FAULT CLASSIFICATION AND SECTION IDENTIFICATION IN DISTRIBUTION NETWORK FOR FASTER SERVICE RESTORATION

A Thesis submitted to the
UPES

For the Award of

Doctor of Philosophy
in
Electrical Engineering-Power Systems

By

Abdul Haleem M I

August 2024

Supervisor
Dr. Madhu Sharma

Department of Electrical and Electronics Engineering
School of Engineering(SOE)
UPES
Dehradun - 248007, Uttarakhand, India

FAULT CLASSIFICATION AND SECTION IDENTIFICATION IN DISTRIBUTION NETWORK FOR FASTER SERVICE RESTORATION

A Thesis submitted to the
UPES

For the Award of
Doctor of Philosophy
in
Electrical Engineering-Power Systems

By

Abdul Haleem M I
(SAP ID: 500043732)

August 2024

Supervisor
Dr. Madhu Sharma
Sr. Associate Professor

Department of Electrical and Electronics Engineering
School of Engineering(SOE)
UPES
Dehradun - 248007, Uttarakhand, India

"In the name of God, the Most Gracious, the Most Merciful"

Dedicated to the cherished memory of my late father and role model, M T Ibrahim Master, and my mother, Ramla Choondathodi, who taught me the value of patience in life. Also, dedicated to my wife, Adila, and son, Abdul Haadhi, as well as to all my teachers who have imparted knowledge throughout my journey, and to all my supporters who have encouraged my personal and professional development.

"If you are lazy to use your brain and health, you are welcoming the spider to build a web on your palate"- MT Ibrahim Master(My Father)

"The thief can only steal your wealth, not your knowledge, and knowledge can always empower your wealth." — Ramla Choondathodi(My Mother)

"Dream is not that which you see while sleeping; It is something that does not let you sleep." — A.P.J. Abdul Kalam

"Anyone who has never made a mistake has never tried anything new."
— Albert Einstein

"Take risks: if you win, you will be happy; if you lose, you will be wise." -Anonymous

"If it doesn't challenge you, it won't change you." - Fred DeVito

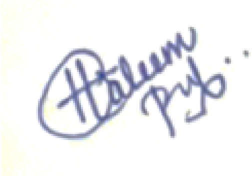
"Challenges persist until they are faced. With self-belief and effort, solutions arise."
- Abdul Haleem M I

"There's a way to do it better - find it." — Thomas A. Edison

June 2023

DECLARATION

I declare that the thesis entitled **"Fault Classification and Section Identification in Distribution Network for Faster Service Restoration"** has been prepared by me under the guidance of **Dr. Madhu Sharma**, Sr. Associate Professor, Department of Electrical and Electronics Engineering, UPES. No part of this thesis has formed the basis for the award of any degree or fellowship previously.



Abdul Haleem M I
Department of Electrical and Electronics Engineering,
School of Engineering [SOE],
UPES
Dehradun - 248007, Uttarakhand, India.
DATE: 26/06/2023

UPES
UNIVERSITY OF TOMORROW

Great Place To Work® Certified MAR 2021–FEB 2022 INDIA

CERTIFICATE

I certify that **Abdul Haleem M I** has prepared his thesis entitled "**Fault Classification and Section Identification in Distribution Network for Faster Service Restoration",** for the award of PhD degree of the UPES, under my guidance. He has carried out the work at the School of Engineering, UPES.

Madhu Sharma

Dr. Madhu Sharma
Department of Electrical and Electronics Engineering,
School of Engineering [SOE],
UPES
Dehradun - 248007, Uttarakhand, India.

Date: 26/06/2023

ABSTRACT

Reliable power supply to end-users is a critical requirement in modern society, and distribution networks(DN) play a crucial role in delivering electricity to consumers. Faults in DN can cause power outages and disrupt service to end-users. Therefore, prompt detection, classification, and identification of fault sections are essential to ensure a reliable power supply. The latest fault detection, classification, and section identification methods should be capable of handling the inherent complexities of the DN and should address the challenges of distributed generation (DG) integration trends providing significant benefits for utilities and end-users. The use of micro-Phasor Measurement Units (μPMUs) can enable faster service restoration, improve fault management, enhance grid reliability and resiliency, provide better monitoring and control, and lead to cost savings.

A Rules-based Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method is proposed in this work for real DN using μPMUs to enable faster service restorations. This method utilizes a set of rules-based algorithms that incorporate the knowledge of power system experts to detect, classify, and identify sections of the fault. The method is based on a comprehensive set of rules developed through a thorough analysis of the DN topology and fault scenarios. The method combines the rules-based algorithms with μPMU data to improve fault management and service restoration processes.

The performance of the proposed method is evaluated using extensive simulations on IEEE 34 node test feeder, and its superiority over existing methods is demonstrated through comparative analysis. The simulation results show that the proposed method accurately detects, classifies, and identifies faults while identifying the faulty section, allowing for faster service restoration and improved grid reliability and resiliency.

The method also demonstrates practical applicability through the validation of realistic μPMU data collected from an IEEE benchmark distribution feeder. The rules-based approach makes the proposed method easily adaptable to different DN topologies and fault scenarios. Rules-based I-FDCSI method has significant implications for the improvement of fault management and service restoration in DN. The method can be applied to real DN with the installation of optimum number μPMUs at strategic locations, enabling more efficient fault management and service restoration. The method also has the potential to be integrated with other grid monitoring and control systems to provide a comprehensive approach to power system monitoring and management.

The developed method for real DN using μPMUs to enable faster service restorations provides a novel and effective solution to the challenges of fault detection, classification, and section identification. The rules-based approach and integration with μPMU data result in improved fault management and service restoration. A total

of 24,480 real-time fault scenarios were simulated using DIgSILENT PowerFactory. The simulation and the validation results of the I-FDCSI algorithm with the real DN benchmark test feeders demonstrate the practical applicability of the proposed method in real-world DN.

ACKNOWLEDGEMENT

I am grateful to the Almighty for the abundant grace and blessings bestowed upon me, which enabled me to successfully complete this journey. I take this opportunity to acknowledge and express my gratitude to all those who supported and guided us during my research work.

I would like to express my sincere gratitude to all those who have contributed to the completion of this research work on "Fault Classification, and Section Identification in DN for Faster Service Restorations."

First and foremost, I extend my heartfelt appreciation to my supervisor, **Dr. Madhu Sharma**, Sr. Associate Professor, Department of Electrical and Electronics Engineering, UPES, Dehradun for her valuable guidance, constant encouragement, and moral support with my work during all stages. Her suggestions and discussions shaped this thesis in the right direction for the successful completion of this work. I would like to thank my Departmental Research Committee members **Dr. Devender Kumar Saini**, Associate Professor, Department of Electrical and Electronics Engineering, UPES, Dehradun and **Dr. Piyush Kuchhal**, professor, Department of Electrical and Electronics Engineering, UPES, Dehradun for their valuable suggestions, insights and encouragement.

I am thankful to my external mentor **Dr. Sajan K Sadanandan**, Associate Principal Researcher-Power System Lead, DEWA R&D Centre, Dubai, UAE for providing invaluable guidance and support throughout the various stages of my research. His expertise and encouragement have played a crucial role in shaping this work.

Also , I would like to thank and acknowledge **Vetrivel S Rajkumar**, PhD Researcher, Intelligent Electrical Power Grids, Department of Electrical Sustainable Energy, TU Delft and **Dr. Peter Palensky**, Chair, Intelligent Electrical Power Grids, Department of Electrical Sustainable Energy, and the ERIGrid 2.0 project team at TU Delft in the Netherlands, as well as their technical and administrative staff, for their coordination, assistance, supervision, and direction in remotely accessing the lab facilities to successfully complete this research work.

I would like to extend my appreciation to the **Intelligent Electrical Power Grids Group at Technische Universiteit Delft in the Netherlands** for their provision of essential resources and facilities that facilitated the progress of this research. Their support and cooperation were crucial in conducting comprehensive simulations and validations on real benchmark DNs utilizing DIgSILENT PowerFactory and RTDS Simulator.

I would like to acknowledge the financial support received from the **Transnational Access program of the EU H2020 ERIGrid 2.0 project with grant agreement number 870620/Intelligent Electrical Power Grids Group at Technische Universiteit Delft in the Netherlands**. Their investment in this research has played a crucial role in making this study possible.

I would like to acknowledge the assistance and moral support provided by the members of the **DEWA R&D Centre-Smart Grid Integration research team**. Their support has significantly contributed to the successful completion of this project. Their commitment to excellence and their willingness to share their knowledge and expertise have been invaluable.

I am grateful to the power system experts who clarified my doubts and concerns throughout my PhD Life, especially **Professor William H. Kersting** (the developer of IEEE Distribution test feeders and author of the book titled "Distribution System Modeling and Analysis"), for providing valuable insights on the IEEE distribution test feeders, load flow validation of the IEEE 34 node test feeder and for considering my doubts and observations in the published results. Additionally, I am thankful to my friends and colleagues who generously shared their insights and expertise during the development of the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method. Their input and feedback have greatly enhanced the reliability and effectiveness of the approach.

I would also like to extend my appreciation to the authors of relevant scientific papers, books, and publications whose research and findings have provided the foundation for my work. Their contributions have broadened my understanding and paved the way for the development of the proposed method. To all the individuals and entities mentioned above, as well as those who have supported me in various ways but are not explicitly named, I extend my deepest gratitude. Your contributions have been invaluable in the successful completion of this research endeavor.

I am profoundly grateful for the unwavering support of my friends and family throughout my research journey. Their love, sacrifices, emotional support, prayers, and constant encouragement have been invaluable. To my friends, thank you for standing by my side and offering insightful perspectives. To my family, your immeasurable love and unwavering belief in me have been the driving force behind my success. I recognize that my achievements would not have been possible without their presence in my life, and I am sincerely thankful for everything they have done. Their support has not only enabled me to complete my research but has also enriched my life in countless ways. As I move forward, I carry their support with me, fueled by confidence and determination to continue making them proud.

Thank you all for your unwavering support, guidance, and encouragement.

Abdul Haleem M I

Contents

Contents

List of Figures

List of Tables

Abbreviations

1 Introduction **1**
1.1 Introduction . . . 1
1.2 Problem Statement . . . 4
1.3 Motivation for Research . . . 5
1.4 Reseacrh Objectives . . . 7
1.5 Thesis Outline . . . 8

2 Literature Review **10**
2.1 Introduction . . . 10
2.2 Fault Location/Identification methods in DN . . . 12
2.2.1 Impedance-Based Methods . . . 15
2.2.2 Traveling wave-based Methods . . . 17
2.2.3 Knowledge-based Methods . . . 19
2.2.4 Integrated Methods . . . 21
2.3 μPMU-based Fault Detection, Classification, and section identification in DN . . . 25
2.3.1 Fault Detection . . . 26
2.3.2 Fault Classification . . . 27
2.3.3 Fault Section Identification . . . 28
2.4 Research Gaps . . . 30
2.5 Conclusion . . . 32

3 Reliability of Power Distribution Networks **34**
3.1 Introduction . . . 34

3.2 Key Reliability Metrices . . . 35
3.2.1 SAIFI (System Average Interruption Frequency Index) . . . 36
3.2.2 SAIDI (System Average Interruption Duration Index) . . . 36
3.2.3 CAIDI (Customer Average Interruption Duration Index) . . . 37
3.2.4 Customer Minutes Lost (CML) . . . 37
3.3 Causes of Power Distribution Network Failures . . . 38
3.3.1 Weather-related Events . . . 38
3.3.2 Human Errors . . . 39
3.3.3 Cybersecurity Threats . . . 39
3.3.4 Overloading and Overvoltage . . . 40
3.4 Reliability Improvement Strategies . . . 40
3.5 Future Trends and Challenges . . . 43
3.6 Conclusions . . . 45

4 Fault Management Process in DN 46

4.1 Introduction . . . 46
4.1.1 Fault Detection . . . 47
4.1.2 Fault Classification . . . 48
4.1.3 Fault Section Identification . . . 49
4.1.4 Fault Section Isolation . . . 50
4.1.5 Service Restoration . . . 50
4.2 Challenges in Fault Management Process and Need for μPMU in DN 51
4.3 Conclusions . . . 52

5 Distribution Network Modelling, Load flow Simulations and Validation 54

5.1 Introduction . . . 54
5.2 Methodology . . . 56
5.3 Distribution Network Selection and Modeling . . . 58
5.4 Load Flow Simulations and Validations . . . 59
5.5 Conclusion . . . 62

6 μPMU-based Realistic Data Generation 64

6.1 Introduction . . . 64
6.2 Methodology . . . 66
6.2.1 μPMU Placement . . . 67
6.2.2 Sizing and Placement of DGs . . . 68
6.2.3 μPMU-Based Real-Time Event Data Generation . . . 70
6.2.3.1 Realistic Real-Time Events . . . 70
6.2.3.2 Data-Generation Settings in DP . . . 71
6.2.3.3 Event Simulations and Plots . . . 72
6.2.4 Results . . . 72

6.2.5 Data Validation . . . 96
6.2.6 Capacitor Bank Switching . . . 97
6.2.6.1 Capacitor Bank Switch-Off Event . . . 97
6.2.6.2 Capacitor Bank Switch-On Event . . . 97
6.2.7 Fault, Trip, CB Open, and Reclose Events . . . 99
6.2.8 DG-Switching Event . . . 102
6.2.9 Other Events . . . 103
6.2.10 Experimental Use Case Test . . . 105
6.3 Conclusions . . . 106

7 I-FDCSI Method Development, Testing and Validation 108
7.1 Introduction . . . 108
7.2 Calculate the Minimum and Maximum Short Circuit Current Ratio per Phase (Min_{SCCR} and Max_{SCCR}) of the Network . . . 112
7.3 Fault Detection Algorithm . . . 116
7.3.1 Rules for Fault Detection without DG and Load Switching . . . 117
7.3.2 Rules for Fault Detection with DG . . . 119
7.3.3 Rules for Fault Detection with Load Switching . . . 119
7.4 Fault Classification Algorithm . . . 120
7.4.1 Rules for Line to Ground Faults (L-G) . . . 121
7.4.1.1 Rules for A-G Fault . . . 121
7.4.1.2 Rules for B-G Fault . . . 121
7.4.1.3 Rules for C-G Fault . . . 122
7.4.2 Rules for Line to Line Faults (L-L) . . . 122
7.4.2.1 Rules for Line to Line Faults (A-B) . . . 122
7.4.2.2 Rules for Line to Line Faults (B-C) . . . 123
7.4.2.3 Rules for Line to Line Faults (C-A) . . . 123
7.4.3 Rules for Line to Line to Ground Faults (L-L-G) . . . 123
7.4.3.1 Rules for Line to Line Faults (A-B-G) . . . 124
7.4.3.2 Rules for Line to Line Faults (B-C-G) . . . 124
7.4.3.3 Rules for Line to Line Faults (C-A-G) . . . 124
7.4.4 Rules for Three Phase Faults (A-B-C) . . . 125
7.5 Fault Section Identification Algorithm . . . 126
7.5.1 Rules for First Line Section ("A") Fault . . . 127
7.5.2 Rules for Rule for Fault Sections at MicroPMU Nodes . . . 127
7.5.3 Rules for Fault Sections at Immediate Line Section after the DS1 of the Reported MicroPMUs with One Upstream (US) and One Down Stream (DS) . . . 128
7.5.4 Rules for Fault Section Identification When MicroPMUs are Installed at Junction Nodes (with One US and Two DS) . . . 128

