DETECTION OF ARCING FAULT IN UNDERGROUND DISTRIBUTION CABLE USING ARTIFICIAL NEURAL NETWORK

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To my beloved mum and dad, sister and all my friends who have always been there, for their support and confidence in me.

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ABSTRACT

Arcing faults can cause substantial damage if they are not detected and isolated promptly. Detection of arcing faults has always been a difficult issue. Those faults tend to be of high fault resistance and hence the fault current is well below maximum load limit and its detection is not possible through the use of overcurrent relays. In the case of overhead lines, the gas generated through arcing is dispersed rapidly. But in the case of underground cables, the generated gas could travel along cable duct and could result in explosion at manhole location, which is dangerous to personnel. The damage can be reduced if arcing faults are detected before they develop into major faults. The general aim of this study is to develop an arcing fault detection algorithm which can detect the presence of arcing fault in underground distribution cable. Arcing faults data are collected through simulations and experiments. The simulations involve the modelling of a simple underground distribution system and two TNB underground distribution systems using Power System Computer Aided Design / Electromagnetic Transient for Direct Current (PSCAD/EMTDC) program. On the other hand, the experiments are conducted in research laboratory. The data collected from the simple underground distribution system are analysed in both time domain and frequency domain to identify the characteristics of arcing fault. A Multi-layer Perceptron (MLP) with Backpropagation (BP) learning is used to discriminate arcing faults from normal load condition. The detection results revealed satisfactory performance in all test cases.

ABSTRAK

Rosak pengarkaan boleh menyebabkan kemusnahan yang besar jika rosak tersebut tidak dikesan dan diasingkan dengan secepat mungkin. Pengesanan rosak pengarkaan selalunya merupakan satu isu yang sukar. Rosak tersebut cenderung kepada rintangan kerosakan tinggi. Oleh yang demikian, arus rosak adalah di bawah had beban maksimum dan rosak tersebut tidak mungkin dapat dikesan melalui penggunaan geganti arus lebih. Dalam kes talian atas, gas yang terjana melalui pengarkaan akan menyerak dengan cepat. Tetapi dalam kes kabel bawah tanah, gas yang terjana akan mengembara di sepanjang saluran kabel dan boleh menyebabkan letupan pada lokasi lurang yang boleh merbahayakan pekerja. Kemusnahan dapat dikurangkan jika rosak pengarkaan dapat dikesan sebelum rosak tersebut berubah menjadi rosak utama. Penyelidikan ini bertujuan untuk membangunkan satu algoritma pengesanan rosak pengarkaan yang dapat mengesan kewujudan rosak pengarkaan pada kabel pengagihan bawah tanah. Data rosak pengarkaan dikumpulkan melalui simulasi dan ujikaji. Simulasi melibatkan pemodelan sebuah sistem pengagihan bawah tanah ringkas dan dua sistem pengagihan bawah tanah TNB dengan bantuan perisian "Power System Computer Aided Design / Electromagnetic Transient for Direct Current (PSCAD/EMTDC)". Sementara itu, ujikaji dijalankan di makmal penyelidikan. Data yang diperolehi daripada sistem pengagihan bawah tanah ringkas dianalisiskan dengan menggunakan domain masa dan domain frekuensi untuk mengenalpasti ciri-ciri rosak pengarkaan. Sebuah rangkai neural pelbagai-aras dengan perambatan-balik digunakan untuk membezakan rosak pengarkaan daripada keadaan beban biasa. Keputusan pengesanan menunjukkan prestasi yang memuaskan dalam kesemua kes yang diuji.

