

Thermal Image and Leakage Current Diagnostic as a Tool for Testing and Condition Monitoring of ZnO Surge Arrester

Novizon^{a,b}, Zulkurnain Abdul Malek^{a*}, Nouruddeen Bashir^a, N. Asilah^a

^aIVAT Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

^bElectrical Engineering, University of Andalas (UNAND), Indonesia

*Corresponding author: zulk@utm.my

Article history

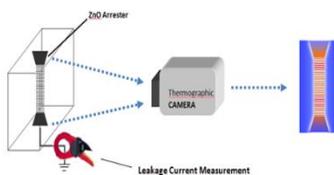
Received :15 February 2013

Received in revised form :

10 June 2013

Accepted :16 July 2013

Graphical abstract



Abstract

This paper presents a study proposing a method to assess the condition of metal-oxide surge arresters. Thermal data using thermal imaging as well as the leakage current third harmonic component were used as tools to investigate the surge arrester aging condition. Artificial Neural Network was employed to classify surge arrester condition with the temperature profile, ambient temperature and humidity as inputs and third harmonic leakage current as target. The results indicated a strong relationship between the thermal profile and leakage current of the surge arrester. This finding suggests the viability of this method in condition monitoring of surge arrester.

Keywords: Zinc oxide arrester; leakage current; thermal image; artificial neural network

Abstrak

Kertas kerja ini membentangkan kajian yang mencadangkan kaedah untuk menilai keadaan penangkap lonjakan logam-oksida. Data haba menggunakan pengimejan haba serta kebocoran arus komponen harmonik ketiga telah digunakan sebagai alat untuk menyiasat penangkap keadaan lonjakan penuaan. Rangkaian neural tiruan telah digunakan untuk mengklasifikasikan keadaan penangkap lonjakan dengan profil suhu, suhu persekitaran dan kelembapan sebagai input dan kebocoran harmonik ketiga semasa penangkap lonjakan. Penemuan ini menunjukkan hubungan yang kuat antara profil terma dan kebocoran semasa penangkap lonjakan. Penemuan ini menunjukkan daya maju kaedah ini dalam pemantauan keadaan penangkap melonjak.

Kata kunci: Logam-oksida penangkap pusan; arus bocoran; gambar terma; jaringan syaraf tiruan

© 2013 Penerbit UTM Press. All rights reserved.

1.0 INTRODUCTION

Rapid growth of modern technology, maintenance plays a more and more important role in many industries. In some industries such as electricity energy industry, reliability and maintenance are one of the most critical issues since a tiny failure may result in inestimable loss as well as fatal disaster.

Traditional maintenance technique is basically breakdown maintenance, also called corrective maintenance, reactive maintenance or unplanned maintenance. It is limited to repair actions or item replacement caused by failures. The predominant characteristic of early maintenance is reactive since it only reacts to faults or failures. A more recent maintenance technique is time-based preventive maintenance (also called planned maintenance). It is proactive maintenance which sets schedules to inspect or perform preventive maintenance instead of just reacting to failures.

One time-based preventive maintenance method is constant-interval based preventive replacement method, in which failure replacements are performed immediately after failures occur and

preventive replacements are performed at constant intervals. The optimization problem is to find the optimal preventive replacement interval to minimize the total expected replacement cost in the long run. Another time-based preventive maintenance method is the age-based replacement method, in which preventive replacements are performed when the component reaches a pre-specified age, and the optimization problem is to find the optimal preventive replacement age. The time-based maintenance technique is an improvement compared to early maintenance techniques, but at the same time makes the cost of preventive maintenance higher and higher. Another type of effective maintenance is condition based maintenance (CBM).

There are three key steps in CBM process: data acquisition, data processing and maintenance decision-making step, as shown in (Figure 1). Data acquisition step is to collect the data related to system health. Data processing step is to process and analyze the acquired data. In maintenance decision-making step, effective maintenance policies will be obtained based on the analyzed information^{1,2}.



Figure 1 CBM process steps

A CBM program consists of two main categories of maintenance techniques: diagnostics and prognostics. Diagnostics focus on faults detection, isolation and identification when they occur, while prognostics attempts to predict faults or failures before they occur. Diagnostics is posterior event analysis and prognostics are prior event analysis. Prognostics are apparently more effective than diagnostics since prognostics endeavors to prevent faults or failures, or at least has prepared spare parts and planned human resources ready for the problems, and thus avoids additional unplanned maintenance cost. Nevertheless, diagnostics cannot be neglected for the reason that prognostics are impossible to be 100% sure to predict faults and failures. Besides, diagnostic can help improve prognostics in the way that diagnostic information can be useful for preparing more accurate event data and hence building better CBM model for prognostics. In addition, diagnostic information can be used as valuable feedback information for system redesign.

