



Faculty of Engineering

**A Single Perceptron Smart Sensor Technique for Pre-fault Monitoring
System in an Indoor Substation**

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A Single Perceptron Smart Sensor Technique for Pre-fault Monitoring System
in an Indoor Substation

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A thesis submitted

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.


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ABSTRACT

Single Perceptron Smart Sensor (SPSS) is a new Ultra-High Frequency (UHF) sensor developed to significantly improve the pre-fault monitoring system for early detection, localization, and identification of the Corona and Arcs Electric Discharges (EDs) in an indoor substation. Corona and Arcs ED constitute a significant threat to electrical safety, the apparatus, and the stability of a power system due to the aging and material degradation in the power apparatus. Hence, an early preventive approach must be performed effectively for pre-fault threat detection. In this research, a novel pre-fault monitoring system utilizing SPSS is developed, embedding a novel Signal Identifier Technique for the Corona and Arcs ED detection, localization, and identification. The SPSS formation integrates a 2-element Linear Array Antenna with a Single Perceptron-Artificial Neural Network (SP-ANN). It detects and localizes the Corona and Arc ED signals based on the Direction of Arrival (DOA) angle. The SP-ANN utilizes a single-layer neuron with less complexity, speedy detection, and localization within seconds. The waveform-based signal feature extraction uses the Signal Identifier Technique for signal identification. Since the frequency range of the Corona and Arcs is undecidable, the accuracy of the pre-fault monitoring is tested for the Corona and Arcs ED at a sampling frequency of 300 MHz to 3 GHz. The SPSS has revealed an accuracy of 99.86% for signal identification with minimal computational complexity, thus giving another practical wireless technique for UHF signal interpretation.

Keywords: Single Perceptron-Artificial Neural Network, UHF Sensor, Corona discharge, Arcs discharge, Pre-fault monitoring

Sebuah Sensor Pintar Perceptron Tunggal Teknik Untuk Sistem Pemantauan Pra-Kerosakan Dalam Sebuah Pencawang Dalaman

ABSTRAK

Pengesan Pintar Perceptron Tunggal daripada Rangkaian Saraf Tiruan (SPSS) merupakan sebuah Pengesan Frekuensi Ultra Tinggi dihasilkan untuk meningkatkan keberkesanan sistem pra-pemantauan kerosakan bagi tujuan pengesanan, penyetempatan dan pengesanan isyarat Nyahcas Elektrik jenis Corona dan Arcs di dalam sesebuah Pencawang Dalaman. Nyahcas Elektrik memberi ancaman yang besar terhadap keselamatan serta kestabilan perkakasan elektrik sistem kuasa di dalam sesebuah pencawang di mana ianya terhasil disebabkan oleh keusangan bahan pada perkakasan elektrik sistem kuasa. Ia boleh mempengaruhi kebolehpercayaan sesebuah peralatan voltan tinggi. Oleh yang demikian, tindakan pencegahan awalan perlu dirancang dengan berhati-hati dan pemantauan kerosakan harus dilaksanakan secara berkesan bagi mengesan ancaman awal kerosakan. Di dalam kajian ini, sebuah sistem pra-pemantauan yang baru telah dihasilkan menggunakan sebuah Pengesan Pintar Perceptron Tunggal daripada Rangkaian Saraf Tiruan serta menyematkan sebuah Teknik Pengesan Isyarat yang baru bagi pengesanan, penyetempatan dan pengesanan terhadap isyarat Nyahcas Elektrik jenis Corona dan Arcs. SPSS ini dihasilkan melalui gabungan sebuah Antenna Tatasusun Lelurus 2-elemen dengan Perceptron Tunggal-Rangkaian Saraf Tiruan (SP-ANN) untuk membentuk sebuah Pengesan Pintar Frekuensi Ultra Tinggi. Ianya berkebolehan untuk mengesan, menyetempat serta mengesan isyarat nyahcas elektrik jenis Corona dan Arcs berdasarkan Sudut Arah Ketibaan (DOA) isyarat. SP-ANN ini terdiri daripada satu lapisan neuron yang boleh mengurangkan kesukaran serta meningkatkan kepantasan proses pengesanan serta

penyetempatan isyarat dalam tempoh milisaat. Pengekstrakan ciri-ciri isyarat melalui bentuk gelombang isyarat dilaksanakan menggunakan Teknik Pengecam Isyarat. Memandangkan tiada penentuan yang khusus terhadap julat frekuensi bagi Nyahcas Elektrik jenis Corona dan Arcs, maka kejituan sistem pra-pemantauan ini telah diuji menggunakan sampel isyarat Nyahcas Elektrik jenis Corona dan Arcs berfrekuensi sekitar nilai 300 MHz hingga 3 GHz. SPSS telah menunjukkan tahap kejituan sebanyak 99.86% terhadap pengecaman isyarat menggunakan kekompleksan pengiraan yang minimum, dengan itu juga memberi satu teknik tanpa wayar yang praktikal untuk pentaksiran isyarat Frekuensi Ultra Tinggi.