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LIST OF SYMBOLS AND ABBREVIATIONS

AC - Alternating Current

ANN - Artificial Neural Network

 bh_j - Biases at the hidden layer

BP - Backpropagation

 by_k - Biases at the output layer

 D_l - Diode in positive half cycle

 D_2 - Diode in negative half cycle

DC - Direct Current

 $E_{initial}$ - Initial error

 E_{min} - Minimum error or global minimum

 E_{ms} - Mean square error for total number of patterns

 E_p - Mean square error for a single pattern

EPR - Ethylene propylene rubber

F - Conventional time-controlled switch

FDS - Fault diagnostic system

FFT - Fast Fourier Transform

H - Hidden layer

 h_j - Neuron in the hidden layer

I - Number of neurons in input layer

 I_2/I_1 - Second harmonic and fundamental frequency ratio

 I_{do}/I_I - DC component and fundamental frequency ratio

IVAT - Institut Voltan dan Arus Tinggi

J - Number of neurons in hidden layer

K - Number of neurons in output layer

Matlab - Matrix Laboratory

MCB - Main circuit breaker

MLP - Multi-layer Perceptron

MSE - Mean square error

P - Total number of patterns contained in the training set

PE - Polyethylene

PILC - Paper insulated lead covered

PSCAD/ Power System Computer Aided Design /

EMTDC Electromagnetic Transient for Direct Current

PVC - Polyvinyl-chloride

R - Nonlinear arc fault resistance

rms - Root mean square

TNB - Tenaga Nasional Berhad

variac - Variable alternating current transformer

VLF - Very Low Frequency

 V_N - DC voltage source in negative half cycle

 V_P - DC voltage source in positive half cycle

 w_{ij} - Weights between input layer and hidden layer

 $W_{initial}$ - Initial weights

 w_{jk} - Weights between hidden layer and output layer

 W_{local} - Weights during local minimum

 W_{min} - Weights during global minimum

X - Input layer

 x_i - Neuron in the input layer

XLPE - Crosslinked polyethylene

Y - Output layer

y_k - Neuron in the output layer

 Z_{in} - Input of arc model

 Z_{out} - Output of arc model

 θ - Operating temperature

 η - Learning rate

 α - Momentum term

 τ - Integration time constant of one second

 δ_j - Error information term at hidden layer

 δ_k - Error information term at output layer

 δt - Integration time step of one cycle Δbh_j - Bias correction term at hidden layer Δby_k - Bias correction term at output layer Δw_{ij} - Weight correction term between input layer and hidden layer Δw_{jk} - Weight correction term between hidden layer and output layer

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CHAPTER 1

INTRODUCTION

1.1 Research Background

In the very early days of underground power distribution, failures of cable and splice were common. Therefore the interest at that time was in arcproofing practices and many researches were devoted to that problem. However, this interest drooped since 1941 because of the paper insulated lead covered cable (PILC) technology reached its maturity that year. The advent of crosslinked polyethylene (XLPE) cables in the 1970s, which seemed to provide an attractive solution of cable aging problem and progress in premoulded-splice technology drastically reduced the number of failures. As a result, cable arcproofing problems were forgotten [1].

Recently, however, new problems such as errors due to inadequate splice assembly, electrical and water treeing in XLPE insulation have started to appear as a consequence of the growing number of arcing faults on underground distribution systems. These faults can cause considerable damage if they are not detected and isolated promptly. The techniques presently used in power systems for fault detections are based on voltages and currents inspection. The changes usually do not occur immediately after the establishment of an arcing fault. The consequence is that the damage at the fault is usually substantial. The damage can be reduced if arcing faults are detected before they develop into major faults [2].

Detection of arcing faults has always been a difficult issue. Those faults tend to be of high fault resistance and hence the fault current is well below maximum load limit and its detection is not possible through the use of overload relays. In the case of overhead line the gas generated through arcing is dispersed rapidly. But in the case of underground cable the generated gas could travel along cable duct and could result in explosion at manhole location, which is dangerous to personnel [3-4].

As far as it is concerned, the Tenaga Nasional Berhad (TNB) does not have specific tools for arcing fault detection and location. Most of the time, they only carry out breakdown repair. Recently, they have embarked on Very Low Frequency (VLF) testing of cable whereby potential weak spot can be detected. Therefore, fault can be prevented during service condition.

