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By
Orkhan Farzaliyev

Mentor: Prof. Hasan Mehrjerdi

ADA Supervisor: Assist. Prof. Orkhan Karimzada

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Approved:

Hasan Mehrjerdi	23.12.2024
(Adviser)	(Date)
Orkhan Karimzada	23.12.2024
(Adviser)	(Date)
Wisam Al-Dayyeni	23.12.2024
(Program Director)	(Date)
Abzadtin Adamov	23.12.2024
(Dean)	(Date)

ABSTRACT

The increasing number of DC microgrids added to contemporary power systems poses great challenges in fault protection and in the location of faults for DC microgrids, whose configurations are preferably ungrounded because the latter removes the need for additional bank configuration. In this thesis, a novel artificial neural network architecture is proposed to perform fault location in ungrounded DC microgrids using selective voltage measurements. The study covers the fundamental requirements for fault location in ungrounded systems and is based on how pole-to-ground voltages act in case of short circuits.

The proposed methodology suggests a complex and sophisticated neural network architecture finely tuned for voltage-based fault detection and location. The architecture relies on measurements from four strategically positioned nodes in the DC microgrid infrastructure and provides a first-of-its-kind fault identification technique based on the principle that the measured voltage at the fault will be equal to zero. In the proposed neural network architecture, several dense layers are sequentially added, followed by applying batch normalization and ReLU activation functions to capture complex nonlinear mappings of fault characteristics. It particularizes the utilization of dedicated voltage normalization schemes and flexible thresholds to improve fault detection and discrimination from normal operating conditions.

This work proposes a unified mathematical approach for the analysis and implementation of voltage-based fault location methods. The proposed system consists of multi-stage processing of data, from voltage normalization followed by feature extraction, fault detection, and fault localization. Robust performance across a wide range of operating conditions and fault scenarios is ensured through advanced optimization techniques and training methodologies.

The experimental work was performed in an advanced test environment integrated with Hardware-in-the-Loop simulation and a laboratory-scale DC microgrid at 250V DC. It allowed examining the proposed technique under different faults, like fault resistance from 0.1Ω reaching 100Ω, single and double faults of transmission lines, and different operating conditions. Incorporating real-time digital simulation capabilities for the time step of 50 microseconds, the validation framework ensured accurate representation of fast transient phenomena during fault events.

Experimental results show outstanding performance indexes that considerably push the limit of the modern technologies in DC microgrid protections. With a mean response time of 2.3 milliseconds, the system established 99.3% detection accuracy, as well as location accuracy above 97.7% for fault resistances up to 50Ω. An evaluation of the performance shows its strong performance within the proposed operating conditions with false positive and negative rates under 0.2%. It proves the practical viability of the proposed system in advancing industrial applications due to its high accuracy under normal, high impedance, and multi-fault scenario conditions.

This study greatly advances theoretical knowledge and practical application for DC microgrid protection systems. The proposed mathematical framework opens new horizons of understanding fault location principles in a setting where voltages and associated strain are used for fault location, and a practical implementation demonstrates the applicability of neural network protection schemes.

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
DC	Direct Current
AC	Alternating Current
GND	Ground
QTY	Quantity
RMS	Root Mean Squared
MG	Microgrid
DCMG	Direct Current Microgrid
ACMG	Alternating Current Micro Grid
ANN	Artificial Neural Network
EF	Earth Fault
PV	Photovoltaic
LL	Line-to-line
LG	Line-to-Ground
ESS	Energy Storage Systems
DER	Distributed generation resources
ReLU	Rectified Linear Unit
FD	Fault Detection
DG	Distributed Generation
PP	Pole-to-Pole
PG	Pole-to-Ground
L-L-G	Line-to-Line-to-ground faults
SVM	Support Vector Machines
kNN	k-nearest neighbors
STFT	Short-Time Fourier Transform
DWT	Discrete Wavelet Transform
ESS	Energy Storage System
RES	Renewable Energy Sourc

CHAPTER ONE

INTRODUCTION

DC microgrids have been recognized to be the promising solution to integrate renewable source power and energy storage systems with DC loads for either grid-connected or isolated applications. Reliably detecting and locating faults in ungrounded systems is one of the most critical challenges facing operation in DC microgrids. An inherent zero-crossing point doesn’t exist in DC microgrids (unlike conventional AC systems) and thus have unique fault characteristics, while traditional protection schemes lose their effectiveness.

Ungrounded direct current microgrids add even more complexity because there is no direct reference to ground, further complicating fault current detection and analysis. While this configuration brings with it a number of advantages, including the ability to continue operating through single-pole-to-ground faults and reduced corrosion risks, it does make the distinction between normal operating conditions and fault occurrences more difficult. Autoencoders in the last few years have really been a very helpful tool for the earth-fault detection and localization in microgrids. Autoencoders are a class of artificial neural network architectures that excel in the very function of learning complex patterns associated with normal operation and identifying anomalies that can represent faults. They learn the underlying patterns of a system's behavior by encoding input data into a lower-dimensional latent space and after that reconstructing it; thus, autoencoders can also recognize deviations that could potentially be faults.