A CBM program can be used to do both diagnostics and prognostics, or either one of them and the above three CBM steps should be followed. Electricity utilities are an industry which produce electric power and distributes to customers. In order to distribute electric power, the system should be reliable and safe. To make power system safe, the electric utilities requires high voltage power system protection which protects the system from lightning over voltage or switching over voltage.

Usually, metal oxide (ZnO) gapless type of lightning arrester is used for protection of power system equipment from overvoltage. The primary function of a zinc oxide surge arrester is to protect the power equipment from overvoltage and to absorb electrical energy resulting from lightning or switching surges and from temporary over voltages.

High voltage arresters are usually very reliable, with a 10-15 year design life. In practice, the life of arrester can reach 20 years with appropriate maintenance. Based on JEC-217-1984, ZnO elements have been considered as an application of continuous operating voltage for 30 years at an ambient temperature of 25°C³. In service failure of arrester is potentially dangerous to utility personnel through explosion and fire, is costly to repair or replace, and may result in significant loss of revenue. In large power utility, the number of arresters in substation and transmission network can be a few hundred to over one thousand.

The arresters age, their internal condition degrades, which increases the risk of failure. Failures are usually triggered by severe conditions, such as lightning strikes, switching transient, stress voltage or other incidents.

There are various techniques and methods to evaluate the condition of surge arrester. The assessment technique using leakage current has been reported by numerous researchers³⁻¹⁶. According to some papers, the leakage current of surge arrester, especially the third harmonic of total leakage current is the good indicator of aging or failure surge arresters^{5,10,11,17}.

Another assessment technique to monitor ZnO arrester degradation is based on the thermal temperature that rises on the arrester body. The thermal behavior of ZnO arrester is an important application consideration. Thermal capability of a design takes advantage of overvoltage protection capability. The thermal capability of ZnO arrester depends on the assembly structure of the arrester. If the heat generated from the ZnO elements due to continuous operating voltages and surges exceeds the thermal

power dissipation of the arrester's housing, the elements will undergo ageing thereby losing their functionality.

The monitoring of surge arresters using thermal image technique by analyzing hot spots have conducted by several researchers^{4,6,12,19,20}. The methodology to extract information to enable the detection and diagnosis of faults in surge arresters use a digital image processing algorithm⁶. Most studies have been limited to the use of the hotpot temperature of arrester to assess the arrester condition.

In light of the above, a CBM of ZnO surge arrester using correlation between the third harmonic resistive leakage current and thermal image is proposed herein. The main idea of CBM of ZnO surge arrester is to predict and prevent a ZnO surge arrester from failure or damage in order to minimize maintenance cost.

■2.0 PREVIOUS STUDIES ON ZNO SURGE ARRESTER CONDITION ASSESSMENT

2.1 The Third Harmonic Leakage Current of ZnO Surge Arrester Detection Assertion Method

The measurement of leakage current flowing through ZnO arrester under normal situations gives the information about the real operating condition of the arrester¹⁷. In last five years, some methods to assess the condition of surge arrester have been developed. The condition of surge arrester based on the third harmonic leakage current has been developed by many researchers^{11,17,21,22,23}. According to Novizon *et al.*¹⁷, the resistive leakage current of a 75 mm diameter ZnO varistor under continuous operating voltage 0.8 pu at 20°C and 50°C were 150µA and 370µA respectively. That means about 40% increasing of resistive leakage current for about 30°C temperature difference. Also Lee and Kang¹¹ investigated the condition of ZnO surge arrester using the third harmonic of the leakage current. A device to separate resistive leakage current from total leakage current was developed by²¹. Another device was developed by²², the device was based on harmonics analysis of the resistive leakage current of the surge arrester.

2.2 Thermal Image Condition Monitoring Assessment

There is no doubt that Infrared (IR) is been widely used by many researchers due to the advances in that area. A thermography inspection is a technique widely used for high voltage electrical equipment monitoring. It plays a vital role in electrical equipment fault diagnosis²⁴. Infrared thermal camera can detect loose connections, unbalance load, overload condition, deteriorating insulation, component deterioration and many other potential problem²⁵⁻²⁷. Its main advantage is the possibility of an inspection far from the equipment, as there is no need for a direct contact. It is also a non-invasive technique being used with equipment operating under high voltage levels or conducting a high current²⁰⁻²⁸.