7.5.5 Rules for Fault Sections at Immediate Line Section after the DS1 of the Reported Junction Node MicroPMUs with One US and Two DS . . . 129
7.5.6 Rules for Fault Sections at Immediate Line Section after the DS2 of the Reported Junction Node MicroPMUs with One US and Two DS . . . 129
7.6 Integration of FDCSI Algorithm . . . 130
7.7 Testing and Validation of Algorithms . . . 132
7.7.1 Fault Detection Test . . . 133
7.7.1.1 No-Fault Event Test . . . 134
7.7.1.2 Fault Event Test . . . 136
7.7.2 Fault Classification Test . . . 137
7.7.2.1 LG Fault . . . 137
7.7.2.2 LL Fault . . . 139
7.7.2.3 LLG Fault . . . 140
7.7.2.4 LLL Fault . . . 141
7.7.3 Fault Section Identification Test . . . 142
7.7.4 I-FDCSI Algorithm Test . . . 142
7.8 Conclusions . . . 143

8 Results and Discussions 144
8.1 Introduction . . . 144
8.2 I-FDCSI Method Results . . . 145
8.2.1 Evaluation of the Method . . . 145
8.3 Discussion . . . 146
8.4 Conclusions . . . 147

9 Conclusions and Future Research 148
9.1 Introduction . . . 148
9.2 Summary of Research Findings . . . 149
9.3 Contribution of the Research . . . 149
9.4 Research Contribution to Power Distribution Industry . . . 150
9.5 Practical Applications of the research works . . . 151
9.6 Conclusions, Limitations and Future Work . . . 153
9.6.1 Conclusions . . . 153
9.6.2 Limitations and Future Work . . . 154

A Network line details, load flow results and realistic network events list 157

B Load flow settings and data generation settings 165

Bibliography **169**

List of Figures

2.1 A general classification of fault location technique in DN 14
2.2 Impeadance Method 15
2.3 Traveling wave Method 17

4.1 A general classification of fault location technique in DN 46

5.1 IEEE 34 feeder modelled in DIgSILENT PowerFactory. 60

6.1 Optimal μPMU locations in the test feeder. 69
6.2 Capacitor bank switch-off event (μPMU7). 74
6.3 Capacitor bank switch-off event (μPMU11). 74
6.4 Capacitor bank switch-on event (μPMU7). 75
6.5 Capacitor bank switch-on event (μPMU11). 76
6.6 CB trip event (μPMU1). 76
6.7 CB trip event (μPMU2). 77
6.8 CB close event (μPMU1). 77
6.9 CB close event (μPMU2). 78
6.10 DG switch-on event (μPMU11). 78
6.11 DG switch-on event (μPMU1). 79
6.12 DG switch-off event (μPMU11). 79
6.13 DG switch-off event (μPMU1). 80
6.14 DG trip event (μPMU5). 80
6.15 DG trip event (μPMU6). 81
6.16 Line section de-energization (μPMU1). 81
6.17 Line section de-energization (μPMU2). 82
6.18 Line section energization(μPMU1). 82
6.19 Line section energization (μPMU2). 83
6.20 ABCN load switch-off event (μPMU7). 83
6.21 ABCN load switch-off event (μPMU11). 84
6.22 ABCN load switch-on event (μPMU7). 84
6.23 ABCN load switch-on event (μPMU11). 85
6.24 BCN load trip event (μPMU1). 85
6.25 BCN load Trip Event (μPMU2). 86
6.26 B-N jumper parted open circuit fault (μPMU1). 86

6.27 B-N jumper parted open circuit fault (μPMU2). 87
6.28 BG fault event (μPMU1). 87
6.29 BG fault event (μPMU2). 88
6.30 Tap lowering (μPMU5). 88
6.31 Tap lowering (μPMU6). 89
6.32 Tap Raising (μPMU5). 89
6.33 Tap raising (μPMU6). 90
6.34 Temporary fault and reclosing (μPMU1). 90
6.35 Temporary fault and reclosing (μPMU2). 91
6.36 Transformer outage (μPMU5). 91
6.37 Transformer outage (μPMU10). 92
6.38 Transformer energization (μPMU5). 92
6.39 Transformer energization (μPMU10). 93
6.40 Transformer trip (μPMU5). 93
6.41 Transformer trip (μPMU10). 94
6.42 Off supply complaint (μPMU1). 94
6.43 Off supply complaint (μPMU10). 95
6.44 Unbalance voltage complaint (μPMU5). 95
6.45 Unbalance voltage complaint (μPMU10). 96
6.46 Capacitor bank switch-off event (voltage variations). 98
6.47 Capacitor bank switch-off event (current variations). 98
6.48 Capacitor bank switch-off event: voltage and current variations validation using real μPMU data [127]. 99
6.49 Capacitor bank switch-on event (voltage magnitude). 99
6.50 Capacitor bank switch-on event (current magnitude). 100
6.51 Capacitor bank switch-on event (voltage and current magnitude) validation using real μPMU data [127]. 100
6.52 B-G fault, trip, CB open, and reclose events observed at upstream. . 101
6.53 B-G fault, trip, CB open, and reclose events observed at downstream. 102
6.54 B-G fault, trip, CB open, and reclose events observed at upstream (Plot a, Plot b) and downstream (Plot c, Plot d) (voltage and current magnitude) [56]. 103
6.55 DG-switching event (voltage and current variations). 103
6.56 DG-switching event observed by the real μPMU [129]. 104
6.57 RTDS testbed for genertaed data validation 106

7.1 Block Diagram of I-FDCSI Algorithm. 111
7.2 IEEE 34 node model with DGs and μPMU locations. 111
7.3 Fault detection flow chart. 118
7.4 Fault classification flow chart. 120
7.5 Fault section identification flow chart. 126
7.6 I-FDCSI Flow Chart. 131

7.7 RTDS testbed for I-FDCSI Algorithm validation 132
7.8 Load switching event results from master μPMU. 134
7.9 DG switching event simulation results from master μPMU. 134
7.10 Tap change event simulation results from the master μPMU. 135
7.11 Capacitor switching simulation results from master μPMU. 135
7.12 A-B-C fault detection simulation results from the master μPMU. . . . 136
7.13 A-B-C fault detection simulation results from the nearest μPMU. . . 137
7.14 LG fault classification simulation results from the master μPMU. . . 138
7.15 LG fault classification simulation results from the nearest μPMU. . . 138
7.16 LL fault classification simulation results from the master μPMU. . . . 139
7.17 LL fault classification simulation results from the nearest μPMU. . . 139
7.18 LLG fault classification simulation results from the master μPMU. . . 140
7.19 LLG fault classification simulation results from the nearest μPMU. . 140
7.20 LLL fault classification simulation results from the master μPMU. . . 141
7.21 LLL fault classification simulation results from the nearest μPMU. . . 141

B.1 Load flow basic settings. 165
B.2 Load flow iteration control settings. 166
B.3 RMS Simulation basic settings. 166
B.4 Data generation step size settings1. 167
B.5 Data generation step size settings2. 167
B.6 Run Simulation Settings. 168

List of Tables

2.1 Comparison of different fault location methods. 24

5.1 Line-to-neutral voltage error deviation from the IEEE published results. 61
5.2 Line-to-neutral angle error deviation from the IEEE published results. 61
5.3 Line current error deviation from the IEEE published results 62
5.4 Line current angle error deviation from the IEEE published results. . 62
5.5 Load flow results from DP model vs. IEEE published results (in brackets). 62

6.1 Investigations on optimal μPMU placements in IEEE 34 node feeder. 68
6.2 DG modeling parameters. 69
6.3 Event category chart and their plots. 75
6.4 Line currents measured at master μPMU 104
6.5 Use case test results: fault and no-fault event classification. 106

7.1 Maximum short circuit currents that can be monitored by each μPMU. 117
7.2 Fault detection algorithm test results. 133
7.3 Fault classification algorithm test results. 142
7.4 Fault section identification algorithm test results. 142
7.5 I-FDCSI algorithm test results. 143

8.1 Evalaution of results. 145

A.1 Line section representation for IEEE 34 node model in DIgSILENT Powerfactory. 158
A.2 Load flow results from DP model (node voltages and angles per phase).159
A.3 Load flow results from DP model (line currents and angles per phase). 160
A.4 List of realistic real-time events generated using DP in the test feeder 161
A.5 List of realistic real-time events generated using DP in the test feeder Cont. 162
A.6 List of realistic real-time events generated using DP in the test feeder Cont. 163
A.7 List of realistic real-time events generated using DP in the test feeder Cont. 164

Abbreviations

DN	Distribution Network
DER	Distributed Energy Resources
DP	DIgSILENT PowerFactory
RTDS	Real-time Digital Simulator
SCADA	Supervisory Control and Data Acquisition
RTU	Remote Terminal Unit
GPS	Global Positioning System
DCC	Distribution Control Centre
DG	Distributed Generation
LV	Low Voltage
DT	Distribution Transformer
OHL	Overhead Lines
SLG	Single Line to Ground
IEEE	Institute of Electrical and Electronics Engineers
PES	Power and Energy Society
DSAC	Distribution System Analysis Committee
NR	Newton–Raphson
CSORI	Complete System Observability Redundancy Index
CI	Cost Index
CB	Circuit Breaker
US	Upstream
DS	Downstream
XF10	Line Transformer
S Capacitor	Shunt Capacitor
SL	Spot Load
DL	Distributed Load
MCB	Miniature Circuit Breaker

MinSCC	Minimum Short Circuit Current
MaxSCC	Maximum Short Circuit Current
IaMeasi	Measured Line Current of phase A
IbMeasi	Measured Line Current of phase B
IaMeasi	Measured Line Current of phase C
ROCOF	Rate of Change of Frequency
RMU	Ring Main Unit
FI	Fault Indicator
RFI	Remote Fault Indicator
VR	Voltage Regulator
μPMU	Micro-Phasor Measurement Unit
PMU	Phasor Measurement Unit
LVDB	Low Voltage Distribution Board
DT	Distribution Transformer
L-G	Line to Ground
L-L	Line to Line
L-L-G	Line to Line to Ground
L-L-L	Line to Line to Line
A	Phase A
B	Phase B
C	Phase C
G	Ground
MinSCCR	Minimum Short Circuit Current Ratio
SAIFI	System Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
CAIDI	Customer Average Interruption Duration Index
CML	Customer Minutes Lost
FD	Fault detection
FC	Fault Classification
FSI	Fault Section Identification
FL	Fault location
ADN	Active Distribution Network
FTU	Feeder Terminal Unit
FDCSI	Fault Detection, Classification and Section Identification
I-FDCSI	Integrated Fault Detection, Classification and Section Identification

Chapter 1

Introduction

1.1 Introduction

The reliability of distribution networks is essential for maintaining continuous power supply, minimizing financial losses, enhancing quality of life, and fostering sustainable development. Various events and procedures are in place within power distribution networks to ensure seamless operation and reliable electricity delivery. These events are further classified into normal and abnormal events. Faults, denoting abnormal events within or outside the network, can potentially interrupt power supply. Internal faults occur within network components like transformers, cables, etc, typically due to equipment malfunctions or short circuits. In contrast, external faults originate from environmental factors like lightning strikes or interference from vegetation. Normal events or planned switching operations entail connecting or disconnecting network components to regulate voltage levels and optimize system performance. Capacitor switching, a type of normal event, facilitates voltage regulation and improves power factor, while reactor switching regulates voltage levels and mitigates fault currents. Tap changing, meanwhile, adjusts transformer winding tap positions to regulate voltage levels and accommodate load variations, ensuring consistent voltage supply to consumers and optimizing network functionality. Normal events aim to enhance network performance. However, fault events in distribution networks can lead to power outages and disrupt service, underscoring the importance of promptly detecting, classifying, and identifying faults to maintain a reliable power supply.

Fault detection, classification, and section identification (FDCSI) in distribution networks have been extensively studied in the literature. However, traditional FDCSI methods have limitations in terms of accuracy, speed, and practical applicability. For instance, conventional fault detection methods based on voltage and current measurements using supervisory control and data acquisition (SCADA) systems have limitations in terms of accuracy, especially for high-impedance faults and incipient faults. Additionally, traditional methods are inadequate for real-time applications given the current trends in distributed generation (DG) penetration and their inherent slow response time.

Micro-Phasor Measurement Units (μPMU) have emerged as a promising technology for real-time monitoring and control of power systems. μPMUs provide high-speed synchronized voltage and current measurements, enabling the detection and classification of faults with high accuracy and speed. The use of μPMUs for FDCSI in distribution networks has been proposed in the literature, with promising results. This thesis proposes a rules-based Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method for real distribution networks using μPMUs to enable faster service restorations. The proposed method is based on a set of rules-based algorithms that incorporate the knowledge of power system experts to detect, classify, and identify faults. The proposed method combines the rules-based algorithms with μPMU data to improve fault management and restoration.

The limitations of conventional FDCSI methods have led to the development of new methods based on advanced sensing technologies, such as μPMUs. μPMUs are devices that provide synchronized voltage and current measurements at high speeds. μPMUs are capable of measuring voltage and current phasors with sub-millisecond accuracy, enabling real-time monitoring and control of power systems. The use of μPMUs for fault location in distribution networks has been proposed in the literature as a promising solution to the limitations of traditional fault location methods.

Based on the synchronized readings from the μPMUs, novel fault detection and classification algorithms have been developed in several research papers. These techniques use high-resolution synchronized data from the μPMUs to identify the problematic area of the distribution network and to detect and categorize various fault kinds. However, the majority of these techniques rely on machine learning algorithms, which demand a significant quantity of training data and computing power. The caliber and accessibility of the training data have an impact on these methods' success as well. Particularly when noise and measurement errors are present, traditional defect detection and classification approaches frequently have poor accuracy and lengthy detection times [1]. μPMUs have become a promising technology in recent years for enhancing the precision and timeliness of fault detection and location in DN [2,3]. Recent years have seen a significant amount of study on the use of μPMUs for DN fault detection and classification [4-6]. However, there is still a need for fault detection and classification methods for DN that are more precise and effective, especially when there is noise, measurement inaccuracy, or distributed energy resources (DERs) present [1]. The author created realistic μPMU data for various real-time events in an unbalanced distribution network to simulate the dynamics of the real grid because real μPMU data were not readily available [4]; the generated realistic data was then verified using publicly available real μPMU data. For several algorithms created as part of this research, the dynamics of fault events and line current fluctuations were used as thresholds. The Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) approach for real DN employing μPMUs is established in this study on the basis of rules. The I-FDCSI approach is based on a set of guidelines created with the help of subject-matter expertise and statistical analysis of the measured data. The suggested method may deliver precise fault detection, classification, and section identification results with a short response time, and it does not require a lot of training data or computational resources. The proposed method's effectiveness has been evaluated in comparison to the widely used fault detection and classification techniques on a real-world benchmark distribution network.

1.2 Problem Statement

The integration of distributed generation (DG) systems and network topology modifications pose additional challenges to fault detection, classification, and section identification in power distribution networks. This system changes and disturbances introduce complexities that traditional fault management methods struggle to address, leading to prolonged service restoration times and reduced operational efficiency. Therefore, there is an urgent need for an advanced fault management approach that can effectively handle these changes and disturbances while expediting service restoration in distribution networks.