The autoencoder-based approach is highly advantageous compared to traditional protection methods of ungrounded DC microgrids. Handling nonlinear characteristics is a very crucial benefit since, under both normal and faulted operating conditions, the characteristics in a DC microgrid usually show complex nonlinear behavior. The linear analysis techniques cannot cope with it, while autoencoders can capture and analyze these intricate relationships with excellence.

Another significant advantage of the implementation is that autoencoder-based methods do not require detailed mathematical modeling of the system components and their interactions. Traditional protection schemes often rely on complex differential equations and precise system parameters, which can be challenging to obtain and may change over time. Autoencoders directly learn from the operational data of the system and hence alleviate such explicit modeling.

Compared to conventional methods, adaptive protection based on autoencoders represents a big step forward. Changes in topology, load conditions, and power flow patterns are relatively common in DC microgrids; hence, the protection system needs to adapt as well. The high flexibility and robustness to changes in operating conditions are brought about by training the autoencoders on learning normal operating patterns in various system configurations.

In addition, this combination of high accuracy with rapid response makes autoencoder-based protection especially valuable. These networks will be capable of processing several system parameters at the same time to detect minor anomalies, perhaps indicative of incipient faults often before they grow into serious problems. Fast fault detection and location is key to preventing sensitive equipment from getting damaged and hence to the stability of a system.

That is, while these complex relations cannot be represented through traditional linear analysis-based methods, the autoencoders do that.

One of the most relevant benefits in using autoencoders is that this approach does not require any complex mathematical modeling of the system's elements and relationships between them. On the other hand, many of the conventional protection schemes are based on complex differential equations and exact parameters of the system, which are very hard to get and can vary with time.

1.1 Problem statement

To detect the earth fault in ungrounded DC Microgrids is one of the hardest tasks for modern relay protection systems.

Modern protection relays, with all their technological advances, still suffer from serious challenges in the detection and localization of earth faults in ungrounded DC microgrids. In these systems, the fault current during earth faults is generally negligible because there is no direct path to ground; hence, conventional relays can hardly distinguish among typical operating and fault conditions.

The sensitivity of the modern relays is often inadequate in order to detect the high-impedance earth faults in ungrounded direct current systems. Although these faults harmless in their initial stages, if they are not detected, they can lead to more dangerous fault conditions. Of course, very sensitive protection schemes are thus required for fault detection that does not generate unreasonably high false indications from system variabilities. At present, relay technology almost exclusively created for alternating current or grounded direct current schemes does not have that kind of powerfully sophisticated discrimination for subtle fault detection. Today's relay technology, developed mainly for AC systems or grounded DC schemes, doesn't have sophisticated enough discrimination capabilities to recognize such subtle fault detection. Moreover, the presence of earth faults in ungrounded DC microgrids adds another dimension of complexity. Traditional distance-based protection schemes lose their effectiveness since, with non-linear fault impedances, there are no unique paths for the current of the fault. Such uncertainty in the fault location may result in longer fault-clearing times and may compromise both the reliability and safety of the system.

These complexities are further compounded in modern DC microgrids integrating renewable energy sources and power electronic interfaces. The high-frequency noise and transients due to the rapid switching actions of power converters mask the fault signatures, making the detection process more difficult. The present relay technology is unable to differentiate these normal switching events from actual fault conditions, leading to missed detections or false tripping. There is, therefore, a strong need for more sophisticated protective mechanisms, able to deal with these limitations and ensure reliable earth-fault detection and it’s localization in ungrounded DCMG. The work proposed has to confront not only the technical challenges of the fault detection and location but also provide real-life implementation within the given existing microgrid arrangement without adversely affecting the system's reliability and stability.

1.2 Definition of Terms

Below, there are very critical terminologies that are going to make clear the concepts, methodologies, and technologies discussed throughout this thesis. The given definitions shall help to give clear technical discussions throughout the document.

DC Microgrid
An interconnected power distribution system operating on direct current (DC) has distributed energy resources, energy storage solutions, and various loads. The system may work in both grid-connected and islanded modes.

Unreferenced Framework
A power system configuration where there is no intentional electrical connection between the current-carrying conductors and the ground (earth). This configuration offers some operational advantages, but brings with it unique challenges in fault detection.

Poles-to-Ground Voltage
The electrical potential difference measured between any current-carrying conductor (pole) and the reference ground point in a DC system. This measurement is very important for fault detection in ungrounded systems.

Fault Location
The precise location within an electrical distribution system where an abnormal current pathway has formed, which will lead to a system fault or deterioration. In the present work, it applies particularly to the location of ground faults in direct current micro-grids.

High-Impedance Fault
One class of electrical fault is characterized by the relatively high values of fault resistance—greater than 10Ω, which yields reduced fault currents, hence increasingly difficult to detect using conventional means.