Kata kunci: *Perceptron tunggal-rangkaian saraf tiruan, pengesan frekuensi ultra tinggi, nyahcas elektrik corona, nyahcas elektrik arcs, pra-pemantauan kerosakan*

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LIST OF ABBREVIATIONS

1-D CNN	One-Dimension CNN
φ -OTDR	Phase-sensitive optical time-domain reflectometry
AF	Array Factor
AFN	Normalized Array Factor
AI	Artificial Intelligence
AIS	Air Insulated Substation
ANN	Artificial Neural Network
BP	Back-Propagation
BPNN	Back-Propagation Neural Network
BP-PSO	Back Propagation-Particle Swarm Optimization
CNN	Convolutional Neural Network
CT	Current Transformer
DCNN	Deep Convolutional Neural Network
DL	Deep Learning
DOA	Direction of Angle
DT	Decision Tree
E	Error
ED	Electric Discharge
ED_EMP	Electric Discharge Electromagnetic Impulse
EFT/B	Anti-Jamming Electrical Fast Transient/Burst
EHV	Extra High Voltage
EM	Electromagnetic
EMG	Electromyography

ENN	Ensemble Neural Network
EP	Electromagnetic Impulse
ET	Total Electric Fields
FBG	Fiber Bragg Grating
FCM	Fuzzy C-means Clustering
FDAS	Fiber-optic distributed acoustic sensing
FL	Fuzzy Logic
GIS	Gas Insulated Switchgear
HV	High Voltage
Hz	Hertz
HFCT	High Frequency Current Transformers
IR	Infrared
IoT	Internet of Thing
LMS	Least Mean Square
LSTM	Long Shot-Term Memory Network
MAV	Mean Average Value
MCNN	MobileNets convolutional neural network
MFCC	Mel-frequency Cepstrum Coefficients
ML	Machine Learning
MLP	Multilayer Perceptron
MNN	Multilayer Neural Network
NCDS	Non-Contact Directional Sensor
P-ANN	Perceptron-Artificial Neural Network
PCA	Principle Component Analysis
PD	Partial Discharge

Pi	Power Intensity Radiated
PNN	Probabilistic Neural Network
PRPD	Phase Resolved Partial Discharge
PS-FBG	Phase-Shifted Fiber Bragg Gratings
PSO	Particle Swarm Optimization
PT	Potential Transformers
RF	Radio Frequency
RFID	Radio Frequency Identification
RP	Radiation Pattern
RIV	Radio Interference Voltage
RSSI	Received Signal Strength Index
SA	Smart Antenna
SP	Single Perceptron
SP-ANN	Single Perceptron Artificial Neural Network
SPSS	Single Perceptron Smart Sensor
SRC	Sparse Representation Classifier
SS	Smart Sensor
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
T-SNE	Analysist-distributed stochastic neighbor embedding
TDOA	Time Different of Arrival
TEV	Transient Earth Voltage
TOA	Time of Arrival
UHF	Ultra-High Frequency
UHV	Ultra-High Voltage

UWB	Ultra-Wide Band
VSWR	Voltage Standing Wave Ratio
WSN	Wireless Sensor Networks

CHAPTER 1

INTRODUCTION

1.1 Background

Over the years, many smart sensors have been developed to improve the detection, localization, and recognition techniques of Electromagnetic (EM) signals. Most of these sensors are engaged with the digital and wireless communication system and are highly implemented in the fault monitoring system in power substations. Recently, Ultra-High Frequency (UHF) sensors have been among the famous techniques for EM measurement, especially in power substations due to the congregation of High Voltage (HV) power apparatuses in the substations. Playing an essential role in the power systems, the transmission, generator, and distribution station substations perform important power generation, transmission, and distribution tasks. Therefore, substation fault monitoring must be conducted speedily, accurately, and effectively to maintain the performance and reliability of the system (Fauzi et al., 2018; Guozhi et al., 2019; Lv et al., 2017; Tang et al., 2021; Zhu et al., 2018; Wang et al., 2017).

For the past years, many researchers have successfully discovered methods to improve the fault monitoring system for conventional substations (Gaouda et al., 2018; Mas'ud et al., 2014; Robles et al., 2016; Sarkar et al., 2016; Sima et al., 2017; Tan et al., 2017; Yongxiang et al., 2017). However, there is still room for improvement since many conventional substations are now slowly being converted into digital substations (Froese, 2017). Note that going digital means digitizing the protection, measurement, and control units. Conventional sensors are replaced by modern digital sensors that allow direct digital communication to the process bus. Copper wires connected point-to-point to the Current

Transformers (CTs) or Potential Transformers (PTs) are replaced by electronic voltage/CTs and fiber optics cables to minimize the exposure to HV electricity and the risk of damage to the equipment. Nevertheless, having this key substation equipment digitized, including sensor data, communications, and sensor signal processing, the substation may still be exposed to the risk of potential hazards such as Electric Discharges (EDs). Therefore, pre-breakdown and pre-fault monitoring is still required to detect the existence of EDs in the substations, which may lead to a complete breakdown of the system (Gataullin, 2020; Kumbhar et al., 2017; Polyakov et al., 2018; Ryan, 2001).