Existing fault management methods often fail to adapt to the dynamic nature of distribution networks due to the limited consideration of system changes and disturbances [7]. The integration of DGs introduces new fault scenarios, such as islanding and reverse power flow, which require specialized fault detection and classification techniques [8]. Furthermore, network topology modifications, such as line reconfiguration or the addition/removal of network elements, can affect fault location identification and section identification accuracy.

To overcome these challenges, a comprehensive solution is required that can seamlessly accommodate system changes and disturbances in fault detection, classification, and section identification. This solution should incorporate advanced algorithms that can analyze and interpret high-resolution synchronized measurements obtained from measurement devices such as micro-phasor measurement units (μPMUs) and effectively adapt to the presence of DGs and modified network topologies. By addressing these challenges, the solution will enhance the accuracy, speed, and adaptability of fault management in distribution networks, thereby reducing service restoration time and improving overall operational efficiency.

1.3 Motivation for Research

The motivation for conducting this research lies in the critical need to enhance the fault management capabilities in power distribution networks, particularly in the context of system changes and disturbances such as the integration of distributed generation (DG) systems and network topology modifications. The traditional fault management methods employed in distribution networks often struggle to adapt to these changes, leading to prolonged service restoration times, decreased reliability, and operational inefficiencies [9].

The integration of DG systems introduces new fault scenarios and complexities that demand advanced fault detection, classification, and section identification techniques. The presence of DGs can lead to islanding conditions, reverse power flow, and changes in fault characteristics, necessitating specialized fault management approaches. Moreover, network topology modifications, including line reconfiguration and the addition or removal of network elements, further complicate fault location and section identification [10].

By addressing these challenges, the proposed research aims to provide an integrated fault detection, classification, and section identification (I-FDCSI) method specifically designed to handle system changes and disturbances. The development of this method is motivated by the desire to overcome the limitations of traditional fault management approaches and enable faster service restoration in distribution networks.

The research motivation is driven by the potential benefits that can be achieved through the implementation of an advanced fault management solution. By effectively handling system changes and disturbances, the I-FDCSI method can enhance fault detection accuracy, streamline fault classification, and improve fault location and section identification. Consequently, this will contribute to minimizing service restoration time, reducing customer disruptions, and optimizing the reliability and resiliency of distribution networks.

Furthermore, the research motivation is strengthened by the growing importance of sustainable and distributed energy resources. The integration of DG systems is becoming increasingly prevalent, necessitating robust fault management strategies. By addressing the unique challenges posed by DG integration and network topology modifications, the proposed research aligns with the broader objective of facilitating the seamless integration of renewable energy sources into distribution networks.

Overall, the research motivation is grounded in the pressing need to develop advanced fault management techniques that can effectively handle system changes and disturbances in power distribution networks. By addressing these challenges, the research aims to contribute to improved service restoration, enhanced reliability, and the efficient operation of distribution networks in the face of evolving energy landscapes.

1.4 Reseacrh Objectives

The main objective of this research is to develop and validate an Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method that can effectively handle the effects of system changes and disturbances, such as the integration of DGs and network topology modifications. The I-FDCSI method aims to provide accurate fault detection and classification in the presence of DG-related fault scenarios and adapt to modified network topologies for reliable fault location and section identification. By achieving these goals, the method will contribute to faster service restoration, enhanced fault management, and improved resiliency in power distribution networks facing system changes and disturbances. The research objectives are systematically outlined as follows.

- Modelling and simulation of a standard IEEE distribution network for the data generation of steady state and dynamic fault conditions.
- Validation of the model accuracy through comparison of load flow study results with the benchmark load flow results published by IEEE Distribution System Analysis Subcommittee and investigation of the effects of system changes and disturbances like the integration of DGs and network topology modifications.

- To develop an accurate and reliable Integrated method for Detection, Fault Classification and Section Identification (I-FDCSI) in DN using topology-focused rules-based Algorithms considering the effects of system changes and disturbances like the integration of DGs and network topology modifications.
- Validation and testing of developed I-FDCSI method with the available or standard real distribution network data.

These research objectives aim to address the limitations of traditional fault management approaches and provide a comprehensive solution that can effectively handle system changes and disturbances in power distribution networks. By achieving these objectives, the study seeks to enhance fault management capabilities, reduce service restoration time, improve reliability, and optimize the operational efficiency of distribution networks.

1.5 Thesis Outline

This thesis consists of nine chapters including the present Chapter 1 of introduction to the research topic. This chapter describes the problem statement, the research's motivation, and the thesis's outline. Chapter 2 provides a review of past literature related to fault location/identification in DN and the μPMU-based Fault detection, classification and section identification techniques and their research gaps along with the objectives of this research works. Chapter 3 explains the reliability of the power distribution networks. Chapter 4 describes the fault management process in DN. The detailed modelling of the distribution network, load flow simulations and their validations are presented in Chapter 5. The μPMU-based realistic data generation along with the experimental test and validation is discussed in Chapter 6. Chapter 7 defines the I-FDCSI method development, testing and validation. The results of the developed I-FDCSI method is discussed in Chapter 8. Chapter 9 summarizes the conclusions and research contributions of the current work and presents practical applications and future work.

Chapter 2

Literature Review

2.1 Introduction

In the realm of electrical power distribution, the ability to swiftly and accurately identify faults is of paramount importance for ensuring a reliable and uninterrupted power supply. Faults in distribution networks can cause power outages, and equipment damage, and pose safety risks. Therefore, the development and implementation of effective fault location and identification methods are crucial for the efficient operation and maintenance of distribution networks.

Faults in distribution networks can arise from various sources, including equipment failures, insulation breakdowns, conductor faults, and external influences such as lightning strikes or vegetation contact. Traditional fault location methods typically involved manual inspections and time-consuming trial-and-error procedures. However, modern advancements in technology have revolutionized fault detection and localization techniques. Today, distribution networks are equipped with intelligent monitoring systems, sensor devices, and communication networks that enable real-time fault detection and localization. These systems collect data from multiple points within the network, utilizing various sensing technologies such as current and voltage measurements, wavelet analysis, and high-frequency transient analysis. The acquired data is then processed and analyzed using sophisticated algorithms and fault identification techniques.

The implementation of efficient fault location/identification methods brings several significant advantages to power distribution companies, operators, and maintenance personnel. Firstly, these methods enable rapid fault detection and localization, leading to faster response times and reduced downtime. By quickly identifying the fault's location, operators can dispatch repair crews to the precise area, minimizing the time required for fault isolation and restoration of the power supply. Moreover, accurate fault location plays a vital role in optimizing maintenance activities. By precisely pinpointing the fault's location, maintenance personnel can focus their efforts on the affected section, reducing unnecessary inspections and repairs elsewhere in the network. This targeted maintenance approach improves the overall efficiency of maintenance operations and helps allocate resources more effectively. Additionally, fault location/identification methods aid in improving the safety of distribution networks. By promptly identifying faults, potential safety hazards can be mitigated or isolated, preventing electrical accidents, fires, and other dangerous situations. Furthermore, these methods assist in identifying recurring fault patterns, enabling operators to analyze the root causes and take proactive measures to prevent future faults, thus enhancing the overall reliability of the distribution network.

The fault location/identification methods are crucial for the reliable and efficient operation of distribution networks. Modern technologies and advanced algorithms have transformed fault detection and localization, enabling real-time analysis of network data to swiftly identify faults and their precise locations. The implementation of these methods brings benefits such as reduced downtime, optimized maintenance activities, and improved safety. As the demands on distribution networks continue to grow, investing in and refining fault location/identification methods will play a pivotal role in ensuring a reliable power supply and maintaining the integrity of distribution networks.

2.2 Fault Location/Identification methods in DN

The DNs are designed as either radial or ring connections with overhead or underground and mixed modes. The associated consumer or customer loads are affected by the sustained DN failures. Customer Minutes Lost (CML) is the term used to refer to this. One of the most significant reliability indices for power providers is the duration of power outages. Therefore, utilities that restore electricity more quickly are included in those considered to be reliable. Most developed and emerging nations and cities have access to reliable power sources and networks to aid in their ongoing growth. Power outages result from malfunctions or failures in any of the associated networks' components owing to a variety of events, including wear and tear, lightning surges, human error, and outside forces impacting or harming the cables or lines. Since customers or consumer loads are directly involved in the power distribution sector, the network might be complicated and have a high failure probability. The ring system is introduced together with the FI, which is used for physical or remote fault identification, to make it easier to restore power supply to users. However, the majority of power restorations following the occurrence of a sustained fault are delayed, mostly because the Fault Section identification (FSI) process takes too long. It occurs primarily as a result of factors including faulty FIs and accessibility problems at the station. The fault location (FL) is an estimate of the distance to the fault location from the feeding point, whereas the fault location (FSI) is the identification of the faulted segment of the DN in which the fault has occurred. The distribution system is susceptible to four primary types of faults:

1 Single-Line to Ground (SLG)

2 Line to Line (LL)

3 Double-Line to Ground (DLG or LLG) and

4 Three-line (LLL)

5 Three-line to Ground (LLLG)

As a result of environmental causes or aging, SLG arises at a rate of 70% defects in DN when any one of the three-phase wires touches the ground [11]. Whenever time two-phase conductors come into touch with one another, LL faults—which account for 15% of all DN faults—occur [11]. The DLG fault happens 10% of the time when any two phases come into contact with the ground [11]. The LLLG fault, which is referred to as the least frequent fault, occurs at a rate of 5% in DNs [11]. But because it generates such a large fault current, this defect is more serious. The feeder circuit breaker breaks the circuit to isolate the problem from a sound section of the network whenever a fault develops on any point of the conductor, branch, or equipment in DNs. Customers who are connected to the feeder will experience a service interruption as a result of the feeder circuit breaker being opened. The result will be poor service quality and revenue declines for the electricity utility.

So, it is important for utilities to find the defect quickly, isolate it, and restore service to the customers who were out of service. The effects of service failure will be lessened via quicker fault discovery. Direct application of transmission network fault diagnosis techniques are prevented by the non-homogeneity of DNs, structural unbalance, circuit tapings or laterals, and penetration of Distributed Generators (DGs). These complications are referred to as intrinsic complications. In order to overcome the difficulties of DNs, various fault identification/location techniques are investigated. The following categories best describe fault identification/location techniques:

1 Impedance-based method

2 Traveling wave-based method

3 Knowledge-based method and

4 Integrated Method

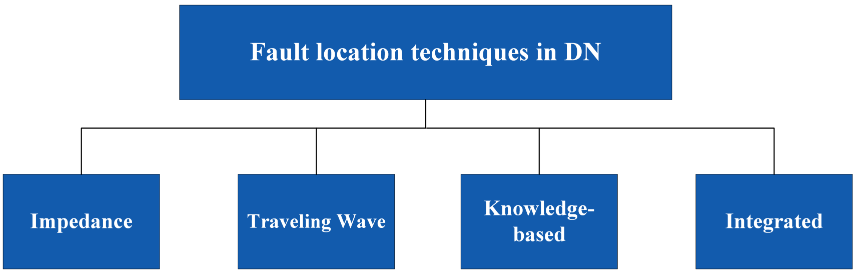


FIGURE 2.1: A general classification of fault location technique in DN

So far, many fault-identifying and locating techniques have been reported in the DNs. Different combinations and extended versions of the main class of fault location shown in Figure 2.1 were investigated in the literature. However, when the DGs are incorporated, the grids make the system more complex, and the existing protective mechanisms are impacted. Finally, the accuracy of fault identification approaches suffers. As a result, more accurate fault-locating or identification strategies must be investigated by addressing all of the intrinsic DN characteristics.

A comparative analysis of the available fault identification or locating methods is performed, and existing challenges and future scopes are highlighted from the examined literature.

2.2.1 Impedance-Based Methods

The impedance approach is a simple and inexpensive way of identifying faults. It locates the fault by using the impedance value measured at the node [11]. This approach measures current and voltage at both line ends. As a result, it can be further subdivided into one-end and two-end techniques [11]. The first method employs feeder-end voltage and current. According to [12, 13], one end technique employs a relatively basic algorithm and does not require communication links for data collection, but fault locating accuracy is hampered by inherent behaviors such as system non-homogeneity, the effect of changeable loads, erroneous relay measurements, and so on. Two-ended techniques may be more accurate. Nevertheless, applying these methods to identify faults requires more data from both ends of the connection.

The impedance-based method is shown in figure 2.2 using a simple circuit.

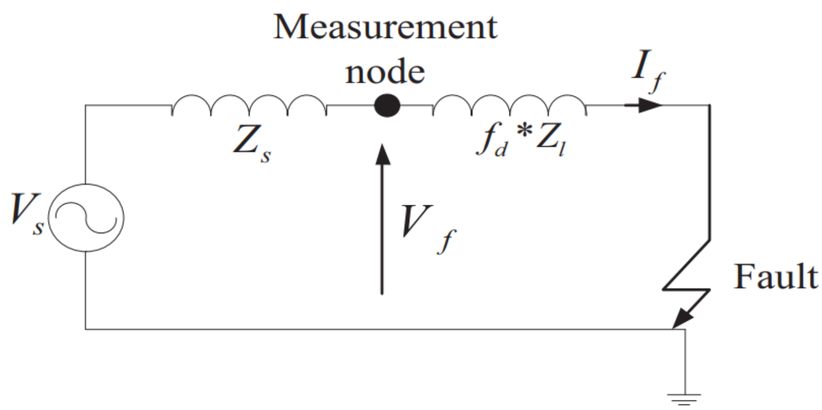


FIGURE 2.2: Impeadance Method

Based on Ohm's Law, voltage and current from the measurement node can be used to find fault distance f_d using the equation 2.1.

$$f_d = (V_f/(I_f \times Z_l\ )) \tag{2.1}$$

where V_f and I_f correspond to the voltage and current during fault, Z_l is the line impedance per unit length, f_d is the fault distance from the measured node, V_s is the source voltage and Z_s is the source impedance [1].

A new impedance-based fault location technique is developed in [14, 15] by considering multiple estimation problems and inherent distribution network characteristics, but only SLG faults were investigated. [16] evaluated a basic impedance-based automatic fault location technique using both induction machine-based and synchronous DGs in different nodes, with static loads and only SLG faults. [17, 18] use Phasor Measurement Units (PMUs) to locate SLG faults, but the distribution grid's inherent properties, DG penetration, dynamic loads, and other types of faults are not taken into account. All fault types were determined in [19] by taking into account static loads and using separate equations for each type of fault. In [20], separate Equations were used to analyze SLG and LLLG while taking into account the DN's non-homogeneous behavior, and faults were located using simulated and fault recorder data. [21] Demonstrates a fault location method based on recorded voltages and currents from Power Quality (PQ) monitoring and substation relays, with investigation limited to SLG and DLG. [22] developed a generalized method that takes into account load variations and measurement errors, but the presence of DGs and line capacitance can be explored further. [23] presented an extended impedance-based location technique that took into account dynamic loads, unsymmetrical lines, and laterals, but it did not address line capacitance. Some studies [24-25] looked at very simplified networks with static loads in the presence of synchronous-based DGs.

According to the review, the main disadvantages of the impedance-based fault identification technique are multiple estimations and a continuous iterative process. The accuracy of these methods is affected by the presence of DGs, laterals, line parameters, dynamic behavior of the loads, noise in data measurements, and issues caused by the non-homogeneous nature of DNs.

2.2.2 Traveling wave-based Methods

The travelling wave method is widely used in transmission lines. It is based on the principle of transmission and reflection of the travelling waves between the line terminal and the fault location.

