$. Data smoothing produces a "smooth" set of values from the trip coil current which has been contaminated with noise. The LOWESS smoothing is introduced in this abrupt changes detection. LOWESS smoothing is an improvement over least squares smoothing when the data are not equally spaced. The following is a brief sketch of the LOWESS algorithm [13-15].

- **Step1:** Choose a fraction f of the data points which is to be used for computation of each fitted value. Let b be the nearest integer to $f.t/2$ where t is the size of the data i. In other words, $2.b$ is the number of points around each element of i, to be used for fitting. We choose f=0.01.
- **Step2:** Let d_i be the distance from i_x to its b_{th} nearest neighbor along the i axis and T be the weight function. Then the weight w_k given to the point (k, i_k) when computing a smoothed value at i_x, is as follows:

$$w_k = T\left(\frac{x_i - x_k}{d_i}\right), T(u) = \begin{cases} (1-|u|^3)^3, & |u| < 1 \\ 0, & |u| \geq 1 \end{cases} \tag{5}$$

- **Step3:** To compute the fitted value at i_x weighted least squares fit is obtained.

$$b_{estimate} = \frac{\sum w_x^2 (2x - t - 1)(k - \bar{i})}{2\sum w_x^2 (k - \bar{i})^2} \tag{6}$$

$$a_{estimate} = \bar{i} - \frac{1}{2} b_{estimate}(t+1) \tag{7}$$

$$i_x^s = a_{estimate} + b_{estimate} i_x \tag{8}$$

And the smoothing set is $i^s = \{i_1^s, i_2^s, \ldots, i_t^s\}$.

B. Change Points Detection (CPD)

We now describe the Change Points Detection (CPD) process that guarantees that the required change points are got. In the proposed method, we have selected extrema information as the feature vector. To reduce the detection time, the extrema are extracted from the smoothed data. This procedure consists of three components, one accounting for the finding extrema process, one accounting for computing Euclidean distances among all extrema and the other accounting for the clustering problem of the Euclidean distances.

In the first component, we want to determine all extrema of given trip coil current data. To do this, we use Golden Section Search, which is an elegant and robust method of locating all extrema in trip coil current data. The book [16] is shown that this method is available for use. We can get the set of extrema

$i^e = \{\cdots, i_j^s, i_k^s, \cdots, i_p^s, i_q^s, \cdots\}$.

In the second component, we compute Euclidean distances between two of closet extrema. For example, in time p, the Euclidean distance between i_p^s and i_q^s is d_p.

$d_p = \sqrt{(p-q)^2 + (i_p^s - i_q^s)^2}$.

And we can get the set of Euclidean distances

$d = \{\cdots, d_j, \cdots, d_p, \cdots\}$.

In the third component, in order to detect the key change points, the set of Euclidean distances d is processed using clustering method. Euclidean distances d are grouped into two clusters: "change points" and "normal points". K-Means is a rather simple but well known algorithm for grouping objects, clustering. Using the kernel K-Means clustering algorithm, the elements in d are clustered into "change points" cluster i_{cp} and "normal points" cluster i_{np}.

$$i_{cp} = \{\cdots, d_p, \cdots\} \xrightarrow{p} \{\cdots, i_p, \cdots\}$$

$$i_{np} = \{\cdots, d_j, \cdots\} \xrightarrow{j} \{\cdots, i_j, \cdots\}$$

The Change Points Detection algorithm is illustrated in Table 2.

C. Dynamic Time Warping Fault Detection

Dynamic time warping (DTW) is an algorithm for measuring similarity between two sequences which may vary in time or speed. DTW has been applied for the data which can be turned into a linear representation. And DTW can be used in partial shape matching application. For details of DTW algorithm, please see [17-18].

Suppose we have two current series, an input sequence Q of length n, and a temple sequence C of length m, where

$Q = q_1, q_2, \ldots, q_i, \ldots, q_n$

$C = c_1, c_2, \ldots, c_j, \ldots, c_m$

To align these two sequences using DTW, we first construct an n-by-m matrix where the (i_{th}, j_{th}) element of the matrix corresponds to the squared distance,

$$d(q_i, c_j) = (q_i + c_j)^2 \tag{9}$$

which is the alignment between points q_i and c_j. To find the best match between these two sequences, we retrieve a path through the matrix that minimizes the cumulative total distance between them. In particular, the optimal path is the path that minimizes the warping cost

$$Path(Q,C) = \min\left\{\sqrt{\sum_{k=1}^{K} w_k}\right. \tag{10}$$

Where w_k is the matrix element $(i,j)_k$ that also belongs to k_{th} element of a warping path, a contiguous set of matrix elements that represent a mapping between Q and C.