Diagnosing electrical equipment with internal faults by way of infrared thermography have been discussed by Niancang²⁹. Some parameters such as: relative humidity, reflected temperature, atmospheric temperature, distance from an object and emissivity can also investigated³⁰. Research on heating winding salient pole synchronous generator conducted by Stipetic *et al.*³¹ The research conducted by Santos³⁴ shows how the usage of infrared (IR) thermal imaging techniques can reduce costs and the necessary time for the calorimetric method application. Also, contribution to the heat transfer coefficient determination and a new approach to consider conduction losses in the generator shaft has been presented by Bortoni³².

Thermography inspections are also being used for ZnO arresters. Study on 96 kV ZnO arresters presenting the most common failures detected in substations and their effects on the thermal image were done by Neto *et al.*¹⁵. They proposed monitoring technique of ZnO arrester using measurement of leakage current and the thermal analysis⁹ classifying surge arresters operative condition as faulty, normal, light, and suspicious⁶ using a digital image processing algorithm based on the historical thermography data.

The temperature behavior of high voltage disconnecter contacts was investigated by Muhr *et al.*³³ They evaluated the contact condition during the normal operation using a thermography camera for realization of a condition based maintenance strategy.

3.0 ARTIFICIAL NEURAL NETWORK

In this research artificial neural network (ANN) back propagation (BP) type was used. The back propagation (BP) algorithm is a kind of supervised learning algorithm. The BP NN contains three layers, input, hidden, and output layers. During the training phase, the training data such as humidity, ambient temperature, maximum and minimum temperature of arrester and temperature whole body of arrester are fed into the input layer.

The data is propagated to the hidden layer and then to the output layer. The ANN used in this study has one output layer that is third harmonic of resistive leakage current. This is called the forward pass of the back propagation algorithm. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with appropriate weights and then summed. The output of the hidden node is the non-linear transformation of this resulting sum. Similarly each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed. The output of this node is the non-linear transformation of the resulting sum.

The output values of the output layer are compared with the target output values. The target output values are those that attempt to teach the network. The error between actual output values and target output values is calculated and propagated back toward hidden layer. This is called the backward pass of the back propagation algorithm. The error is used to update the connection strengths between nodes, weight matrices between input-hidden layers and hidden-output layers are updated. During the testing phase, no learning takes place, meaning all weight matrices are not changed. Each test vector is fed into the input layer. The feed forward of the testing data is similar to the feed forward of the training data.

In this study, the input data of neural network is a statistical data of thermal imaging obtained from thermal image segmentation and histogram. While output data is third harmonic leakage current that has been classify into three categories based on operational condition.

4.0 EXPERIMENTAL

The thermal image of gapless surge arrester was captured using NEC 4700 thermal camera as illustration in (Figure 2).

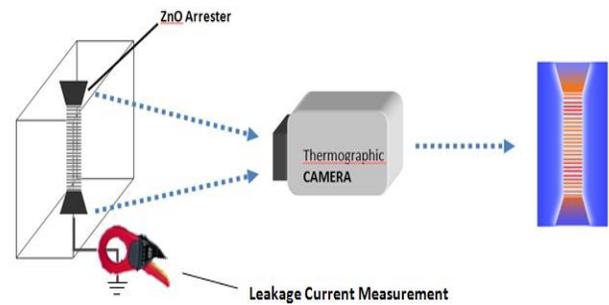


Figure 2 Experimental set up

All data regarding to temperature such as temperature whole arrester, ambient, maximum and minimum temperature were obtain using the histogram of thermal image and exported to excel format. The temperature distribution data is 180 rows for each arrester. Using statistical analysis the thermal data was compressed into seven parameters such as maximum, minimum, kurtosis, skewness, mean, average and mode.

The third harmonic of leakage current of surge arrester was concurrently measured using SCAR10 leakage current measurement device. The data put in the same file with the temperature data.

Feed forward back propagation (FFBP) neural network was employed to correlate between temperature from thermal image and third harmonic of gapless surge arrester. Neural network program was written in MATLAB software. For training purpose, the temperature distribution, ambient and humidity were inputs of neural network. The third harmonic of the leakage current is an output or target of the neural network as shown in flowchart (Figure 3).