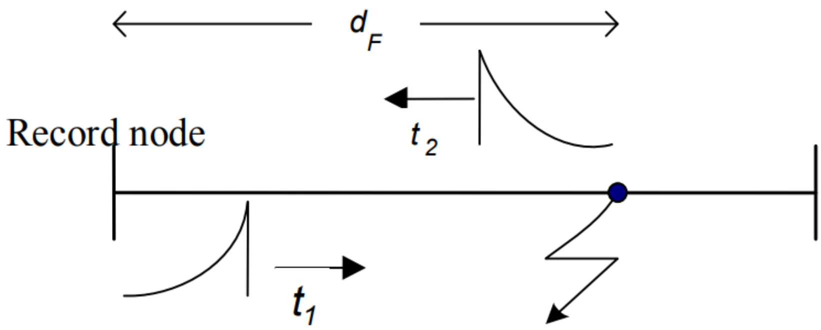


FIGURE 2.3: Traveling wave Method

Figure 2.3 shows a representation of traveling wave method, where t_1 is the time taken by the fault wave to travel from measuring node to the faulty point, t_2 is the time taken by the reflected wave to travel from the faulty point to the measuring node and v is the propagation velocity. The distance to the fault d_F is found using the equation 2.2.

$$d_F = v(t_2 - t_1)/2 \tag{2.2}$$

A method for a branched network is proposed that can overcome the limitations of the traveling wave-based method by using the parameters of fault-induced high-frequency transients [26]. Fault recorders are installed on all branches to assist in locating faults anywhere on the DN or on any branch. The characteristics and frequency of fault transients are determined using the continuous Wavelet Transform (CWT) and recorded voltage. It also investigates the possibility of a fault at various locations in order to precisely locate the fault [27]. As an improvement to the method described in [27], the shortcomings are investigated, and an algorithm for constructing a specific mother wavelet from fault voltage transients is proposed. It produces satisfactory results for non-homogeneous DNs [28]. As an improvement to the method proposed in [28], [29] incorporates CWT frequency and time-domain information. This method was experimentally tested, and the results show significant improvements in the method's accuracy [28]. However, the addition of any laterals to the DN has an effect on the performance of algorithms. This method was validated and tested to ensure its use in real DNs for locating faulty sections and restoring service. The review demonstrates that these methods rarely rely on network data. This includes the line impedance and the load requirements. As a result, these techniques are unresponsive to mathematical inaccuracies. According to studies, these methods provide highly accurate results for locating faults in distribution and transmission networks with a single line. However, the situation is different for DNs, which have many laterals and load taps with shorter lines of connection, resulting in the reflection of traveling waves. As a result, while using these algorithms, the DN requires measurement devices. Because most DNs have numerous load taps, laterals, and branches, traveling wave-based methods face difficulties in the fault location process due to the possibility of wave reflection on the branching or joining points.

This results in an incorrect estimation of fault locations. As a result, researchers are continuing to work on these methods in order to find a better solution for accurately locating the fault in DNs with many complexities.

2.2.3 Knowledge-based Methods

These methods can be used for complex fault current input and output in DGs and feeders. Individual multi-layer neural networks are trained for different fault classes in order to calculate the distance between the DGs and all sources. It is proposed to use an SVM classifier to avoid the complex nature of the fault estimation problem by properly classifying the types of faults and source fault levels [31]. In this case, the measured steady-state current and voltage (three phases) are fed into an individually trained network for each class of fault to calculate the fault reactance. The wavelet transform is used to extract the high- and low-frequency elements of voltage and current transients, and the SLG fault is located by integrating it with a fuzzy neural network [32]. Support vector regression is used to establish a link between current and voltage transients and fault location (SVR). The fault location is estimated by integrating the Discrete Wavelet Transform's time, amplitude, and frequency characteristics (DWT). For very small networks, the results of SVR techniques are preferable to those of ANN-based techniques with fewer training samples [33]. The measured transient voltage is decomposed using the wavelet transform, and the resulting data is fed into the neural network to locate the fault [34]. The wavelet transform is used in [35] to extract the required features from measured current transients. The features for training neuro-fuzzy logic are then used to identify the section of the network where the fault has occurred. The same technique can be used to locate and identify faulty DN sections.

Advancements in automation technologies have opened up new avenues to enhance fault location methods in ADNs. Intelligent location methods, utilizing feeder terminal unit (FTU) measurement fault data, have been proposed. Commonly employed intelligent location methods include the cuckoo algorithm [136], slime mould algorithm [137], artificial intelligence algorithm [138], Pet nets [139], linked-list method [140], particle swarm optimization [141], genetic algorithm(GA) [142], Improved genetic algorithm [143], quantum genetic algorithm [144], multi-verses optimization [145], etc. These methods establish a relationship function between fault feeders and the uploaded current code information of the FTU. The fault location is then treated as an optimization problem, integrating the fault evaluation function with intelligent algorithms. Among these approaches, GA stands out as one of the most widely used methods due to its parallelism and self-organization. It is a successful heuristic search technique commonly employed for fault location problems. Emulating the process of iterative evolution through genetic changes, the GA algorithm initiates a random search using stochastic-generated finite individuals. The solution evolves with each generation until convergence is achieved [146]. According to the review, the advantages of knowledge-based methods are that they produce relatively accurate results and are quick to implement. The knowledge-based method's main limitation is that it must be trained on a large number of real or simulated faults. In addition, if the topology of the DN is changed, whether minor or major, the training phase must be repeated several times to obtain accurate results. Aside from these issues, the knowledge-based method calculates the fault distance from the substation or measuring point rather than locating the fault. Multiple fault location estimations may exist in DNs with complex topologies. As a result, these issues must be addressed when dealing with networks in this category.

2.2.4 Integrated Methods

These are various fault-locating techniques combined. Techniques, such as multiple estimations, are combined to overcome their limitations. [36] described a fault location technique that combined impedance and voltage sag. In [37], current and voltage data from Advanced metering infrastructure were compared with simulated data to locate faults, whereas in DN [38], stored current and voltage data from a digital fault recorder was used to locate faults.

An advancement in compressive sensing fault location is presented in [39], where the voltage vector was generated by using voltage data collected from a few network nodes using smart meters with fewer dimensions than the impedance matrix. In addition, by concatenating the rows of the impedance matrix, a current vector was generated.

[40] shows a compressive sensing method for calculating the current vector using a voltage and impedance matrix. If smart meters are not used on all nodes, the current vector can be determined using the norm minimization method. An integrated technique is used in [41] to classify the type of fault and estimate its location. For classification, a learning algorithm was used, and an impedance-based technique was used to pinpoint the exact location of the fault. [42] suggests combining traveling waves, impedance, and knowledge-based techniques. To detect and classify the fault, the wavelet transform is used. The ANN method is used to locate the faulty network segment, and an impedance-based technique is used to locate potential fault locations. The exact location of the identified faulty portion is confirmed by matching it with the various fault locations.

By combining an impedance technique and a traveling wave-based algorithm to calculate the distance of the fault and identify possible locations, multiple location estimation issues are avoided [43]. The superior components (frequency) of the fault transients are discovered using transient-based analysis. In the frequency and time domains, the correlation method is used to find the correct results.

[44] proposes a method that is a hybrid of traveling wave and impedance-based methods. The frequent The fault path is identified by extracting components of the traveling waves using DWT. When a fault is discovered, non-affected portions of the network are reduced to equivalent impedances. The fault is located by using the identified path, an impedance-based algorithm, and the substation measurements. This method can also be used to identify faulty sections in DNs with multiple branches because the fault path can be easily routed from the fault transient waves.

[45] employs an impedance-based algorithm to identify potential fault locations. After that, two techniques are used to pinpoint the exact location of the fault. The simulation is performed in both methods for similar fault types at each fault location and the voltage is recorded. The first technique compares simulated and measured values to determine the exact location, whereas the second technique uses a matching analysis on the frequency spectrum of simulated fault samples and recorded fault transients.

The research presented in [46] proposes a method for monitoring voltage using smart meters. This will provide information about the section where the voltage is lower due to a fault occurrence. For identifying potential locations, an impedance-based algorithm is used. It can easily filter the number of fault locations because it is an iterative process.

However, its performance on high-impedance faults remains unknown. An impedance-based method for DNs with DGs is proposed in [47]. The impedance-based algorithm is used to find the fault current. During faults, the bus voltage and voltages at each DG are calculated. To determine the correct location, the smallest difference between all identified locations is found using measured and calculated voltages.

For almost all integrated methods, with or without DGs, measurement devices at various points on the DN are required. According to studies, the majority of DNs in the presence of DGs have an impact on the network's security schemes. This further complicates the fault-finding process by providing incorrect information from the connected measuring and indicating devices. When compared to other methods, it produces satisfactory results even for complex DNs.

Despite having more requirements, integrated methods can overcome the limitations of other methods. The main benefit is that it can outperform multiple fault location estimations. This is critical during the fault detection process. If the fault location techniques produce multiple estimates, it is difficult for the utility's respective staff to precisely locate or identify it. As a result, locating the true fault location takes time once more. Meanwhile, the service failure will affect consumers connected to the corresponding network. These methods also require training data, high sampling rate measurements, and sparse voltage measurements. Despite having more requirements, these Methods can help to avoid confusion over multiple fault locations. Both the Distribution Control Room Engineer and the Field Engineer or Operator will face challenges during this situations. During multiple estimations, they have a difficult time identifying the fault location or faulty section identification during the supply restoration process. This may result in improved service. Prolonged service interruptions due to the delay in fault section Identification adversely affect the reliability indices of the power utilities. To address these issues, more precise and reliable integrated methods must be investigated.

The comparison of different fault location/identification techniques is briefly described in Table 2.1.

Table 2.1: Comparison of different fault location methods.

Methods	Requirements	Advantages	Limitations
Impedance Methods[12-25]	Feeder V and I DN Configuration Line data	Applicable to both modern and traditional DNs	Multiple estimations
Traveling wave Methods[26-29]	DN Configuration Large data samples Communication	Unaffected by the parameters of DN Offers satisfactory solutions to most of the limitations of impedance methods	Difficulties in DNs with complexities
Knowledge-based Methods[30-35] & [136-146]	Feeder V and I DN configuration Line data Large data samples Communication	Executes in faster mode Gives Accurate results	Performance depends on the quality and quantity of training data Need to train again whenever DN configuration gets modified
Integrated methods[36-47]	Feeder V and I DN configuration Line data Large data samples Communication	Overcomes the limitations of multiple estimations Applicability in complex DN	Need to Integrate all the required methods to get the desired results

Different types of fault location and identification techniques were reviewed and compared, including impedance, traveling wave, knowledge-based, and integrated methods. Based on the foregoing, it can be concluded that locating and identifying faults in traditional, complex, and modified DNs with high accuracy remains a promising field, despite the fact that most available techniques face various types of challenges. High installation and maintenance costs for Distribution Substation Automation, the inherent properties of distribution grids, the presence of Distributed Generation Sources, frequent changes in network topologies, and so on are the primary challenges. Among the techniques examined, integrated methods are more accurate and have the potential to overcome the evolving challenges of DN. As a result, it is necessary to investigate the enhancement of existing fault location and identification techniques or to develop an integrated technique that uses time-synchronized high-resolution measurements from new-generation measurement devices such as PMUs to address all of the newly evolved DN challenges in order to meet and improve reliability indices.

2.3 μPMU-based Fault Detection, Classification, and section identification in DN

The efficient and reliable operation of power systems is crucial for the modern world's electricity supply. Fault detection, classification, and section identification play pivotal roles in ensuring the stability and resilience of power grids [48]. Traditional methods relying on supervisory control and data acquisition (SCADA) systems, however, face limitations such as low sampling rates and insufficient coverage [49]. To overcome these challenges, researchers have turned to micro-Phasor Measurement Units (μPMUs) as a promising solution for fault analysis in DNs.

By exploring the current state-of-the-art research, the review aims to identify the methodologies, algorithms, and techniques used in this field, as well as the challenges and opportunities for further advancements. The focus will be on signal processing techniques for feature extraction from μPMU measurements, machine learning and pattern recognition algorithms for fault classification, and algorithms for fault section identification. Additionally, the review will investigate the integration of μPMU data with other sources of information, such as SCADA measurements and communication networks, to enhance the accuracy and reliability of fault detection and classification.

Through a thorough evaluation of different approaches, the review will highlight their strengths, limitations, and potential areas for improvement. It will serve as a valuable resource for researchers, engineers, and practitioners involved in power system monitoring, control, and protection, providing them with a comprehensive understanding of the current knowledge and advancements in μPMU-based fault analysis. Furthermore, the review will identify research gaps and propose future directions, including the exploration of advanced fault detection algorithms capable of handling complex scenarios and the integration of emerging technologies like artificial intelligence and big data analytics into μPMU-based fault diagnosis systems. Ultimately, this review seeks to contribute to the development of more accurate, reliable, and efficient fault detection, classification and section identification techniques in DNs, leveraging the capabilities of μPMU technology.

2.3.1 Fault Detection

Fault detection in distribution networks (DN) is a critical task for ensuring a reliable and efficient power supply. μPMUs are emerging as a promising technology for fault detection in DNs [50]. μPMUs can provide high-accuracy, synchronized, and time-stamped measurements of voltage and current phasors, which can be used for fault analysis [51]. Several studies have been conducted to investigate the use of μPMUs for fault detection in DNs.

A data-driven event classifier is developed to effectively classify power-quality events in [52]. The investigations carried out in [53] with an abnormal event detection framework are effective on an actual distribution network with μPMUs. Anomaly Detection Using Optimally Placed Sensors in Distribution Grids is described in [54]. A study is carried out in [55] on the unexpected disruptive events interrupting the normal operation of assets in distribution grids can eventually lead to permanent failure with expensive replacement costs over time. The transient effect of fault on the load level as well as the feeder level is examined in [56]. In [57], μPMU data is used for fault detection, location identification, and faulty phase identification.

Overall, μPMUs have shown great potential in fault detection in DNs, and various algorithms have been proposed for this task. The choice of the algorithm depends on the specific requirements of the application and the characteristics of the DN. Further research is needed to investigate the performance of these methods under different operating conditions and to develop more advanced fault detection algorithms based on μPMUs.

2.3.2 Fault Classification

A practical method that can accurately and quickly identify the type of fault occurring in a distribution grid was developed and compared in [57]. An intelligent fault classification scheme for distribution systems that utilize artificial neural networks and fault current angles to accurately classify series, shunt, and simultaneous faults, leading to improved distribution system security by detecting cable disruptions is proposed in [58]. The technique proposed in [59] needs fault-on voltages of all the nodes connected to the end of lines/branches in order to classify and locate different types of faults. A study described in [60] analyzes machine learning techniques for fault classification in electrical distribution networks, utilizing data from PMUs installed throughout the network and simulating various fault scenarios, resulting in 33 fault types. The above-mentioned studies contribute to the advancement of fault type identification and classification techniques, offering opportunities for improving distribution system reliability and performance utilizing real-time scenarios or events happening in the networks.