This warping path can be found using dynamic programming to evaluate the following recurrence

$$r(i,j) = d(i,j) + \min\{r(i-1, j-1), r(i-1, j), r(i, j-1)\}$$

where $d(i,j)$ is the distance found in the current cell, and $r(i,j)$ is the cumulative distance of $d(i,j)$ and the minimum cumulative distances[19-21].

In this type of fault detection technique, the theoretical data is converted to templates. The diagnosis process consists of matching the test data with stored templates. A fault is detected if the distance is larger than the threshold value. The distance is based upon dynamic programming. This is called the DTW fault detection.

The implementing processes of the fault detection method are illustrated in Fig 4.

TABLE II.
CHANGE POINTS DETECTION ALGORITHM

Step	ALGORITHM : Change Points Detection
1:	**Input:**
2:	trip coil current *i;*
3:	**Output:**
4:	change points i_{cp};
5:	**Functions:**
6:	LOWESS smoothing function: LOWESS()
7:	Locating all extrema function: extrema ()
8:	Computing Euclidean distances function: Euclidean ()
9:	K-Means clustering function: K-Means ()
10:	**Algorithm:**
11:	Smoothed Data i^s= LOWESS(i);
12:	Smoothed Data extrema i^e= extrema (i^s);
13:	Euclidean distances d= Euclidean(i^e);
14:	change points i_{cp} = K-Means (d);

IV. EXPERIMENT

The experimental system includes hardware composition and software system used for trip coil current signal acquisition and fault detection software. The system offers PC-Based oscilloscope that have the performance and features necessary to monitor trip coil current waveform data.

ACS712 is a linear current sensor. The device consists of a precise, low-offset, linear Hall sensor circuit. Applied current flowing through this copper conduction path generates a magnetic field which is sensed by the integrated Hall IC and converted into a proportional voltage. Device accuracy is optimized through the close proximity of the magnetic signal to the Hall transducer. A precise, proportional voltage is provided by the low-offset, chopper-stabilized BiCMOS Hall IC, which is programmed for accuracy after packaging. The output of the device has a positive slope when an increasing current flows through the primary copper conduction path, which is the path used for current sensing.[22]

The data acquisition platform uses DSO3064 digital oscilloscope which has 4 Channels Oscilloscope,60MHz Bandwidth, 200MS/s sampling rate and 10k--16M memory depth. The software environment consists of Matlab and a newly developed fault diagnosis library. (Fig.5)

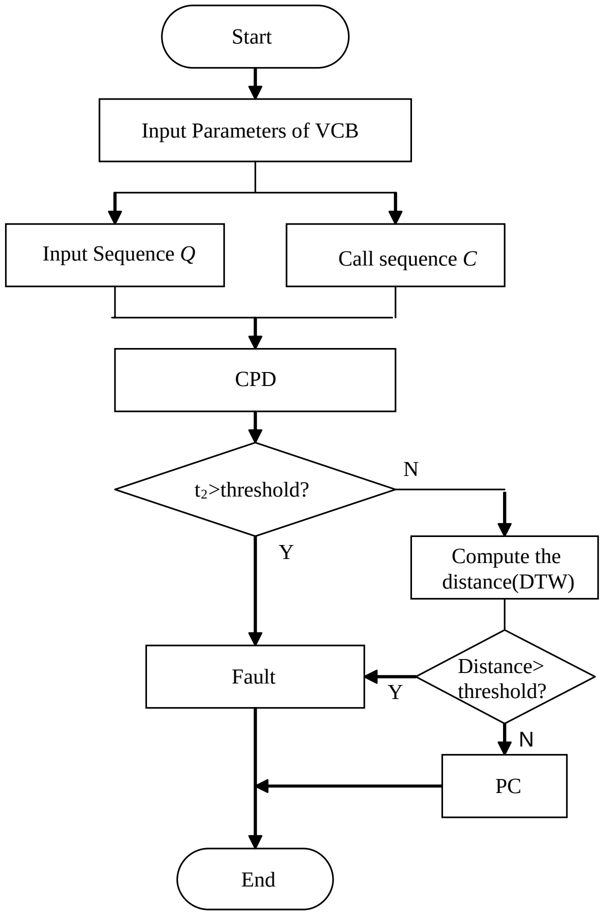


Figure.4 the implementing processes of the fault detection method

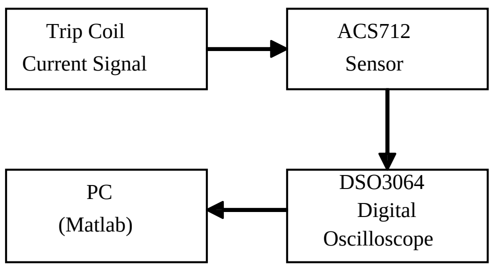
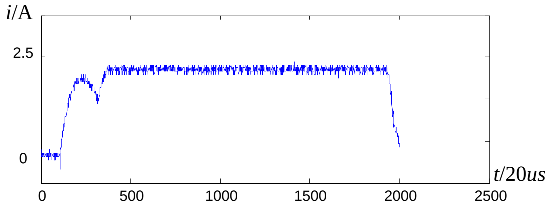