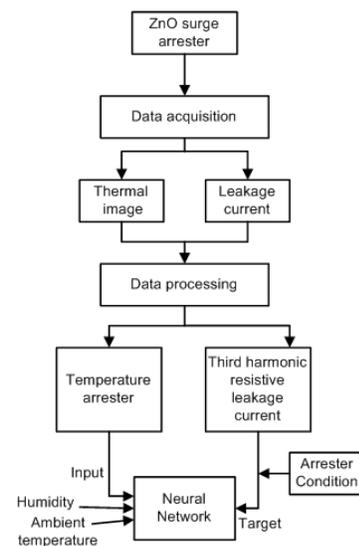


Figure 3 Training flow chart

For testing purpose, only the temperature distribution, ambient and humidity were used and the result is the third harmonic leakage current. The flowchart of testing neural network is shown in (Figure 4).

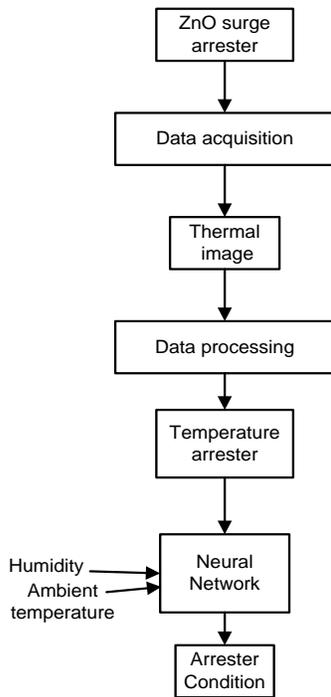


Figure 4 Testing flow chart

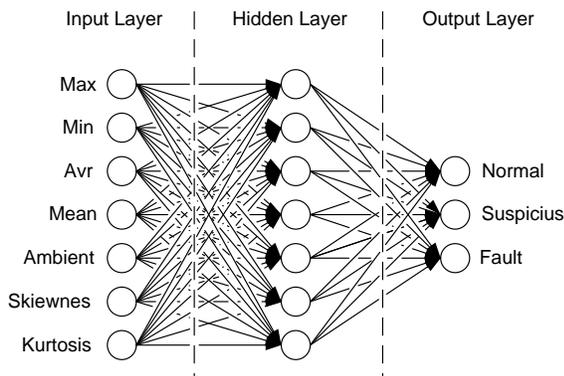


Figure 5 Structure of networks used to implement the diagnosis method

Neural Network Topology: The thermal image diagnosis presented in this study uses a set of neural network to process the input variables. Each neural network has the three-layer structure shown in Figure 7. A brief description of each layer is presented:

- **Input layer** —uses a node for each input variable Figure 5 shows 7 input nodes. The network uses feed forward back propagation network with initial weights choosing randomly. Each node has a weight associated. These weights are adjusted during the training phase.
- **Hidden layer** — in this layer all the nodes use sigmoid transfer function
- **Output layer**—this layer has three nodes whose value indicates the operational condition. The diagnosis qualifies the surge arrester in accordance with its operational condition, and can be assigned the following value:

- Surge arrester in normal condition (label with 1).
- Surge arrester in suspicious condition (label with 2).
- Surge arrester in faulty condition (label with 3).

5.0 RESULT AND DISCUSSION

Figure 6 shows one of the result of thermal image of 132 kV gapless surge arrester in Taman Perling Johor Bahru which was captured in the night. The histogram of thermal image shows in (Figure 7) and temperature data of histogram is shows in Table 1.