2.3.3 Fault Section Identification

A study conducted in [61] on the precision of fault location in power networks using phasor measurement units (PMUs) and the impedance matrix, highlighting the method's effectiveness in considering uncertainties and achieving optimal response regardless of fault type or resistance, with an evaluation conducted on a 14 bus distribution network. in [62], a study demonstrates the suitability of PMU-based state estimation processes in active distribution networks for fault detection and identification, utilizing parallel synchrophasor-based state estimators with augmented topologies and a metric for solution selection, as validated through real-time simulations of various fault types and network configurations. The proposed process scheme proves effective for both active and passive networks, with different fault locations and types. A fault location method for multi-source distribution networks using phasor measurement units (PMUs) is described in [63]. The method utilizes voltage and current information from PMUs to calculate candidate fault locations, distances and then leverages voltage phase relationships to accurately determine the actual fault location while eliminating false positives, demonstrating high position accuracy in simulations even with high levels of distributed energy resource penetration and high-resistance faults. A fault location identification method for smart distribution networks using a state estimation algorithm with real-time data from simulated phasor measurement units (PMUs), achieving accurate fault location identification in the presence of distributed generation and both balanced and unbalanced fault types is presented in [64]. A novel fault location method for distribution systems is introduced utilizing synchrophasor measurements obtained from phasor measurement units (PMUs), enabling accurate fault identification within 1% accuracy of the line length, regardless of network topology, fault type, or PMU placement [65].A fault location method for distribution networks using phasor measurement units (PMUs) and power system state estimation, where an optimization problem is formulated to determine the faulty section and location based on PMU data and voltage differences between grid lines, demonstrating simplicity, efficiency, and high accuracy in fault location identification on a tested IEEE 123-node distribution feeder [66]. A novel technique is presented in [67] for fault location tracking in distribution networks using Phasor Measurement Units (PMUs) and Iterative Support Detection, demonstrating its effectiveness in enhancing system reliability and continuity of supply through accurate fault location identification in various network topologies and conditions. In [68], a fault section location method using Convolutional Neural Network based on data obtained from distribution level phasor measurement units, provides accurate and robust fault section identification in medium and low voltage distribution networks, overcoming the limitations of traditional methods in weak fault feature scenarios. A machine learning-based fault location method is proposed in [69], utilizing μPMUs in smart distribution networks, to accurately identify fault sections regardless of fault characteristics and distributed generation (DG) performance, with notable accuracy in fault section identification demonstrated through simulations of various fault types on the 11-node IEEE standard feeder equipped with three DGs. In [57], the method for location identification utilizes data from two μPMUs and relies on the compensation theorem, while fault detection and identification of the faulty phase are determined through analysis of magnitude shifts in voltage and current phasors using discrete wavelet transform.

Several existing methods have been proposed for fault detection, classification and localisation in distribution networks, including traditional methods based on voltage and current measurements, and more advanced methods using machine learning algorithms and intelligent systems. However, these methods have several limitations, including low accuracy, high computational requirements, and the need for complex hardware. A simple and easy-to-implement approach, with low computational requirements, making it suitable for real-time applications is to be investigated to meet the evolved challenges of today's DN.

2.4 Research Gaps

Both traditional fault management approaches and machine learning-based methods have limitations when it comes to effectively handling system changes and disturbances in power distribution networks. Traditional approaches often struggle to adapt to the complexities introduced by the integration of distributed generation (DG) systems and network topology modifications. They lack the necessary flexibility and adaptability to accurately detect, classify, and identify faults under these changing conditions.

On the other hand, machine learning-based approaches have shown promise in fault management. However, they often rely heavily on historical data for training, which may not capture the dynamic nature of distribution networks and the unique challenges introduced by system changes and disturbances. Moreover, these models can lack interpretability and explainability, which hinders their adoption in critical fault management applications.

There is a research gap in the development of a comprehensive fault management approach that overcomes the limitations of traditional and machine learning-based methods and effectively handles system changes and disturbances. A rules-based Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method offers a potential solution to this gap. By leveraging expert knowledge and statistical analysis of realistic measurements, the rules-based approach can provide simple and interpretable fault management decisions for DCC operators.

The rules-based I-FDCSI method utilizes high-resolution synchronized measurements obtained from μPMUs to accurately detect, classify, and identify faults and faulty sections within the distribution network. The method incorporates a set of rules developed based on expert knowledge and statistical analysis, allowing it to adapt to system changes and disturbances, such as DG integration and network topology modifications.

Addressing this research gap by developing and validating a rules-based I-FDCSI method would contribute to the advancement of fault management in power distribution networks. The method's transparency, interpretability, and adaptability make it a promising alternative to traditional and machine learning-based approaches. By adopting a rules-based approach, distribution network operators can benefit from reliable, explainable, and efficient fault detection, classification, and section identification. The rules-based I-FDCSI method has the potential to significantly improve service restoration time, enhance reliability, and optimize the operational efficiency of distribution networks in the face of system changes and disturbances.

2.5 Conclusion

The review highlighted the importance of modeling a DN and conducting load flow studies to understand the behavior of the network under normal and fault conditions. This step is crucial for establishing a baseline and providing the necessary data for fault analysis. Several studies were reviewed that emphasized the significance of accurate modeling and load flow validation to ensure the reliability of fault detection and classification algorithms. Moreover, the literature review emphasized the need for developing topology-focused rules-based algorithms for fault classification and section identification in DN. These algorithms should consider the unique characteristics of DN, such as the presence of radial feeders, complex network configurations, and the integration of DGs. By focusing on network topology, these algorithms can effectively identify faulted sections and classify the type of fault accurately.

The review also identified research gaps in the existing literature, including the need for comprehensive validation of fault classification and section identification algorithms under various system changes and disturbances. The integration of DGs and network topology modifications can significantly impact the fault behaviour in DN, and it is crucial to account for these factors during the algorithm development and validation process.

In light of the research gaps and objectives, the proposed research aims to address these challenges by developing an accurate and reliable IFDCSI method for fault classification and section identification in DN. This method will utilize topology-focused rules-based algorithms that consider the effects of system changes and disturbances. The validation of the developed method will involve extensive testing under different scenarios, including the integration of DGs and network topology modifications.

Overall, the findings from this literature review underscore the importance of accurate modeling, load flow studies, and the development of topology-focused rules-based algorithms for fault detection and classification in DN. The proposed research will contribute to the advancement of fault analysis techniques in DN and provide practical solutions for enhancing the reliability and operation of distribution systems in the presence of DG integration and network topology modifications.

Chapter 3

Reliability of Power Distribution Networks

3.1 Introduction

The reliability of power distribution networks is of paramount importance in ensuring the seamless delivery of electricity to consumers. Power distribution networks form the crucial link between the high-voltage transmission system and end-users, encompassing a complex network of substations, transformers, distribution lines, and customer connections. The reliable functioning of these networks is essential for various sectors such as residential, commercial, industrial, and institutional, as well as critical infrastructure facilities. Reliability in power distribution networks refers to the ability of the system to provide an uninterrupted and high-quality electricity supply to consumers, minimizing the frequency and duration of power outages. Achieving and maintaining high levels of reliability requires a comprehensive understanding of the causes of failures, the implementation of appropriate improvement strategies, effective reliability evaluation and modeling techniques, and the adoption of best practices. This chapter explores the various aspects related to the reliability of power distribution networks, aiming to provide insights into enhancing network performance and mitigating disruptions.

Power distribution network reliability is crucial for ensuring economic productivity, public safety, and the overall well-being of communities. The impact of power outages can be significant, leading to financial losses for businesses, disruption of essential services, and inconvenience for individuals. Various factors can contribute to power distribution network failures, including equipment malfunctions, weather-related events, human errors, cybersecurity threats, and overloading [70]. To improve reliability, utilities and operators employ several strategies, such as system redundancy, regular maintenance and inspection, fault detection and isolation techniques, distribution automation and control systems, load management strategies, and the integration of distributed generation and microgrids [71]. Additionally, reliability evaluation and modeling play a vital role in understanding network performance, identifying areas for improvement, and making informed decisions regarding network planning and operation. By studying case studies, best practices, and future trends and challenges, this chapter aims to provide a comprehensive understanding of power distribution network reliability and the strategies employed to ensure uninterrupted and high-quality electricity supply to consumers.

3.2 Key Reliability Metrices

Reliability metrics are essential tools for quantitatively assessing the performance and quality of power distribution networks [71]. These metrics provide valuable insights into the frequency and duration of power interruptions, enabling utilities and operators to measure and track the reliability of their systems [72]. The following section discusses the key reliability metrics commonly used in evaluating power distribution networks:

3.2.1 SAIFI (System Average Interruption Frequency Index)

SAIFI is a crucial reliability metric that represents the average number of interruptions experienced by customers within a specific time frame [73]. It quantifies the frequency of power outages and is calculated by dividing the total number of customer interruptions by the total number of customers served during a given period. SAIFI is typically expressed as interruptions per customer per year and provides an indication of the overall reliability of the power distribution network.

3.2.2 SAIDI (System Average Interruption Duration Index)

SAIDI is another important reliability metric that measures the average duration of interruptions per customer within a specific time frame [74]. It quantifies the duration of power outages and is calculated by dividing the total customer interruption duration by the total number of customers served during a given period. SAIDI is usually expressed in minutes or hours and provides insights into the average outage duration experienced by customers, reflecting the reliability of the power distribution network.

3.2.3 CAIDI (Customer Average Interruption Duration Index)

CAIDI is a reliability metric that represents the average duration of interruptions experienced by a customer per interruption event. It is calculated by dividing the total customer interruption duration by the total number of customer interruptions during a given period. CAIDI provides insights into the average outage duration per event and helps identify the effectiveness of restoration efforts and the responsiveness of the power distribution network in resolving interruptions promptly [75].

3.2.4 Customer Minutes Lost (CML)

CML is a metric used to quantify the total duration of time that customers are without power during an outage. It represents the cumulative sum of the minutes of interruption experienced by each customer affected by the outage [76]. CML provides valuable insights into the extent of customer inconvenience and disruption caused by power outages. By tracking CML, utility companies can assess the overall impact of outages on their customers and use this information to improve their outage management strategies, prioritize infrastructure investments, and enhance reliability to minimize customer minutes lost in the future. Additionally, CML is often used as a key performance indicator (KPI) to monitor the effectiveness of power distribution systems and evaluate the success of outage response and restoration efforts.

These key reliability metrics play a crucial role in assessing the performance and effectiveness of power distribution networks. By analyzing and monitoring these metrics, utilities and operators can identify areas of improvement, implement targeted reliability enhancement strategies, and evaluate the impact of their efforts to ensure uninterrupted and high-quality electricity supply to customers.

3.3 Causes of Power Distribution Network Failures

Power distribution network failures can occur due to various factors, and understanding their relative contributions is crucial for utilities and operators to prioritize mitigation efforts and allocate resources effectively [77]. The following section explores the primary causes of power distribution network failures along with their estimated percentage contributions:

Conductor failure is a significant contributor to power distribution network failures, accounting for approximately 70% of the total incidents [78]. Ageing infrastructure, inadequate maintenance, and manufacturing defects can lead to the malfunctioning of critical components such as transformers, switchgear, circuit breakers, and cables. Insulation degradation, thermal stresses, and electrical faults within the equipment contribute to failures. To address this cause, utilities must prioritize equipment maintenance, condition monitoring, and timely replacements to minimize the risk of failures.

3.3.1 Weather-related Events

Severe weather conditions contribute to power distribution network failures and service interruptions [79]. Storms, hurricanes, snowstorms, ice storms, and high winds can cause physical damage to power lines, poles, and associated infrastructure.

Falling trees, debris, and flooding further exacerbate the impact. Climate change-induced extreme weather events pose an increasing risk to the network's reliability. Utilities need to strengthen infrastructure resilience, undertake proactive vegetation management, and implement weather monitoring systems to mitigate the effects of weather-related failures.

3.3.2 Human Errors

Construction errors, improper installation, inadequate training, and maintenance mistakes contribute to system failures. Operational errors, such as misconfigurations and incorrect adjustments during routine maintenance, testing, and troubleshooting, can also lead to disruptions. Utilities should prioritize training programs, quality control measures, and the use of standard operating procedures to minimize human-related failures.

3.3.3 Cybersecurity Threats

In the digital era, cybersecurity threats are one of the major challenges that evolved in the smart grid transformation of Distribution networks [80]. Hackers, malicious actors, and cybercriminals target control systems, communication networks, and data centres, aiming to disrupt operations or gain unauthorized access. Cybersecurity breaches can compromise network integrity, cause service disruptions, and lead to outages. Robust cybersecurity measures, including network monitoring, intrusion detection systems, strong access controls, and employee awareness training, are essential to mitigate the risks associated with cyber threats.

3.3.4 Overloading and Overvoltage

Overloading occurs when the demand for electricity exceeds the network's capacity, leading to strain on components and potential failures [81]. Overvoltage, on the other hand, refers to voltage levels exceeding the specified range, which can damage equipment and cause insulation breakdowns. Inadequate network planning, increased electricity consumption, voltage fluctuations, and faults in neighbouring transmission systems contribute to these conditions. Implementing effective load management strategies, monitoring systems, and voltage regulation mechanisms is necessary to mitigate overloading and overvoltage-related failures.

Understanding the percentage contributions of these causes helps utilities and operators prioritize their efforts to enhance power distribution network reliability. It may vary from utility to utility based on different network and geographical conditions. By allocating resources based on the relative significance of each cause, utilities can implement targeted strategies, preventive maintenance programs, and infrastructure upgrades to mitigate failures and ensure reliable electricity supply to consumers.

3.4 Reliability Improvement Strategies

Enhancing the reliability of power distribution networks is crucial for ensuring uninterrupted electricity supply to consumers. To achieve this, utilities and operators implement various strategies and technologies to mitigate failures and improve network performance [82]. The following section explores some key reliability improvement strategies in distribution networks:

Investing in infrastructure upgrades and expansion is a fundamental approach to improving network reliability. This includes replacing aging equipment, such as transformers, switchgear, and cables, with modern and more reliable counterparts [83]. Upgrading to smart grid technologies enables better monitoring, control, and automation of the distribution network, enhancing its resilience [84]. Additionally, expanding the network capacity and redundancy through the installation of new substations, feeders, and distribution lines reduces the risk of overloading and improves overall system reliability.

Implementing proactive maintenance practices and condition monitoring techniques is crucial for identifying and addressing potential failures before they occur. Regular inspections, testing, and preventive maintenance activities help detect and rectify equipment issues, such as insulation degradation, loose connections, and abnormal operating conditions. Advanced monitoring technologies, including sensors, remote diagnostics, and predictive analytics, enable real-time monitoring of equipment health, allowing for proactive maintenance interventions and minimizing the risk of unexpected failures [85].

Rapid fault detection and isolation are critical for minimizing outage durations and restoring power supply promptly. Implementing fault detection devices, such as fault indicators and circuit breakers with fault detection capabilities, enables faster identification of fault locations [86]. Automated fault isolation systems, such as sectionalizers and auto-reclosers, can isolate faulty sections and restore power to the unaffected areas, reducing the impact of faults on the entire network. Remote monitoring and control systems enhance the efficiency of fault management processes and enable faster response times [87].

Integrating distributed generation (DG) sources, such as renewable energy systems and cogeneration units, into the distribution network can improve reliability and resilience [88]. DG systems reduce dependency on centralized generation and transmission infrastructure, enhancing the network's ability to withstand disruptions [89].

Microgrids, which operate as localized power systems with interconnected DG resources, can operate independently or in parallel with the main grid during outages, ensuring a reliable power supply to critical loads and reducing the overall impact of network failures.

Maintaining optimal power quality is essential for ensuring the reliable and efficient operation of electrical devices. Implementing power quality monitoring and management measures, such as voltage regulation, harmonic mitigation, and reactive power compensation, helps mitigate issues such as voltage sags, surges, flickers, and harmonics [90]. Enhanced power quality management reduces equipment stress, improves operational efficiency, and minimizes the risk of equipment failures and subsequent network disruptions.