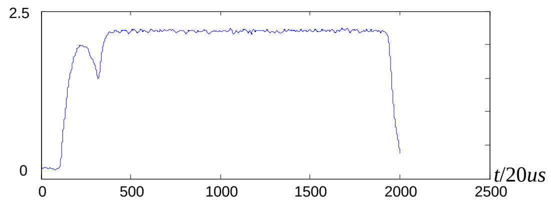
Figure.5 Experimental system

A. Change Points Detection Experiment

We sample the sequence of the trip coil current with a fixed sampling rate 50 kHz. The sequence is shown in Fig. 6(a). In this sequence, the true signal amplitudes changes rather smoothly as a function of the time values, whereas many kinds of noise are seen as rapid, random changes in amplitude from point to point within the signal. We attempt to reduce the noise by LOWESS smoothing. In this smoothing, the sequence of the trip coil current is modified so that individual points that are higher than the adjacent points are reduced, and points that are lower than the adjacent points are increased. This leads to a smoother sequence and it is shown in Fig. 6(b).



(a) the sequence of the trip coil current



(b) the smoother sequence of the trip coil current

Figure.6 LOWESS smoothing

The CPD algorithm requires the identification of all local extrema in the smoother sequence. Fig.7 shows performance results of the algorithm for identification of extrema.

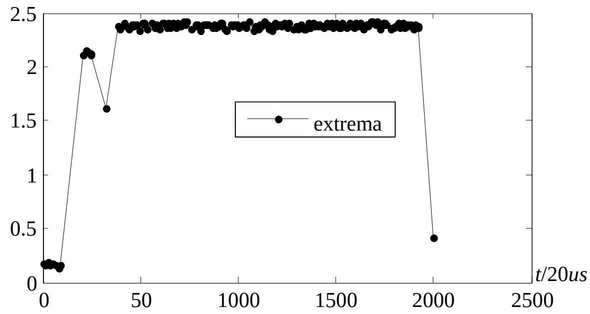


Figure.7 Identification of extrema

By computing the Euclidean distances between these extrema, we obtain the distance sequence shown in Fig.8.

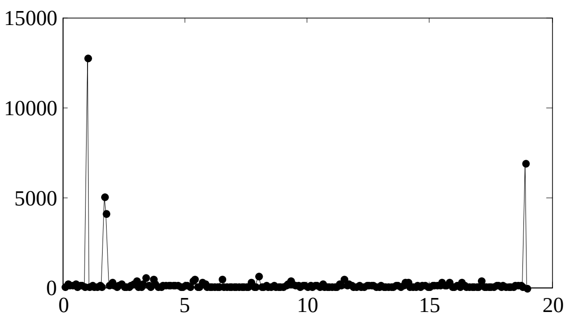


Figure.8 Distance sequence

Cluster distance sequence into two disjoint subsets which are shown in Fig.9.We get the key points in the sequence of the trip coil current by the change point's subset in Fig.10.

B. DTW Fault Detection Experiment

This experiment presents the analysis of current signals to identify and quantify common faults from a trip coil based on DTW algorithm. Experimental data sets of normal signal and abnormal signal have been studied using DTW algorithm. We can obtain better fault detection and diagnosis results, as depicted in Fig. 11 and 12. Results show that the method is effective.