1.2 Literature Reviews

In the past many investigations have been performed and methodologies have been suggested in arcing faults detection. They are based on examining different characteristics of currents and voltages in time, frequency, and time-frequency domains.

The time domain method utilized the random behaviour of the fault current by comparing the positive and negative current peaks in one cycle to those in the next cycle to measure the flicker in the current signal [5]. By comparing the positive peak to the negative peak, the asymmetry of the current was calculated for each cycle. Referring to reference [6], the time domain analysis involved comparing changes in currents and voltages over a period of one or a few cycles during the arcing faults stage against the normal conditions. From the analysis, a most reliable indicator of an arcing fault was a surge in the absolute increments in the effective values of the synthesized neutral current.

The frequency domain method was used to monitor the harmonic contents of phase currents or some coefficients measuring waveform distortion [7-8]. Referring

to reference [6], the frequency domain analysis compared the harmonic contents of the phase and neutral currents during normal and arcing fault conditions. The Fast Fourier Transform (FFT) was used to calculate the harmonic contents for the analysis. Besides that, a general measure of the current waveform distortion, a distortion coefficient, was used for analysis. From the analysis, the most characteristic features of arcing faults were appearance of the direct current (DC) component in the phase currents and an increased level of the second harmonic of the phase and neutral currents.

For the time-frequency domain method, wavelet transforms was used to analyse the transient behaviour of arcing faults in both time and frequency domain. Reference [9] proposed an application of Morlet wavelets in high impedance fault detection. The advantage of wavelet transform approach is more efficient than FFT in monitoring fault signals as time varies. Besides that, Lazkano, A. et al [10] proposed an arcing fault detection method and evaluated the detection rate and the security level based on Wavelet Packet Analysis. The method involved analysis of three-phase unbalance current using decomposition of the signal by means of Wavelet Transform technique. Apart from that, reference [6] applied time-frequency analysis to determine how the frequency behaviour of a signal changes over time. The analysis was carried out by decomposing a signal into a set of components using a wavelet transformation. The effectiveness of this method is strongly affected by the choice of a wavelet family, decomposition level, sampling rate and arcing fault behaviour.

On the other hand, artificial neural networks (ANNs) were also used to discriminate the arcing faults from the normal currents. Sultan, A. F. et al [11] proposed a high impedance arcing faults detection algorithm through a feed forward three layer ANN structure using the Backpropagation (BP) training algorithm. Phase currents were entered as input variables of the ANN. The algorithm performed well in identifying faults disrupted by arc noise as well as good discrimination between faults and fault-like loads. Reference [12] proposed a fast and efficient ANN-based fault diagnostic system (FDS) for distribution feeders. The main functions of this diagnostic system were detection of fault occurrence, identification of faulted sections and classification of faults into types. The FDS has been achieved through a

cascaded, multiplayer ANN structure using the BP training algorithm. The substation current and voltage phasors in addition to the unbalanced feeder current and voltage sequence phasors were entered as input variables of the ANN. Apart from that, reference [13] suggested a high impedance fault detection method that uses a BP ANN as a fault detector. One cycle fault current was divided into equal spanned four windows according to voltage phase and applied FFT to current waveform in each window. FFT magnitudes of the harmonic current were entered as input variables of the ANN.

Comprehensive expert systems were implemented that combine some of the above methods to increase sensitivity and eliminate false tripping. Reference [14] suggested a fault detection system for high impedance faults with specific descriptions of the detection algorithms and the "intelligent" fault decision element. Besides that, reference [15] proposed the use of multiple algorithms to detect various types of faults. The faults detector included an expert decision maker to decipher incoming data, to determine the status and health of a distribution feeder.

There was another alternative approach to detect the presence of arcing fault and determines it's location by analysing acoustic, thermal (infra-red) and electromagnetic radiation generated by the arcing fault [2]. The technique was implemented by using a variety of sensors and a microprocessor based system, and tested in the laboratory.