Developing resilience plans and disaster preparedness strategies is crucial for mitigating the impact of natural disasters and extreme weather events [91]. This includes implementing robust emergency response procedures, conducting risk assessments, establishing backup power systems, and reinforcing critical infrastructure against potential hazards. By identifying vulnerabilities and implementing appropriate resilience measures, utilities can minimize downtime, expedite restoration efforts, and improve the overall reliability of the distribution network [92].

By implementing these reliability improvement strategies, utilities and operators can enhance the performance, resilience, and reliability of power distribution networks. The integration of advanced technologies, proactive maintenance practices, fault management systems, and resilience planning enables utilities to deliver a more robust and dependable electricity supply to consumers.

3.5 Future Trends and Challenges

As power distribution networks continue to evolve, several future trends and challenges are expected to impact their reliability. Understanding these trends and addressing associated challenges is crucial for utilities and operators to ensure the continuous and reliable delivery of electricity. The following section explores some of the prominent future trends and challenges in the reliability of power distribution networks:

The increasing integration of renewable energy sources, such as solar and wind, into distribution networks poses both opportunities and challenges for reliability [93]. While renewable energy can contribute to a cleaner and more sustainable energy system, it's intermittent nature and decentralized generation can introduce operational challenges. Utilities will need to develop effective strategies for managing the variability and uncertainty associated with renewable energy sources to maintain system stability and reliability [94]. Advanced forecasting techniques, energy storage systems, and demand response programs will play critical roles in integrating renewable energy while ensuring grid reliability.

The electrification of transportation, including electric vehicles (EVs), is expected to significantly impact power distribution networks. The widespread adoption of EVs and the increasing demand for electric charging infrastructure will place additional stress on the distribution grid. Utilities must anticipate and address the increased load demands, ensure sufficient capacity, and implement smart charging solutions to mitigate potential overloads and voltage instability. Additionally, managing the growth in electricity demand due to population growth, industrial expansion, and technological advancements requires proactive planning and investments in grid infrastructure to maintain reliability [95].

The digital transformation of power distribution networks, driven by advancements in sensors, communication technologies, and data analytics, offers new opportunities for improving reliability. The deployment of advanced monitoring and control systems enables real-time visibility into network operations, facilitating proactive fault detection, rapid response, and predictive maintenance. However, the increasing complexity of digital systems introduces cybersecurity risks and the need for robust security measures. Ensuring the reliability and integrity of digital grid infrastructure and protecting against cyber threats will be critical challenges to address [96].

Many power distribution networks around the world are facing aging infrastructure, which can lead to increased failure rates and reduced reliability [97]. The challenge lies in managing and upgrading the existing assets while optimizing investment costs. Implementing effective asset management strategies that prioritize infrastructure upgrades, condition-based maintenance, and life-cycle assessments can extend the lifespan of equipment and enhance overall network reliability. Additionally, utilities need to develop strategies for integrating new technologies and modernizing the distribution infrastructure to improve reliability and performance.

With the growing frequency and intensity of extreme weather events due to climate change, power distribution networks face increased vulnerability. Severe storms, hurricanes, floods, and wildfires can cause widespread damage to infrastructure and result in prolonged power outages [98]. Building resilience against these events requires robust disaster preparedness plans, improved vegetation management, hardened infrastructure, and enhanced monitoring systems. Integrating microgrids and distributed energy resources can also enhance the ability to quickly restore power to critical facilities and minimize the impact of weather-related disruptions.

Addressing these future trends and challenges requires a proactive and comprehensive approach from utilities, policymakers, and stakeholders. Embracing innovative technologies, investing in grid modernization, promoting renewable energy integration, and implementing robust resilience strategies will be crucial for ensuring the reliability and sustainability of power distribution networks in the future.

3.6 Conclusions

The reliability of power distribution networks is vital for ensuring uninterrupted electricity supply. Key strategies for improving reliability include proactive maintenance, infrastructure upgrades, fault detection, and resilience planning. Various factors contribute to network failures, including equipment malfunctions, weather events, human errors, cybersecurity threats, and overloading/overvoltage conditions. Future trends and challenges, such as the integration of renewable energy, electrification of transportation, grid digitization, aging infrastructure, and resilience to extreme weather events, require proactive planning and strategic investments. Collaboration between utilities, researchers, and technology providers is crucial for driving advancements in grid infrastructure and monitoring systems. Continued research and development are needed to address emerging challenges and identify innovative solutions. Ultimately, by prioritizing reliability improvement strategies and adapting to changing circumstances, utilities can deliver a resilient and dependable electricity supply to meet the needs of society.

Chapter 4

Fault Management Process in DN

4.1 Introduction

The fault management process in real-time begins with the detection of a fault event by the CTs of the circuit breaker (CB) connected to feeder panels. Over-current, earth faults, and sensitive earth faults in general can be classified based on the capabilities of the bay control and protection unit. Until this point, the distribution control center (DCC) operator can see the status of the feeder CB, the type of fault, histogram data, and so on from the supervisory control and data acquisition (SCADA) system. If the respective feeder network is completely automated and the communication channels perform well during the occurrence of the fault, the automated switch status and remote fault indicator status are also visible to the operators.

FIGURE 4.1: A general classification of fault location technique in DN

Figure 4.1 depicts the fault management process from the occurrence of a DN fault to the restoration of service to the greatest number of customers possible. While implementing the fully automated distribution feeder network, most utilities become selective based on the priority loads connected, such as the ruler's building, emergency services, schools, festival centers, and so on. However, due to the high installation and maintenance costs, the majority of DNs in many utilities remain unautomated [99]. Most DNs around the world are less visible and observable than DCCs [100]. This delays the identification of faulty network sections. FSI is regarded as the most important and difficult task in the fault management process. After the fault section has been properly identified, it can be isolated manually or by opening the automated switches from the DCC. The primary goal is to isolate the faulty section of the DN from the healthy portion of the DN and then restore service to the healthy networks. The isolated faulty section will be observed to check and repair the faulty cable or conductor, and after ensuring the section's complete healthiness, it will be returned to service to keep the system running normally. FSI is an important process, but each step of the fault management process, from detection to service restoration, plays an important and systematic role in contributing to system reliability indices such as the system average interruption frequency index (SAIFI), the system average interruption duration index (SAIDI), and so on. The reliability matrices [101] are used to evaluate the performance of fault location isolation and service restoration techniques.

4.1.1 Fault Detection

The first step in restoring the power system is fault detection (FD). Components connected to the network by damage and field operation crews who work on the network 24 hours a day, seven days a week to ensure the continuity of service from the utility to the connected customers or their loads. Utilities use a variety of protection devices to detect faults in DN, whether they are temporary or permanent. Temporary Because the conductors are left exposed to nature, faults such as sensitive earth faults are common in overhead lines (OHL). Any natural phenomenon, such as extreme weather, will have a direct impact on the lines. Sensitive earth faults are used to detect these types of faults. Relays are typically installed at substation feeding panels. Most OHL feeders will have this type of relay, and when such a fault occurs, the CB recloses at 145 ms [56] from the time it was tripped. If the CB successfully closes and connects the circuit to the feeding substation, the fault is identified as temporary. If the CB trips again, the fault is identified as permanent..

4.1.2 Fault Classification

Even though fault classification (FC) is not particularly useful information during the FD process when compared to FSI in pure underground cables, it still provides line patrolling crews with more insights or situational awareness while identifying the exact locations of faults. in OHL, as well as a mix of OHL and UG DN. Traditional utility grids, which are equipped with single-phase transformers to feed customer loads, can use these classified faults to identify fault locations by gathering various information, such as customer outage complaints, GPS locations of customers and transformers, and so on. Modern DN, on the other hand, is outfitted with three-phase transformers. As a result, detected and classified faults play fewer roles in FSI, particularly in urban or underground DN, but are useful in locating faults in OHL and Mixed DN.

4.1.3 Fault Section Identification

Fault section identification (FSI) is the identification of the exact faulted section of the DN. In most cases, this will be the UG cables or OHL, as they have a higher risk of failure due to factors such as differently aged conductors or cables, more joints with a mix of old and new cables, different insulation types in cables joined together, vegetation growth near the OHL, extreme weather conditions, and so on. When compared to transmission lines, the equipment or other components connected to the real DN, such as ring main units (RMUs), distribution transformers (DTs), and low-voltage distribution boards (LVDBs), are less likely to fail. In practice, cable termination failures such as termination flashovers can cause RMUs to fail, but this is extremely rare. In this case, the faulty section will be the combination of cables and RMU. Identifying the fault sections is the most difficult and time-consuming task for DCC operators and field crews during the fault management process. Traditional DNs have fault indicators (FI) installed at almost all nodes, but remote fault indicators (RFI) are only installed at a few nodes due to the large investment requirements. The logic behind FSI is to precisely identify the faulty section, isolate it from the healthy portion of the DN, and restore service to as many customers as possible. Even though utilities are implementing advanced monitoring devices, communication technologies, and distribution automation projects such as RFIs, automated switches, and RF mesh communication technologies, it is still limited to a small number of assets or priority/critical loads [102]. The reason is simple: high investment and maintenance costs, aging assets, and feasibility issues. with the integration of variously aged assets and their integration limitations with cutting-edge communication technologies. To avoid additional investment costs, the utility employs a diverse mix of assets and communication technologies. Although various technologies and devices are installed to speed up the FSI process, malfunctions and failures of such devices (fault indicators, other monitoring devices, automated switches, etc.) make the fault management process more critical and challenging, as incorrect identification of faulted sections leads to the recreation of fault events while energizing the wrong healthy portions [103]. This even damages the various power system components and poses potential safety issues for operational crews and customers. This could have an impact on the utilities' image. In order to avoid these consequences, the failures or malfunctions of these fault monitoring devices must be addressed.

4.1.4 Fault Section Isolation

Following the occurrence of any permanent fault in the DN, the line cannot be energized without isolating the faulty section, as this results in an energizing towards a fault and re-enactment of the fault event. This could put the men and machinery involved in danger. As a result, section isolation is critical. This is normally accomplished by activating the manual or automated switches at both ends of the respective cable section [104].

4.1.5 Service Restoration

This is the last step in the fault management procedure. When the isolation is complete, it means that the rest of the network, or the healthy proportions of the network, are safe to re-energize and restore the service to a healthy state. portions. The reliability indices, primarily SAIDI and SAIFI, are determined by how quickly and frequently customers' service interruptions are restored [105].

4.2 Challenges in Fault Management Process and Need for μPMU in DN

When the various stages of the fault management process in real distribution systems are compared, the FD is the simplest because all DN are equipped with relays. and well-coordinated security systems. The FSI stage is the most difficult in the fault management process because the identification time is solely determined by the number of faults in current monitoring devices such as fault indicators (FIs), remote fault indicators (RFIs), and switches or automated switches at both ends of the sections. According to the author's experience, these fault current monitoring devices, both with and without the capability of communicating their status to SCADA, fail or malfunction during the FD process. This complicates the fault management process even further. In some cases, automated switches lose control of the SCADA or fail to carry out the SCADA's open or close commands. These failures can occur for a variety of reasons, including hardware or software failure. and communication outages, and a field crew is required to physically visit the stations to manually operate the switches. The FSI has a limited number of monitoring Devices in general, and their failures and malfunctions are the main challenges of real DN [106]. Synchrophasors are measurements of voltage, current magnitude, and phase angle that are synchronized [107]. Using synchronized measurements of these parameters, grid operators can see the state of the grid. When compared to traditional sensor measurements, such as SCADA, they provide greater precision and accuracy, better temporal resolution, and cross-location synchronization. As operators and planners, we must manage the increasing penetrations of variable generation and controllable energy resources, and this data is becoming increasingly important. As a result, while applying synchrophasor technology to the distribution tier is appealing, sensing in distribution systems is more difficult than transmission because the signals of interest are smaller and the number of nodes is larger. higher [108]. A micro-PMU is a type of phasor measuring unit designed specifically for use in distribution circuits (or PMU). When in PMU mode, the device reports a phasor (magnitude and angle) defining each waveform with two samples per cycle, or 120 samples per second. GPS time is used to synchronize phasor measurements across locations. [109] stamping. The PMU time-stamping has nanosecond and microsecond precision thanks to GPS. As a result, the PMU network can measure phase variations on the order of hundredths of a degree, which are common in distribution circuits but too small to be monitored by transmission PMUs [110]. The angle discrepancies and variations in distribution require a higher degree of accuracy than in transmission due to the different X/R ratios [110]. Micro-PMUs improve distribution system monitoring, analysis, and control, allowing utilities to improve grid performance, optimize operations, and increase reliability [111]. They offer useful information for distribution planning, system optimization, and decision-making. As a result, distribution operations become more efficient and resilient. Aside from current and voltage magnitude, phase angle provides information on power flow direction. for topology research. In terms of calculating loads on a per-phase basis, line-level measurement outperforms smart metering. Despite the fact that PMUs have a variety of parameter monitoring capabilities, investigations of short circuit faults are best observed in current values and a few voltage variations.

4.3 Conclusions

The Fault Management Process is critical for ensuring the reliability of power distribution networks. It entails detecting and locating faults, then taking the necessary actions to resolve them. To improve the process, technologies such as fault prediction and self-healing systems are being developed. Communication and coordination among stakeholders must be effective. A solid fault management process increases network reliability, decreases downtime, and ensures a consistent power supply. Ongoing research and advancements in network monitoring technologies such as PMUs will improve the reliability and resilience of power distribution networks.

Chapter 5

Distribution Network Modelling, Load flow Simulations and Validation

5.1 Introduction

Distribution test feeder modelling, load flow simulation, and results validation are important steps to undertake before starting a fault detection, classification, and section identification research for the following reasons:

Accurate Representation: Distribution test feeder modelling provides a mathematical representation of the distribution network, capturing its components and their interconnections. This ensures that the research is based on a realistic and accurate model, reflecting the actual electrical characteristics and topology of the distribution system. It enables researchers to work with a standardized and validated platform, enhancing the credibility and reliability of the research outcomes.

Understanding System Behavior: Load flow simulation allows researchers to study the steady-state operating conditions of the distribution network. It provides valuable insights into voltage profiles, power flows, and losses under various operating scenarios. By understanding the normal behavior of the system, researchers can develop a baseline understanding of how faults may affect these parameters and how they propagate through the network. This knowledge is crucial for fault detection, classification, and section identification algorithms.

Performance Evaluation: Load flow simulation helps in evaluating the performance of the distribution network. It provides information on voltage regulation, power losses, and system stability. Researchers can use this information to establish performance criteria for fault detection, classification, and section identification algorithms. By setting appropriate thresholds and benchmarks based on the simulated results, researchers can assess the effectiveness and accuracy of their proposed methods.

Validation of Results: Results validation is an essential step to ensure the reliability and accuracy of the research findings. By comparing the simulated results with measured data or validated models, researchers can verify the performance of their fault detection, classification, and section identification algorithms. Validation allows them to assess the level of agreement between the simulated and actual system behavior and identify any discrepancies or limitations in their proposed methods. It enhances the confidence in the research outcomes and provides a basis for further improvements and enhancements.

Real-World Application: Distribution test feeder modelling, load flow simulation, and results validation enable researchers to develop fault detection, classification, and section identification algorithms that can be effectively applied to real-world distribution systems. By starting with a well-modeled and validated test feeder, researchers can ensure the applicability and scalability of their research outcomes to actual distribution networks. This helps in developing practical and effective solutions that can be implemented in real-world scenarios, leading to improved fault management and system reliability.