Many approaches to fault detection in substation monitoring have been reported, with simulation results suggesting effective detection, localization, and recognition of the substation faults caused especially by Dielectric Breakdown (Arias et al., 2018; Christina et al., 2018; Moreira et al., 2020; Srisongkram et al., 2019). However, it is still a major issue in power systems, originating mostly in insulation degradation, thus producing EDs such as Corona and Arc discharges. The application of sensors from the groups of Photodetector and Ultraviolet sensors is still preferred by some researchers to get a rapid diagnosis and prognosis of the causes of faults, which enables appropriate measures to be taken. The common sensors used for fault detection are Acoustic Emission, Radio Interference Voltage (RIV) Measurement, Infrared (IR) Thermography, Electric Field Measurement, Visual Observation, and Ultraviolet Camera. However, these sensors depend on the visibility of the light emitted by EDs and the use of the EM spectrum, which is limited to 10^{14} Hz (100 THz) (P. R. Hoole et al., 2013). Currently, sensors such as array antennas and UHF sensors have been used to replace the conventional sensors in detecting and localizing the ED to improve the efficiency of substation fault monitoring (Azam et al., 2022; Ghanakota et al., 2022; Nobrega et al., 2019; Rhamdhani et al., 2022; Uwiringiyimana et al., 2021; Wu et al., 2022;

Xavier et al., 2021; Yadam et al., 2021, 2022; Zhu et al., 2019). In general, an ED in a substation indicates the presence of cracks, voids, or other insulation degradation within the electrical equipment. It can lead to equipment failure, serious accidents, and electric breakdown of the power distribution system (Mohan et al., 2019; Shahsavarian et al., 2020; Tsyokhla et al., 2019a; Zamudio-Ramirez et al., 2019; Zhang et al., 2019). When an open circuit occurs at a conventional CT, for example, the inductive circuit can produce hazardous conditions. HV on the secondary load (depending on the load) may develop and lead to ED in the form of flashovers and arcing, which put the substation or personnel at great risk, and the stability of electrical equipment could be disturbed. The most common EDs are Electric Corona Discharge and Electric Spark/Arc, which can be detected not only on the overhead HV power transmission lines but also frequently inside substations that consist of substation equipment like transformers, circuit breakers, and switches. Moreover, the ED measurement techniques rely on the different physical activities of the ED. Many factors affect the ED activities, such as environmental temperature, humidity, voltage, and load. Therefore, the ED frequency spectrums also vary depending on different environmental conditions. Based on the antenna characteristics and background noise for the detection, the frequency spectrums of the ED, such as Corona and Arc, are widely distributed across a range of 300 MHz – 3 GHz with various types (Affendi et al., 2020; Bruzzone, 2021; Chai et al., 2018; Dukanac, 2018; Hamdani et al., 2018; Laksono et al., 2020; Li et al., 2018; Thiviyathan et al., 2022).

1.2 Problem Statement

In the past, researchers have successfully developed high-performance and ultra-modern techniques to provide a better way for HV equipment insulation condition monitoring systems. However, these techniques do not include a pre-monitoring system for

the entire substation environment at a time. Mostly, the monitoring system focuses on individual equipment such as transformers, Gas Insulated Switchgear (GIS), or transmission cables, and frequently, the insulation condition is only realized when the damage has already long occurred on the equipment due to lack of pre-monitoring action. Although the designed systems include high performance, efficient, and smart characteristics for insulation condition monitoring of ED detection, localization, and recognition, there are constraints in the implementation. This is due to the extensive data and memory system required for smart signal recognition. Hence, multiple applications of sensors are required to improve signal detection and localization from multi-ED sources concurrently. Furthermore, the implementation requires high costs for new upgrading works and installation to replace the existing monitoring system.

The smart signal recognition technique requires an extensive data system, such as data storage and memory for the dataset libraries, to support recognition methods for multiple ED sources. When the processed sample data does not match any of the datasets in the data libraries system, the recognition is considered to fail. This is the drawback of the modern signal recognition. Hence, conventional methods and techniques are still preferable. However, a conventional periodic manual checking system is time-consuming and is less practical, especially for substations in rural areas. Based on the limitations, a novel pre-fault monitoring system utilizing a wireless smart sensor called a Single Perceptron Smart Sensor (SPSS) is developed to detect and localize the early formation of Corona or Arcs ED signals based on its single source direction of arrival angle (DOA), embedding a novel SP-Identifier Technique for Corona or Arcs ED signal identification.