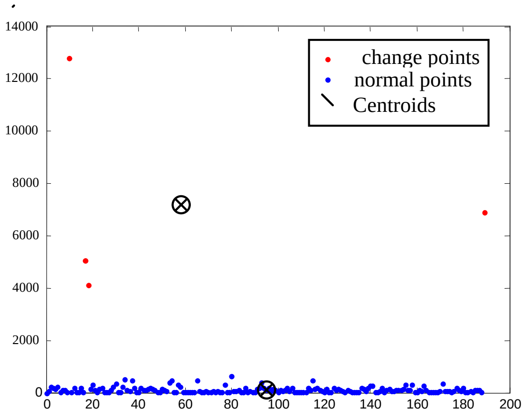


Figure.9 K-Means Clustering

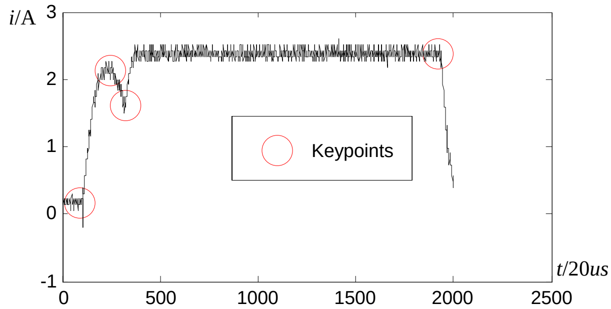


Figure.10 the key points in the sequence of the trip coil current

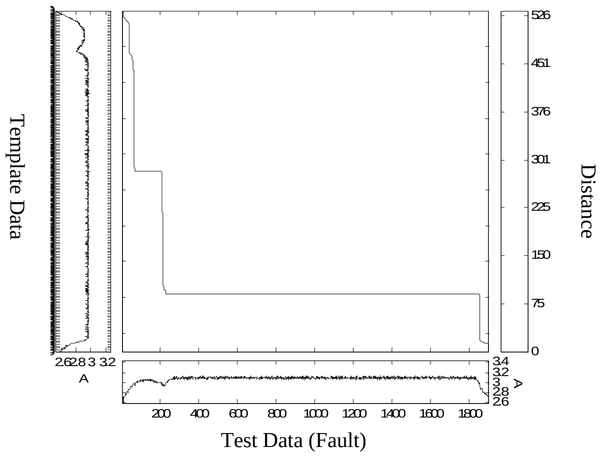


Figure. 11 Abnormal signal

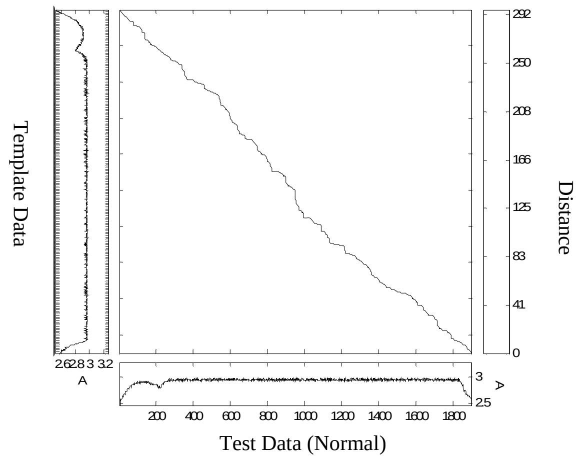


Figure. 12 Normal signal

V. CONCLUSIONS

This paper summarizes the key features of the model-based fault detection framework for vacuum circuit breaker and the methodology scheme is proposed. At first, the mathematical model has been developed for the dynamic characteristics of the close coil. The results of simulation show that the accuracy of the dynamic-state model equations is satisfactory. Secondly, the algorithm of change points detection for applications in fault detection for a trip coil is presented. The algorithm includes three parts which are data smoothing, extrema search and K-Means clustering. Fault analysis processing is based on dynamic time warping technology. Thirdly, fault analysis processing is based on dynamic time warping technology and the change points detection algorithm. Experimental results prove the effectiveness of the methodology in the vacuum circuit breaker fault detection.

ACKNOWLEDGMENT

This project is funding by Appropriative Researching Fund for Professors and Doctors, Guangdong University of Education (No. 11ARF04). This project is funding by ministry of education of China (MCM20121051), higher school science and technology innovation project of Guangdong Province (No. 2012KJCX0079), Economic and Information Technology Commission Project of Guangdong Province (No. GDEID2011IS064) and Dongguan City (No.DG201101).

REFERENCES

[1] B.V.Klimenko, "The control of polarized bistable electromagnetic actuators of medium voltage vacuum circuit breakers", *Russian Electrical Engineering*, Vol.83, pp.243-248, May 2012.

[2] Y. Luo, X. Duan and Z. Tian, "Status Monitoring and Digital Communication of the Intelligent Vacuum Circuit Breaker in Smart Grid", *Journal of Computational Information Systems*, Vol. 21, pp.8707-8715, August 2012.

[3] S. M. Strachan, S. D. J. McArthur, B. Stephen, J. R. McDonald and A. Campbell, "Providing Decision Support for the Condition-Based Maintenance of Circuit Breakers Through Data Mining of Trip Coil Current Signatures", *IEEE Trans. on Power Delivery*, Vol.22, pp.178-186, January 2007.