In summary, undertaking distribution test feeder modelling, load flow simulation, and results validation before starting a fault detection, classification, and section identification research is crucial. These steps provide researchers with an accurate representation of the distribution system, a comprehensive understanding of its behavior, performance evaluation metrics, and a validation framework for their proposed algorithms. This ensures that the research is grounded in realistic conditions and enhances its credibility, applicability, and effectiveness in real-world distribution systems.

5.2 Methodology

To achieve the objectives of distribution test feeder modelling, load flow simulation, and results validation, the following methodology is typically employed:

Data Collection: Gather detailed information about the distribution network, including the physical parameters of its components such as distribution lines, transformers, voltage regulators, distributed generation units, and loads. This data includes resistances, reactances, ratings, and connectivity information.

Distribution Test Feeder Modelling: Develop a mathematical representation of the distribution network based on the collected data. Utilize modeling techniques to accurately capture the electrical characteristics and interconnections of the components. Ensure that the model reflects the topology, ratings, and operational constraints of the actual distribution system [112].

Load Flow Simulation: Utilize load flow analysis techniques to solve the power flow equations and determine the steady-state operating conditions of the distribution network. Select an appropriate numerical method, such as the Newton-Raphson method, Gauss-Seidel method, or Fast Decoupled method, to iteratively solve the nonlinear algebraic equations. Consider factors such as power injections, reactive power control, line losses, and voltage regulation mechanisms in the simulation.

Results Validation: Compare the load flow simulation results with measured data from the distribution network or with validated models. Use key performance metrics such as voltage profiles, power flows, and losses for the comparison. Apply statistical analysis techniques, such as root mean square error or percentage error, to quantify the differences between the simulated and measured values. Assess the level of accuracy and reliability achieved by the simulation.

Model and Methodology Improvements: Identify any discrepancies or limitations in the simulation results and the validation process. Make necessary adjustments or improvements to the distribution test feeder model and load flow simulation methodology. Incorporate feedback from the validation process to enhance the accuracy and reliability of the analysis. This iterative process helps in refining the model and methodology for better results.

Research Application: Apply the validated model and load flow simulation methodology as a foundation for fault detection, classification, and section identification research. Utilize the understanding of the system behavior, performance evaluation metrics, and the validation framework to develop and test the proposed algorithms.

Assess the effectiveness and accuracy of the algorithms in detecting and classifying faults and identifying faulted sections.

Continuous Validation and Improvement: Continuously validate the results of the fault detection, classification, and section identification research against measured data or validated models. Incorporate feedback and adjust the algorithms as necessary to improve their performance. This iterative process ensures the continuous enhancement of the methodology and its applicability to real-world distribution systems.

By following this methodology, engineers and researchers can achieve accurate distribution test feeder modelling, reliable load flow simulation, and robust results validation. This provides a solid foundation for research and analysis in fault detection, classification, and section identification, leading to improved fault management and system reliability in distribution networks.

5.3 Distribution Network Selection and Modeling

The IEEE 34-node test feeder qualified as the best candidate for the analysis among the available benchmark test feeders. This feeder is a genuine DN located in Arizona. The feeder's system voltage is 24.9 kV. The feeder is notable for its length and light load, as well as the requirement for two in-line regulators to maintain the specified voltage limits and other factors. The DN is unbalanced by nature, with both "spot" and "distributed" loads and shunt capacitors; an in-line transformer reduces the voltage for a shorter portion of the feeder to 4.16 kV. [113]. The length of the feeder and the unbalanced loading could aid in generating realistic dynamics on the DN and visualizing them using PMUs' high-resolution data-measurement capability. DP is used to create real-time events and scenarios for the test feeder.

Using the feeder component data from [112] and reference data from [147], the IEEE 34 node is perfectly modeled. The DP has a large component library and features that allowed to model the network without making any assumptions about how the components were connected. The DP allows for the modeling of three-phase, four-wire systems, which is critical for modeling the unbalanced three-phase DN[113]. The nodes are used to place the spot loads, and the distributed loads are connected in the middle of the line. The network's line sections are labeled as shown in Appendix A's Table A1. The feeder is modeled without a substation transformer because the published load flow results do not take it into account when generating load flow results. However, for this study, an external grid connection with 1.05 p.u. as the reference phase-to-phase voltage for the base node 800 is chosen. The voltage regulator (VR) tap positions for regulators 1 and 2 remain as 12-05-05 (A-B-C) and 13-11-12 (A-B-C), respectively. Figure 5.1 depicts the DP model of the test feeder. The components with red dotted lines represent the phase A-N connection; the components with yellow dotted lines represent the phase B-N connection; the components with blue dotted lines represent the phase C-N connection; and the components with black dotted lines represent the phase ABC-N connection. The DGs modelled are highlighted in grey colour.

5.4 Load Flow Simulations and Validations

The load flow algorithms are used to determine the line flows and voltages for a significant power system based on the provided load and generation data. It is a critical and fundamental tool for power system analysis, and it is used both during the operational and planning phases. Single-phase power Flow methods are commonly used in systems where unbalances can be ignored. However, the three-phase

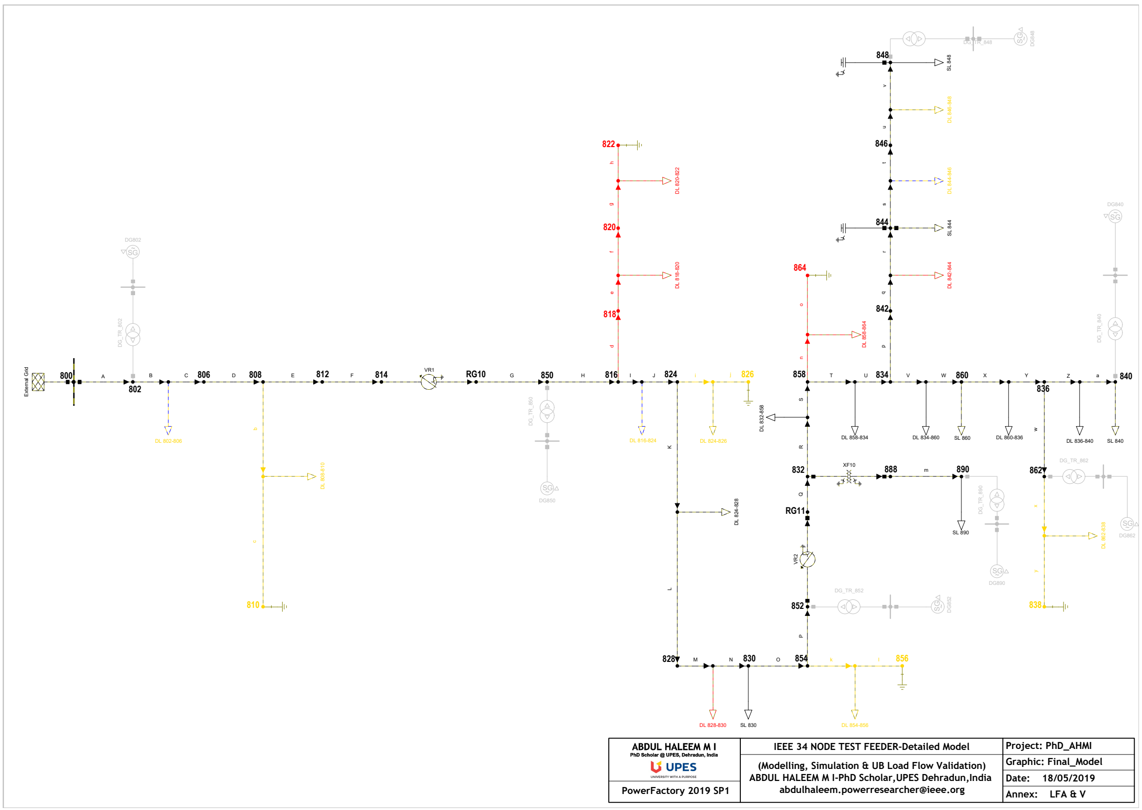


FIGURE 5.1: IEEE 34 feeder modelled in DIgSILENT PowerFactory.

balanced hypothesis does not apply to distribution systems. A three-phase load flow algorithm with full three-phase models is required in these cases. Furthermore, it is critical to resolve the load. flow problem as soon as possible because several applications, particularly distribution automation and optimization, require their solution on a regular basis [114-115]. A number of load flow algorithms designed specifically for DN have been proposed in the literature. These compositions are divided into two categories. In the first category [116-117], bus voltages were used as state variables to solve the load flow problem. This classification was based on a DN's overall topology. The most well-known load flow mechanism in this area is the Gauss implicit Z-Bus approach [118-119]. This technology, which has been adopted by many power companies, has been used in a variety of applications. The Newton-Raphson (NR) algorithm was proposed in [120] to accelerate three-phase load flow by using rectangular-form voltages as state variables. Branch voltages are used as state variables in [121] to solve the load flow problem using an innovative quick three-phase load flow method for unbalanced radial distribution systems that employs the NR algorithm. Because it best fits the nature and behavior of the network model, the load flow calculation method chosen in DP is an unbalanced, 3-phase (ABC) NR (current equations). Figures B.1 and B.2 of Appendix B show the load flow simulation settings used in the DP. The load flow simulation results are very similar to those published by the IEEE. PES DSAC [113]. The DP model with node voltages and line sections produces the load flow. Appendix A contains currents and their angles (Tables A2 and A3, respectively). Tables 5.1 and 5.2 display the percentage errors in node voltage and angle after comparing them to published load flow values. The current lines are listed in Tables 5.3 and 5.4. Errors in magnitude and angle percentage. Table 5.5 displays the results of three iterations of the DP model load flow.

TABLE 5.1: Line-to-neutral voltage error deviation from the IEEE published results.

	A-N Voltage *	**B-N Voltage ***	**C-N Voltage ***
Minimum Error	−0.0021	−0.0007	−0.0002
Maximum Error	0.0002	0.0004	0.0006
Average Error	−0.0001	0.0001	0.0000

* per unit.

TABLE 5.2: Line-to-neutral angle error deviation from the IEEE published results.

	A-N Angle *	**B-N Angle ***	**C-N Angle ***
Minimum Error	−0.0091	−0.0001	−0.0006
Maximum Error	0.0737	0.0000	0.0000
Average Error	0.0095	0.0000	−0.0001

* degree.

The comparison of the load flow analysis results shows that the results exactly match the results provided by the IEEE DSAC report, with very minimal errors.

TABLE 5.3: Line current error deviation from the IEEE published results

	Line A *	Line B *	Line C *
Minimum Error	−0.0256	−0.0067	−0.0020
Maximum Error	0.2857	0.0322	0.0285
Average Error	0.0111	0.0020	0.0017

* Ampere (A).

TABLE 5.4: Line current angle error deviation from the IEEE published results.

	Line A Current Angle *	Line B Current Angle *	Line C Current Angle *
Minimum Error	−0.0004	−0.0029	−0.0128
Maximum Error	0.0014	0.0004	0.0004
Average Error	0.0000	0.0000	−0.0003

* degree.

TABLE 5.5: Load flow results from DP model vs. IEEE published results (in brackets).

	Active Power (kW)	Reactive Power (kVAr)	% Error
Total System Input	2043.13 (2042.872)	290.47 (290.258)	kW = 0.0001 kVAr = 0.0007
Total Load *	1769.66 (1769.824)	1051.47 (1051.547)	kW = 0.0000 kVAr = 0.0000
Total Losses	273.47 (273.049)	35.28 (34.999)	kW = 0.0015 kVAr = 0.0080

* Total Power factor = 0.86 (0.8597).

5.5 Conclusion

In summary, distribution test feeder modelling, load flow simulation, and results validation are crucial technical components in power system analysis for distribution networks. The accurate representation of the distribution system through meticulous modelling enables researchers to gain a detailed understanding of system behavior and characteristics. By employing load flow simulation techniques, researchers can evaluate the system's steady-state operation and assess performance metrics such as voltage regulation, power flows, and losses.

Results validation is an integral part of the process, ensuring the reliability and accuracy of the analysis. By comparing the simulated results with measured data or validated models, researchers can verify the performance of their proposed algorithms and methodologies. Key performance metrics, such as voltage profiles and power flows, are compared using statistical analysis techniques, providing insights into the level of agreement between simulated and actual system behaviour.

By following a systematic methodology that includes data collection, modelling, load flow simulation, and results validation, researchers can establish a robust foundation for fault detection, classification, and section identification research. This methodology allows for an accurate representation of the distribution system, evaluation of its performance, and development of effective algorithms. The application of this methodology contributes to enhancing the reliability, efficiency, and stability of distribution networks.

Ultimately, the combination of distribution test feeder modelling, load flow simulation, and results validation facilitates advancements in fault detection, classification, and section identification research. The technical rigour and validity of these processes enable researchers to develop practical and applicable solutions that can be implemented in real-world distribution systems, leading to improved fault management, enhanced power quality, and increased system reliability.

Chapter 6

μPMU-based Realistic Data Generation

6.1 Introduction

Monitoring, protection, and control procedures become increasingly complicated as distributed energy resources (DERs) enter distribution networks (DNs). This is true due to the structure of power DNs and the two-way flow of current from different sources to loads. In order to increase the system's situational awareness, it is crucial to closely monitor the grid dynamics of the entire DER integration process using synchronized high-resolution real-time measurement data from physical sensors installed in the DN. μPMUs have been incorporated into the DN in order to help with this. μPMUs can measure frequency and the rate at which frequency changes, as well as voltage, current, and their phasors, in contrast to conventional measurement devices (ROCOF). This study suggests a technique for producing accurate event data for a real utility Service by strategically placing μPMUs. To produce real-time event-based realistic μPMU data for various situational awareness applications in an imbalanced DN, an IEEE 34 test feeder with 12 μPMUs deployed in key places is used. Using node voltages and line currents, the various no-fault and fault events were examined. In order to conduct numerous situational awareness and fault location studies in a real, unbalanced DN, the author generated this data using his real-time utility grid operation experience. The DN was modeled using the DIgSILENT PowerFactory (DP) program. For a variety of event detection, classification, and section identification research projects, data-driven algorithms can be developed using the realistic μPMU data that was obtained.

A rules-based integrated fault detection, classification, and section identification (I-FDCSI) system for actual distribution networks (DN) using micro-phasor measurement units (μPMUs) is created in the second part of the research. By leveraging high-resolution synchronized realistic measurements from strategically placed μPMUs, the proposed technique detects and categorizes various fault types and locates the defective portion of the distribution network. The I-FDCSI approach is founded on a set of guidelines created through expert knowledge and statistical analysis of measurements collected from realistic scenarios. The algorithms largely employ line currents per phase reported by the several μPMUs to determine the minimum and maximum short circuit current ratios. The algorithms were then improved by simulating all potential classes and types of faults at all potential network segments with various fault parameter values. By using the high-precision measurements offered by μPMUs to find, categorize, and sectionalize defects, the suggested I-FDCSI technique gets over DN's fundamental challenges. The new IFDCSI approach is further tested and validated on a genuine distribution network with all feasible real-time events, and its effectiveness is contrasted with that of traditional fault detection, classification, and section identification methods to ensure its applicability. The results demonstrate that the I-FDCSI approach is more precise and responds more quickly than traditional methods, enabling quicker service restoration and raising the DN's reliability and resilience indices.