Artificial Neural Network (ANN)
A computational model designed to find patterns in data, with inspiration from biological neural networks. In the context of this thesis, it specifically refers to architecture developed for fault location determination.

Dense Layer
A layer in a neural network where all the neurons are connected to all the neurons in the next layer, allowing full feature extraction of the input data.

ReLU Activation
The Rectified Linear Unit activation function, mathematically expressed as $f(x) = \max(0, x)$, brings non-linearity to the processing capabilities of neural networks.

Batch Normalization
A technique to normalize the inputs of every layer, which improves the stability of training and reduces the internal covariate shift in deep neural networks.

SoftMax Function
A mathematical function used in the output layer for the classification of fault locations that converts a vector of numeric values into a probability distribution.

Terminology for Measurement and Analysis

Voltage Normalization
The process of scaling voltage measurements to a standardized range, usually [0,1], in order to enhance the efficiency and performance of neural network training.

Detection Accuracy
The percentage of correct fault identifications, regarding the total number of fault instances, is calculated with the expression (True Positives + True Negatives)/(Total Samples) × 100%.

Temporal Response
The duration from the onset of a fault to the effective detection and localization of that fault by the protection system, generally quantified in milliseconds.

False Positive Rate
Percentage of normal operating conditions that are incorrectly identified as fault conditions, which indicates the system reliability.

Location Accuracy
The precision with which a system can determine the physical location of a fault; this is usually stated in terms of percentage or distance error.

Real-Time Digital Simulator (RTDS)
A specialized computing system designed for real-time simulation of power systems, which can accurately represent electromagnetic transients and control system responses.

Hardware-in-the-Loop (HIL)
A methodological approach to testing, which combines real hardware components with real-time simulation, thus enabling in-depth validation of protection systems under realistic application scenarios.

Sampling Frequency
The rate at which voltage measurements are taken in digital form is usually expressed in Hertz, or as samples per second.

Computational Overhead
The time taken by the neural network to process the input data and present a result for fault location contributes to the overall response time of the system.

Confidence Metric
A numerical measure of the system's confidence in its fault location determination, normally expressed as a value between 0 and 1.

Average time for Identification
The average time required by the system to detect and isolate a failure is called by analysis for different failure situations and operating conditions. System Reliability The ability of the protection system to perform its assigned tasks reliably under specified conditions over a long period is typically measured by a set of performance parameters.

1.3 Significance of the Study

With the world slowly moving toward efficient and sustainable energy solutions, DC microgrids are posing as a very potential technology. They promise better energy efficiency, more effective integration of renewable sources, and higher reliability than traditional AC grids. They also bring in the challenges of how to keep the system stability and quickly identify the faults whenever they occur.

Autoencoder neural networks are a cutting-edge machine learning technique that revolutionizes the methods used in fault detection and localization of direct current microgrids. These neural networks are very adept for this task as they can identify intricate patterns in data without the necessity of annotated fault samples, hence showing tremendous adaptability to different configurations of microgrids under different operating conditions. The use of autoencoders in the application of fault detection in DC microgrids cannot be underestimated. Traditional methods of fault detection face inherent challenges posed by characteristics of DC systems, unlike their AC counterparts, such as no zero-crossing points and very fast propagation of faults. Autoencoders are able to handle data from multiple sensors at high speed and locate any anomalies with high precision, possibly indicating faults, in a very short time.

Autoencoders can capture relationships among system variables via the compression induced by mapping the input data into a lower dimensionality representation. This technique will enable the identification of slight deviations from known operating parameters that may be overlooked by traditional methods. In addition, the encoding and decoding process also cancels out intrinsic noise, so the accuracy of fault detection is improved. The autoencoder-based fault detection is realized by collecting data from the different sensors in the DC microgrid, training the autoencoder with normal operating data, and then using it for real-time anomaly detection. This way, fast fault detection is not only enabled but also contributes to locating faults based on the patterns of detected anomalies.

The benefits of advanced fault detection go well beyond the basic identification of problems. It contributes much to the general reliability and stability of systems. It also reduces downtime, prevents cascading failures, and allows for targeted maintenance and repair through the ability to quickly identify and precisely localize faults—all very important when the application in question cannot afford an interruption in the supply of power, such as in hospitals or data centers.

Moreover, autoencoder-based fault-detection mechanisms can be easily integrated within the existing protection architectures, such that preliminary warnings concerning incipient faults are provided in order to increase the accuracy in the localization of faults. Putting all these principles into practice culminates in ways for the development of new-generation protection systems characterized by a high degree of flexibility and sophistication, including their self-reconfiguration properties while maintaining real-time operability.

Autoencoders have been widely applied in this field with great potential; however, many challenges remain. The search for robustness against different types of faults and optimization of the autoencoder architecture for specific microgrid setups is an open field for further investigation. Like any system based on artificial intelligence, there is an obvious need to develop explainable methods that allow building trust in these fault detection methods.