Figure 6 Thermal image 132 kV arrester

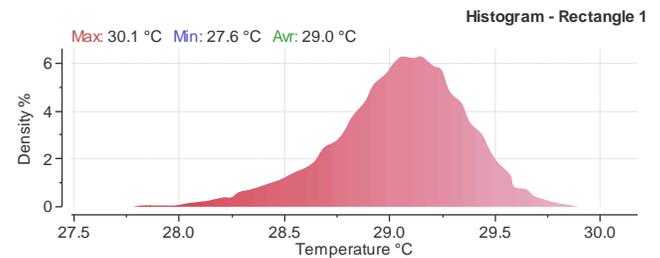


Figure 7 Histogram of arrester thermal image

Table 1 Histogram data of arrester thermal image

Temperature °C	Density %	Temperature °C	Density %	Temperature °C	Density %
27.2852	0.06	28.3315	0.7	29.2471	6
27.5032	0.06	28.3751	0.8	29.2907	5.1
27.5468	0.06	28.4187	0.9	29.3343	4.5
27.5904	0.06	28.4623	1.1	29.3779	3.7
27.6993	0.06	28.5059	1.2	29.4215	3.2
27.7429	0.06	28.5495	1.3	29.4651	2.4
27.7865	0.06	28.6149	1.5	29.5087	1.9
27.8301	0.06	28.6585	1.6	29.5741	1.4
27.8737	0.06	28.7021	2.2	29.5959	0.9
27.9173	0.06	28.7457	2.4	29.6395	0.8
27.9609	0.1	28.7893	2.8	29.6831	0.5
28.0045	0.1	28.8329	3.5	29.7267	0.3
28.0481	0.2	28.8765	4.2	29.7703	0.2
28.1135	0.2	28.9201	5	29.8139	0.1
28.1353	0.3	28.9637	5.5	29.8575	0.1
28.2007	0.4	29.0073	6	29.9011	0.1
28.2443	0.4	29.0509	6.5	29.9665	0.1
28.2879	0.6	29.0945	6.5	30.0101	0.1
28.3315	0.7	29.1599	6.5	30.0537	0.1
28.3751	0.8	29.2035	6.2	30.0676	0.1

Training of neural network was ran using 250 arrester data. Another set of 61 arrester data (which were different from the training data) were used to test the ANN. Error training was set 0.1 percent and epoch 10.000. Neural network training and testing was ran with different hidden layer and learning rate. If O is a vector of

n predictions, and T is the vector of the true values, then the MSE of the predictor is $MSE = \frac{1}{n} \sum_i^n (T_i - O_i)^2$. Training parameter is shown in Table 2 where hidden layer and learning rate was 5 and 0.03.

Table 2 Training parameters

Input layer	7
Output layer	3
Hidden layer	5
Learning rate	0.03
Numbers of iteration	10.000
Minimum error	0.00001

Error training result is shown in (Figure 8) starting from 0.06 and decrease until 10e-5 at epoch 10e3. Referring to (Figure 9), it can be seen from the training confusion matrix only condition two is bad, where there are 12% of output class misclassified to target 1 and 6% to target 3 respectively.

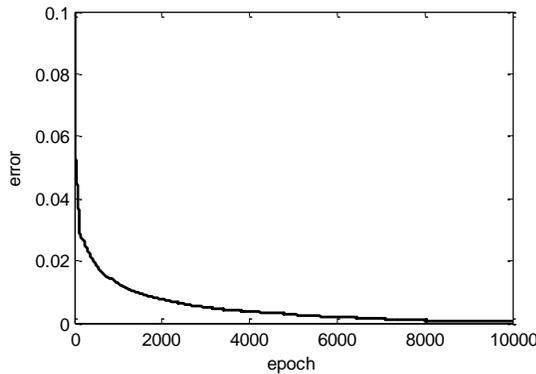


Figure 8 Error training neural network

The classification 1 and 3 is correctly classified into target which each class is 100% accurate. Total all correct class is 91.2%.

Training Confusion Matrix				
Output Class	Target Class			
	1	2	3	
1	51 25.0%	0 0.0%	0 0.0%	100% 0.0%
2	12 5.9%	65 31.9%	6 2.9%	78.3% 21.7%
3	0 0.0%	0 0.0%	70 34.3%	100% 0.0%
	81.0% 19.0%	100% 0.0%	92.1% 7.9%	91.2% 8.8%

Figure 9 Training confusion matrix

Testing neural network using 61 set data testing produce 59 correct classify and only 2 data set unclassified as shown in (Figure 10). The overall accuracy and error of the ANN were 96.72% and 3.28% respectively.

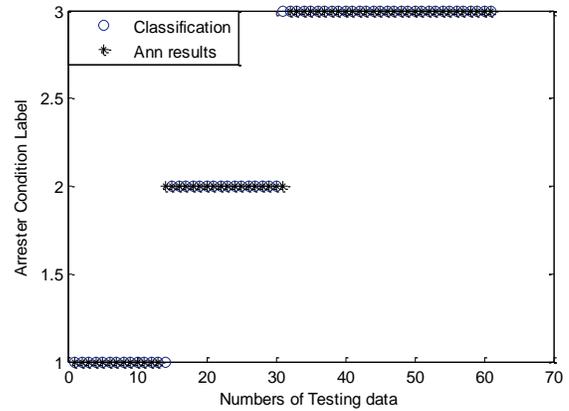


Figure 10 Testing result of neural network

The relationship between output and target investigated using regression linear is shown in (Figure 11). The regression linear R equal to 0.975 implying that the output to target is close enough.