Apart from that, Kim and Russell [16] developed an algorithm to analyse the transient behaviour of various events on distribution feeders by quantifying wave distortion with the crest factor. The identification method discriminated arcing faults from most normal system events and provided an alternative method for improving the security of the fault or no fault decision.

Most of the studies mentioned above were based on the field tests data, which are limited to specific conditions and circumstances. Some of them are complicated and time-consuming. Some few methods are simpler and faster in computation, but have difficulty in giving the reasonably accurate results.

Therefore, the aim of this research is to develop an arcing fault detection algorithm using Artificial Neural Network (ANN). The developed algorithm integrates the time domain method with the frequency domain method and applying the ANN for arcing fault pattern recognition. Phase currents, DC component and fundamental frequency ratio (I_{2}/I_{1}) were entered as input variables of the proposed ANN. This ANN based detection algorithm offers the best alternative as it provides the potential for online field training and customisation using actual field arcing faults data. Early detection of arcing fault in underground distribution cable before it reaches a catastrophic state could allow TNB to schedule corrective action to minimise customer inconvenience.

The main contribution of this research is the development of ANN based arcing fault detection algorithm. The modellings of the TNB 11 kV underground distribution system in Taman Rinting, Masai, Johor (PPU Taman Rinting 11 kV) and TNB 6.6 kV underground distribution system in Pasir Gudang, Johor (PMU PGIE 6.6 kV) into the PSCAD/EMTDC program are also a part of the research contribution. Besides, an experiment conducted in research laboratory to gather arcing fault data is another contribution to this research.

1.3 Research Objectives

The general aim of this project is to develop a detection algorithm which can detect the presence of arcing fault in underground distribution cable. The particular aims of the research work are outlined as follows:

- i) To study the existing established methods for detection of arcing fault in underground distribution cable.
- ii) To study and identify the characteristics of arcing fault that occurs in underground distribution cable.

- iii) To model and simulate the underground distribution system for arcing fault's data collection.
- iv) To set up an experiment for arcing fault's data collection.
- v) To develop an arcing fault detection algorithm using Artificial Neural Network (ANN).

1.4 Structure of Thesis

All the work done in this research is presented systematically in seven chapters.

Chapter 2 introduces the underground power cables and their components, which include the types of conductor, insulator and external protection of cables. In addition, this chapter also presents the most usual types of faults that occur in underground distribution cable.

Chapter 3 describes the Artificial Neural Networks (ANNs), which is used for arcing fault pattern recognition. The arcing fault pattern recognition technique discussed here is the Multi-layer Perceptron (MLP) with the learning algorithm of Backpropagation (BP).

Chapter 4 explains the arcing fault data collection approach and methodology. Arcing fault data are collected through simulations and experiments. The simulation involves the modelling of underground distribution systems and is performed using Power System Computer Aided Design / Electromagnetic Transient for Direct Current (PSCAD/EMTDC) program. Meanwhile the experiment is conducted in research laboratory.

Chapter 5 discusses the development of arcing fault detection algorithm. The data collected are analysed in both time domain and frequency domain to identify the characteristics of arcing fault. The network architecture, training patterns and

learning algorithm are described. In this chapter also, the flowchart of the arcing fault detection algorithm with step-by-step explanation is presented.

Chapter 6 compares the performance between the two pattern recognition networks. The network with better performance is selected and used in the proposed arcing fault detection algorithm. Furthermore, this chapter presents the evaluation and discussion on the results of arcing fault detection algorithm. The developed algorithm is tested with the two TNB distribution systems simulations database and the experimental database.

Chapter 7 presents the conclusions of the research as well as some constructive suggestions for the future development of the algorithm. This chapter will conclude the effectiveness of utilizing the ANN in arcing fault pattern recognition. As for future development, some suggestions are made based on the limitations of the developed algorithm in this research.