[4] S. Beattie, "Circuit breaker condition assessment by vibration and trip coil analysis ",*IEE Colloquium on Monitors and Condition Assessment Equipment*, pp.1-5, December 1996.

[5] B. Falahati, Z. Darabi, Mirrasoul J. Mousavi and Y. Fu, "Stochastic Latency Assessment in Substation Automation Systems," *2012 IEEE PES General Meeting*, pp.36-40, July 2012.

[6] A.V. Schneider, S.A. Popov, A.V. Batrakov, G. Sandolache and S.W. Rowe, "Diagnostics of the Cathode Sheath Expansion After Current Zero in a Vacuum Circuit Breaker", *IEEE Trans. on Plasma Science*, Vol.39, pp. 1349 – 1353, June 2011.

[7] N. Du, Y. Guan, J. Zhang, J. Niu, S. Yao and G. Xu, "Phenomena and Mechanism Analysis on Overvoltages Caused by 40.5-kV Vacuum Circuit Breakers Switching Off Shunt Reactors", *IEEE Trans. on Power Delivery*, Vol.26, pp.2102 – 2110, April 2011.

[8] P. Rao, J. Huang and X. Hu,"Testing of circuit breakers using coil current characteristics analysis", *IEEE International Conference on Control and Automation*, pp. 185-189, August 2009.

[9] Z. Li, G. Tan, Y. Li," Fault diagnosis based on improved kernel Fisher discriminant analysis", *Journal of Software*, Vol.7, pp.2657-2662, December 2012.

[10] Y. Xu, S. Xiu, "A new and effective method of bearing fault diagnosis using wavelet packet transform combined with support vector machine", *Journal of Computers*, Vol.6,pp.2502-2509, November 2011.

[11] M.Basseville and I.V. Nikiforov, *Detection of Abrupt Changes: Theory and Application*, Prentice-Hall, Inc., Simon & Schuster Company , Englewood Cliffs, NJ, 1993.

[12] D.B. Durocher and L. Walls, S. Becker, "Understanding Circuit Breaker Design and Operation to Improve Safety and Reliability in Underground Mining", *IEEE Trans. on Industry Applications*, Vol.49,pp.3-9, January 2013.

[13] A.V. Gribok, M.J. Buller, R.W. Hoyt, J. Reifman,"A Real-Time Algorithm for Predicting Core Temperature in Humans", *IEEE Trans. on Information Technology in Biomedicine*, Vol.14,pp.1039 – 1045, April 2010.

[14] Z. Wang, A. Maier, N.K. Logothetis and H. Liang, "Extraction of Bistable-Percept-Related Features From Local Field Potential by Integration of Local Regression and Common Spatial Patterns", *IEEE Trans. on Biomedical Engineering*, Vol.56, pp.2095- 2103,August, 2009.

[15] W. S. Cleveland, "Robust Locally Weighted Regression and Smoothing Scatterplots", *Journal of the American Statistical Association*, Vol.74,pp.829-836, January 1979.

[16] H. William, *Numerical Recipes 3rd Edition: The Art of Scientific Computing*,Cambridge University Press, 2007.

[17] H.Sakoe and S.Chiba," Dynamic Programming Algorithm Optimization for Spoken Word Recognition", *IEEE Trans. on Acoustics, Speech and Signal Processing*, Vol. 26, pp. 43-49, January 1978.

[18] C. A. Ratanamahatana and Keogh. E. "Everything you know about Dynamic Time Warping is Wrong", *Third Workshop on Mining Temporal and Sequential Data, in conjunction with the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp.78-82, June 2004.

[19] G. Ding, L. Wang, P. Yang, P. Shen, S. Dang," Diagnosis model based on least squares support vector machine optimized by multi-swarm cooperative chaos particle swarm optimization and its application", *Journal of Computers*, Vol. 8, pp.975-982, April 2013.

[20] B. Jablonski, "Quaternion Dynamic Time Warping", *IEEE Trans. on Signal Processing*, Vol.60,pp.1174-1183, March 2012.

[21] Y. Chen, K. Chen and M.A. Nascimento, "Effective and Efficient Shape-Based Pattern Detection over Streaming Time Series", *IEEE Trans. on Knowledge and Data Engineering*, Vol.24, pp.265-278, February 2012.

[22] http://allegromicro.com/en/Products/Current-Sensor-ICs/Zero-To-Fifty-Amp-Integrated-Conductor-Sensor-ICs/ACS712.aspx

[23] Z. Xu, J. Wu, S. Qu, "Prediction model based on moving pattern", *Journal of Computers*, Vol. 7, pp.2695-2701, November 2012

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