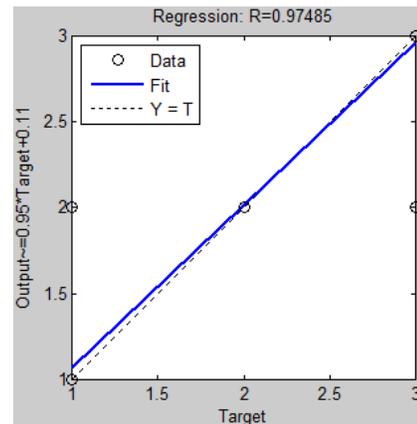


Figure 11 Regression testing result

6.0 CONCLUSION

In this study, thermal image data of ZnO surge arrester and third harmonic of resistive leakage current have been shown to be strongly correlated with aging/degradation. This strong relationship can be used as tool to diagnose surge arresters in relation to ageing/degradation employing neural network to classify the operational condition of arrester.

Acknowledgement

The authors would like to thank the Research Management Centre (RMC), Universiti Teknologi Malaysia for the financial and management support provided under VOT 00H41.

References

- [1] A. K. S. Jardine, et al. 2006. A Review on Machinery Diagnostics and Prognostics Implementing Condition-based Maintenance. *Mechanical Systems and Signal Processing*. 20: 1483–1510.
- [2] Z. Tian, et al. 2009. Condition Based Maintenance Optimization Considering Multiple Objectives. *Journal of Intelligent Manufacturing*. 1–8.

- [3] T. Tada, et al. 2002. A Diagnosis Of Remaining Life Characteristics Of ZnO Type Surge Arresters (1st stage) for 275 kV Power Systems. In Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES. 3: 2233–2238.
- [4] X. Chen, et al. 2008. Research of Infrared Diagnosed of Faults of Arrester. In High Voltage Engineering and Application. ICHVE 2008. International Conference. 637–640.
- [5] C. A. Christodoulou, et al. 2009. Measurement of the Resistive Leakage Current In Surge Arresters Under Artificial Rain Test and Impulse Voltage Subjection. *Science, Measurement & Technology, IET*. 3: 256–262.
- [6] C. A. Laurentys Almeida, et al. 2009. Intelligent Thermographic Diagnostic Applied to Surge Arresters: A New Approach. *Power Delivery, IEEE Transactions*. 24: 751–757.
- [7] J. Jun and W. Yu. 2010. Research on Online Monitoring of Arrester. In 2010 China International Conference on Electricity Distribution, CICED 2010, September 13, 2010 - September 16, 2010, Nanjing, China.
- [8] C. Srisukkhom and P. Jirapong. 2011. Analysis of Electrical and Thermal Characteristics of Gapless Metal Oxide Arresters Using Thermal Images. In Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2011 8th International Conference. 677–680.
- [8] E. T. Wanderley Neto, et al. 2006. Monitoring and Diagnosis of ZnO Arresters. *Latin America Transactions, IEEE (Revista IEEE America Latina)*. 4: 170–176.
- [9] Z. Abdul-Malek, et al. 2008. A new Method to Extract the Resistive Component of the Metal Oxide Surge Arrester Leakage Current. In Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International. 399–402.
- [10] B.-H. Lee and S.-M. Kang. 2005. A New on-line Leakage Current Monitoring System of ZnO Surge Arresters. *Materials Science and Engineering B*. 119: 13–18.
- [11] E. T. W. Neto, et al. 2004. Electro-thermal Simulation of ZnO Arresters for Diagnosis Using Thermal Analysis. In Transmission and Distribution Conference and Exposition: Latin America, 2004 IEEE/PES. 338–343.
- [12] K. L. Wong, et al. 2004. Emission-based Condition Monitoring Technique for ZnO Surge Arrester. In Proceedings of the Seventh IASTED International Conference on Power and Energy Systems, November 28, 2004 - December 1, 2004, Clearwater Beach, FL, United states. 234–237.
- [13] C. Karawita and M. R. Raghuvver. 2006. Onsite MOSA Condition Assessment-A New Approach. *Power Delivery, IEEE Transactions*. 21: 1273–1277.
- [14] E. T. W. Neto, et al. 2006. Failure Analysis in ZnO Arresters Using Thermal Images. In Transmission & Distribution Conference and Exposition: Latin America, 2006. TDC '06. IEEE/PES. 1–5.
- [15] W. Zhou, et al. 2008. Design of On-line Monitoring Device for MOA used in 10kV Distribution Network. In Condition Monitoring and Diagnosis, 2008. CMD 2008. International Conference. 407–411.
- [16] J. Lundquist, et al. 1990. New Method for Measurement of the Resistive Leakage Currents of Metal-Oxide Surge Arresters in Service. *Power Delivery, IEEE Transactions*. 5: 1811–1822.
- [17] S.-B. Lee, et al. 2010. Analysis of Thermal and Electrical Properties of ZnO Arrester Block. *Current Applied Physics*. 10: 176–180.
- [18] C. A. L. Almeida, et al. 2005. Intelligent Detection and Diagnosis of Lightning Arrester Faults Using Digital Thermovision Image Processing Techniques. Orlando, FL, USA. 109–120.
- [19] C. Ying-Chieh and L. Yao. 2009. Automatic Diagnostic System of Electrical Equipment Using Infrared Thermography. In Soft Computing and Pattern Recognition, 2009. SOCPAR '09. International Conference. 155–160.
- [20] Z. Abdul-Malek, et al. 2008. Portable Device to Extract Resistive Component of the Metal Oxide Surge Arrester Leakage Current. In Power Engineering Conference, 2008. AUPEC '08. Australasian Universities. 1–5.
- [21] L. Huijia and H. Hanmei, 2010. Development of Tester of the Resistive Leakage Current of MOA. In Power and Energy Engineering Conference (APPEEC), 2010 Asia-Pacific. 1–4.
- [22] A. Gakiya Kanashiro, et al. 2011. Diagnostic of Silicon Carbide Surge Arresters Using Leakage Current Measurements. *Latin America Transactions, IEEE (Revista IEEE America Latina)*. 9: 761–766.
- [23] C. Yang, et al. 2008. Infrared Technology in the Fault Diagnosis of Substation Equipment. In Electricity Distribution, 2008. CIGRE 2008. China International Conference. 1–6.
- [24] Z. Azmat and D. J. Turner. 2005. Infrared Thermography and Its Role in Rural Utility Environment. In Rural Electric Power Conference. B2/1–B2/4.
- [25] L. Baoshu, et al. 2006. HV Power Equipment Diagnosis Based on Infrared Imaging Analyzing. In Power System Technology, 2006. PowerCon 2006. International Conference. 1–4.
- [26] L. Huangqiang, et al. 2009. Research on HV-Power Equipment Diagnosis by Infrared Image Edge Detection," in Power and Energy Engineering Conference, 2009. APPEEC 2009. Asia-Pacific. 1–4.
- [27] Z. Korendo and M. Florkowski. 2001. Thermography Based Diagnostics of Power Equipment. *Power Engineering Journal*. 15: 33–42.
- [28] H. Nianchang. 1998. The Infrared Thermography Diagnostic Technique of High-Voltage Electrical Equipments with Internal Faults. In Power System Technology, 1998. Proceedings. POWERCON '98. 1998 International Conference. 1: 110–115.
- [29] Baran, et al. 2010. Thermographic Diagnostic of Electrical Machines. In Electrical Machines (ICEM), 2010 XIX International Conference. 1–3.
- [30] S. Stipetic, et al. 2011. Measurement of Excitation Winding Temperature on Synchronous Generator in Rotation Using Infrared Thermography," *Industrial Electronics, IEEE Transactions*. 1–1.
- [31] E. C. Bortoni, et al. 2010. Hydro Generator Efficiency Assessment Using Infrared Thermal Imaging Techniques. In Power and Energy Society General Meeting, 2010 IEEE. 1–6.
- [32] M. Muhr, et al. 2006. Thermography of Aged Contacts of High Voltage Equipment. *Elektrotechnik und Informationstechnik*. 123: 537–543.
- [33] L. dos Santos, et al. 2008. Infrared Thermography Applied for Outdoor Power Substations. Orlando, FL, USA. 69390R–11.