6.2 Methodology

Based on the author's real-time DN operation experience and the data's availability to model the network in the modeling and analysis tool, the realistic data-generation approach considers the possibility of producing all of the realistic events anticipated by the author. The key issue that arose throughout the methodology's development was how to maintain the data more realistic in nature while incorporating real-time events. But by choosing the most appropriate network from dependable sources and using a capable network modeling and analysis tool, the issue was resolved. The rigorous seven-step methodology used in this study to analyze the behavior of a real-world DN. The choice and modeling of the real DN came first. After performing a load flow analysis on the network, the outcomes were checked against previously released findings to assure accuracy. The network's μPMUs and DGs were then carefully positioned to enable accurate system behavior monitoring. The definition and configuration of real-time events followed, with specific attention paid to making sure that the event kinds and characteristics were indicative of real-world conditions. The data-generation settings were also established in order to produce precise and representative data. The numerous real-time occurrences were then simulated after which the outcomes were plotted for study. To assure the correctness and dependability of the findings, the data was checked in the end.

6.2.1 μPMU Placement

Because of their communication limitations and high cost, traditional μPMUs used in transmission networks are not ideal for radial DN. The introduction of μPMUs with high reporting rates is appropriate for DN and may provide real-time synchrophasor data such as frequency, ROCOF, and voltage phasors. Furthermore, optimal μPMU deployment at smart radial DN buses reduces the financial burden. When placing the μPMUs in the modeled IEEE 34 DP model, only one main condition is taken into account. The condition is to achieve total deployment cost minimization while maintaining full system observability, so that the generated events can be observed by at least one of the μPMUs in order for the event to be situationally aware. Various optimization techniques, as well as a complete system observability redundancy index (CSORI) and cost index, are used to determine the best solutions (CI). The highest CSORI value ensures maximum system redundancy. The total cost of optimal μPMU deployment is determined by CI [122].

A graph-theoretic approach was used in [123] to identify the critical buses where μPMUs should be installed for effective monitoring. [124] proposes a hybrid approach based on a global search algorithm to determine the optimal subset of buses for μPMU placement.

[125] proposes a heuristic algorithm based on the k-means clustering technique for determining the optimal placement of μPMUs. Table 6.1 shows that the test feeder can have 12 optimal locations for cost-effective installations while maintaining full system observability. Because node 850 is a DG connection node, and the downstream node with lateral tappings can be observed, the one with node 850 is considered instead of node 814; additionally, the regulator (RG10) output parameters must be monitored rather than the regulator input parameters to set the desired

tap positions if the DGs are not integrated. The locations of μPMUs are chosen through a simulation study in which the node voltages and line currents reported by these μPMUs can be used to observe the planned realistic events. The DP does

TABLE 6.1: Investigations on optimal μPMU placements in IEEE 34 node feeder.

Method	Approach	No. of µPMUs	Optimal Locations
[122]	Deployment cost minimization	12	802, 810, 814, 820, 824, 834, 838, 840, 846, 854, 864, and 888
	Full system observability	12 *	802, 808, 820, 824, 834, 836, 846, 850, 854, 858, 862, and 888
[123]	Full system observability	12	802, 808, 814, 820, 824, 834, 836, 846, 854, 858, 862, and 888
	Full system observability	12 *	802, 808, 850, 820, 824, 834, 836, 846, 854, 858, 862, and 888
[124]	Full system observability (with Min. No. of µPMUs)	12	802, 808, 814, 820, 824, 834, 836, 846, 854, 858, 862, and 888
	Full system observability (with Min. No. of µPMUs)	12 *	802, 808, 850, 820, 824, 834, 836, 846, 854, 858, 862, and 888
[125]	Full system observability	12	802, 808, 814, 820, 824, 834, 836, 846, 854, 858, 862, and 888

* Optimal locations selected for data generation.

not have a μPMU component in the toolbox, but the μPMU's features, such as the magnitude of the voltage, current, and their angles, frequency, and so on, can be generated as output while generating the output data of the nodes and line sections. This data-generation study concentrated on the magnitude of μPMU node voltages, line currents, and angles. These parameters will be collected from the 12 optimally placed μPMUs in the feeder, as shown in Figure 6.1. Eleven of the twelve μPMUs are three-phase, while one is single-phase.

6.2.2 Sizing and Placement of DGs

There are many different types of DGs, ranging from conventional to renewable; however, this study is not specific to any one type of DG source. The main goal of this effort is to integrate DGs at various locations in order to recognize and record

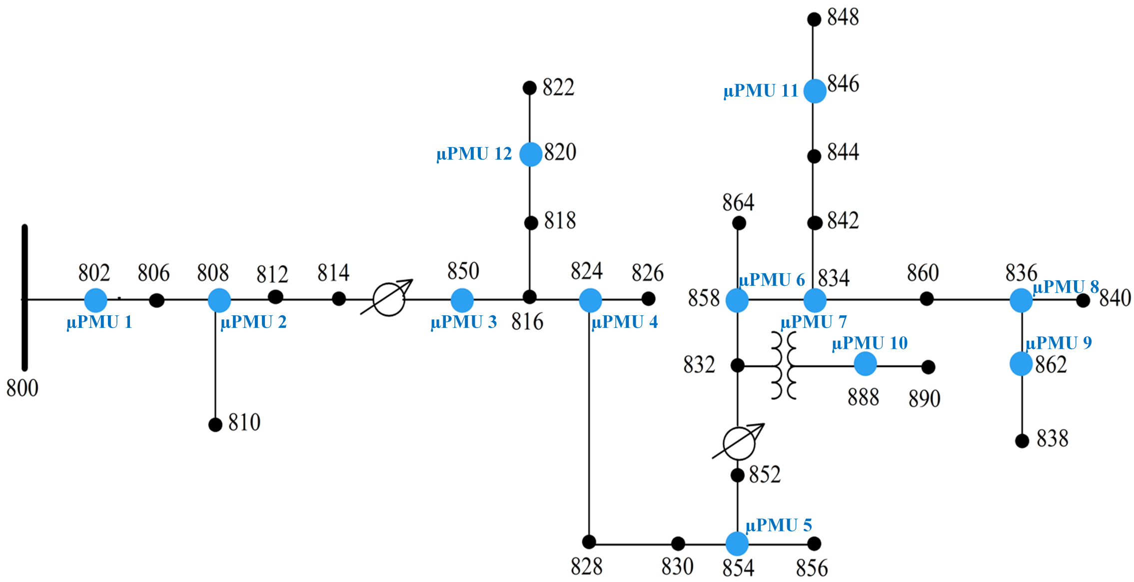


FIGURE 6.1: Optimal μPMU locations in the test feeder.

their influence during various real-time occurrences using μPMU data. Each DG was modeled as a synchronous generator. The power levels used for a DG intended to supply 20% of the test feeder load, as well as the DG modeling parameters shown in table 6.2, were obtained from [126]. The parameters that were not listed were set to the DP defaults. A 500 kVA transformer in a delta-delta configuration was used

TABLE 6.2: DG modeling parameters.

V_{rated} = 480 (V)	kVA_{rated} = 410 (kVA)	P_{rated} = 350 (kW)
V_{Sched} = 1 (p.u.)	Q_{max} = 0.5 (p.u.)	Q_{min} = −0.25 (p.u.)
pf = 0.8536585	X_d = 1.76 (p.u.)	X_q = 1.66 (p.u.)
$X_{d'}$ = 0.21 (p.u.)	$X_{q'}$ = 0.18 (p.u.)	$X_{d''}$ = 0.13 (p.u.)
$X_{q''}$ = 0.11 (p.u.)	r_a = 0 (p.u.)	r = 0 (p.u.)
r_{1r} = 0 (p.u.)	X_{1r} = 0 (p.u.)	X_0 = 0 (p.u.)

to connect the DGs to the nodes. The modeling parameters for these transformers were based on the 500 kVA line transformer used in the chosen feeder. Because only three-phase DGs were used, DGs were installed only on three-phase nodes and three-phase radial tappings, or laterals. With the exception of the substation and the voltage regulators, radial tapping from 832 is the only area of the circuit that operates at 4.16 kV. It also houses the circuit's line transformer. The only capacitors in the circuit are located at 844 and 848 on the radial tapping from 834. There were numerous DG locations that were feasible. The modifications were tried on the radial tapping points as well as the main feeder, near and far from the substation, and near the voltage regulators. Connection nodes 802, 840, 848, 850, 852, 862, and 890 were specifically evaluated. Each DG was built with a default size of 20% of the original feeder load, resulting in a 410 kVA unit with a 350 kW planned real-power output. The study focuses on the use of DGs at various feeder locations to generate data for various real-time occurrences and their classes.

6.2.3 μPMU-Based Real-Time Event Data Generation

At a sampling rate of 120 Hz (or one sample every 0.008333 s), the optimally placed μPMUs record four fundamental measurements on three phases, for a total of 12 measurement channels: voltage magnitude, current magnitude, voltage phase angle, and current phase angle. This paper generates 30 minutes of μPMU data in the real rural overhead DN, taking into account planned and unplanned outage events. The author defines 109 real-time events based on his real-world grid operation experience. This includes 62 planned and 47 unplanned network events. In 30 minutes, the 12 μPMUs collect and report 16,848,000 data points.

6.2.3.1 Realistic Real-Time Events

Because it is inherent in nature and has many complexities to address, the unbalanced overhead DN has a high number of real-time events. The goal of using an unbalanced overhead DN is to incorporate all of the relevant real-time network events. The events range from the planned to the unexpected. Even though most events can fall into both categories, events caused by the activation of protection devices are considered unplanned, while all scheduled events are considered planned. To keep the events as realistic as possible, almost all event types are included, covering various components and locations in the test feeder. The test feeder model generated 109 realistic events, which are listed in Table A.4–A.6 of Appendix A. Capacitor bank switching, circuit breaker (CB) switching, CB trip, DG switching, DG trip, line de-energization, line energization, load switching, load trip, overhead line (OHL) jumper events, fault events, temporary faults, tap-changer events, transformer outage and energization, transformer trip, fault-clearing events, and customer low-voltage complaints are among the events.

6.2.3.2 Data-Generation Settings in DP

The chosen test feeder is flawlessly modeled in DP and is absolutely necessary for the data generated. The events are defined in relation to the DN model elements that have been selected. Specific components are used to classify events as switching, fault, or fault-clearing. The features include a variety of execution time options in hour, minute, and second formats, as well as the ability to change the phase type individually. Furthermore, they permit the use of various fault classes, impedance levels, and the percentage of fault location distance in the line section. The data-generation settings must be chosen with extreme care if the generated data resolution is to match that of the actual data supplied by the μPMU. The RMS simulation is run with all of the simulation occurrences using the DP settings listed below. The default initial condition settings for the unbalanced three-phase ABC system are RMS values (electrical and mechanical transients) with a step size of 0.008333. (120 measurements per second). All other simulation settings are set to the default values. Figures B.3–B.6 of Appendix B show the main simulation settings used in the DP for data generation.

6.2.3.3 Event Simulations and Plots

109 intended events are simulated by selecting the relevant component in the model and providing the type of event, execution time, selected element action, phases impacted, percentage of line section fault location, fault type, impedance, and other parameters. If any changes to the simulation settings are needed, the list of simulation events can be modified further.

Because twelve μPMUs have already been installed at the optimal nodes, the focus of this study is solely on measuring them. Despite the fact that μPMU devices can monitor a wide range of properties, the study only considers the node voltage (line-to-neutral) and line currents. The data-production criteria were created with the intention of using these data for future work on event detection, categorization, and section identification. The phase-to-neutral voltage is measured due to the unbalanced loading on the test feeder, which includes a number of single-phase to neutral and two-phase to neutral loads. Each μPMU generates two fundamental graphs: phase current vs. time and node voltage (phase to neutral) vs. time.

6.2.4 Results

The plots shown here for each event represent the μPMUs in the network that have been most impacted by that event. The plots are in per-unit values of the line-to-neutral voltage and line currents of the relevant μPMUs over time in seconds. The results show that when the capacitor bank is turned on, the voltage magnitude increases to compensate for the reactive power and decreases when it is turned off.

The line currents reported by the μPMUs upstream (US) and downstream (DS) are affected by the initial switching conditions. Line current undershoots and overshoots are observed during both capacitor switch-on and switch-off events.

Line voltages drop to zero during main CB tripping events, while line currents drop to zero following a switching spike, depending on the cause of the tripping. In the event of a failure, the voltage on the affected line or lines will drop to zero, while the current will rise to the fault level and remain there until the circuit breaker trips. When the CB closes, the voltage rises from zero to the nominal network voltage, and the current surges to the maximum current before settling back to the normal load current value after a few seconds. The results of DG switch-on events show a drop in line voltages and a rise in line currents, but both values return to normal after a few seconds, whereas the DG switch-on event indicates a voltage and current increase in the nearest μPMU and a voltage and current drop in the farthest μPMU. Similarly, all of the key real-time events observed in an unbalanced DN selected for this study, as well as their impact on node voltages and line currents from the relevant μPMUs, are listed in Table 6.3.

The realistic data generated for a variety of real-world grid events demonstrate their applicability in a wide range of use cases, including real-time μPMU data-based predictive maintenance of critical assets (transformers, OHLs, CBs, DGs, etc.). μPMU dynamics assist with real-time asset health monitoring and aging analysis. Aside from these applications, the data can be used for offline analytics for network planning, scheduled maintenance, topology changes, and so on.

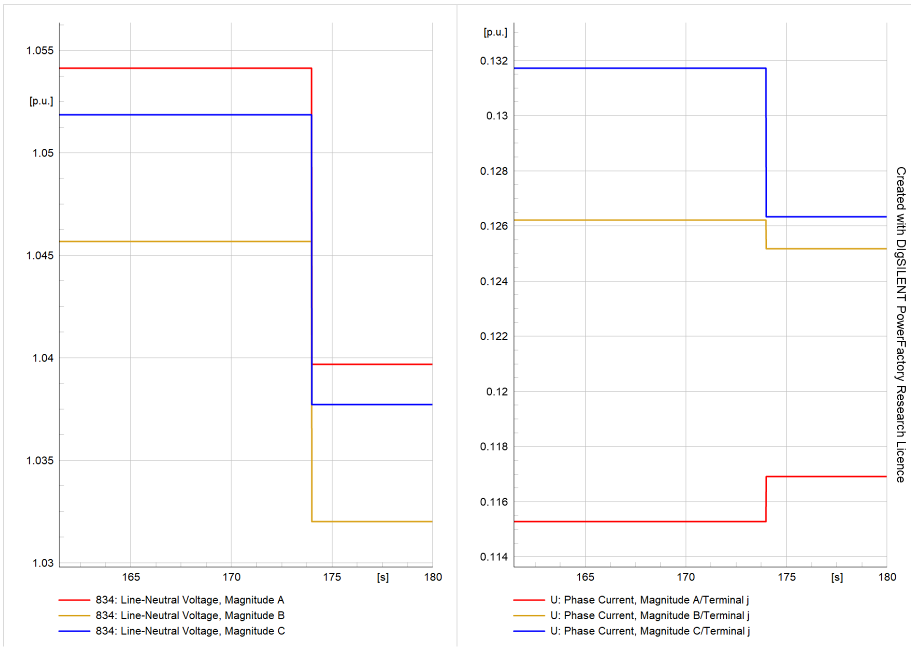


FIGURE 6.2: Capacitor bank switch-off event (μPMU7).

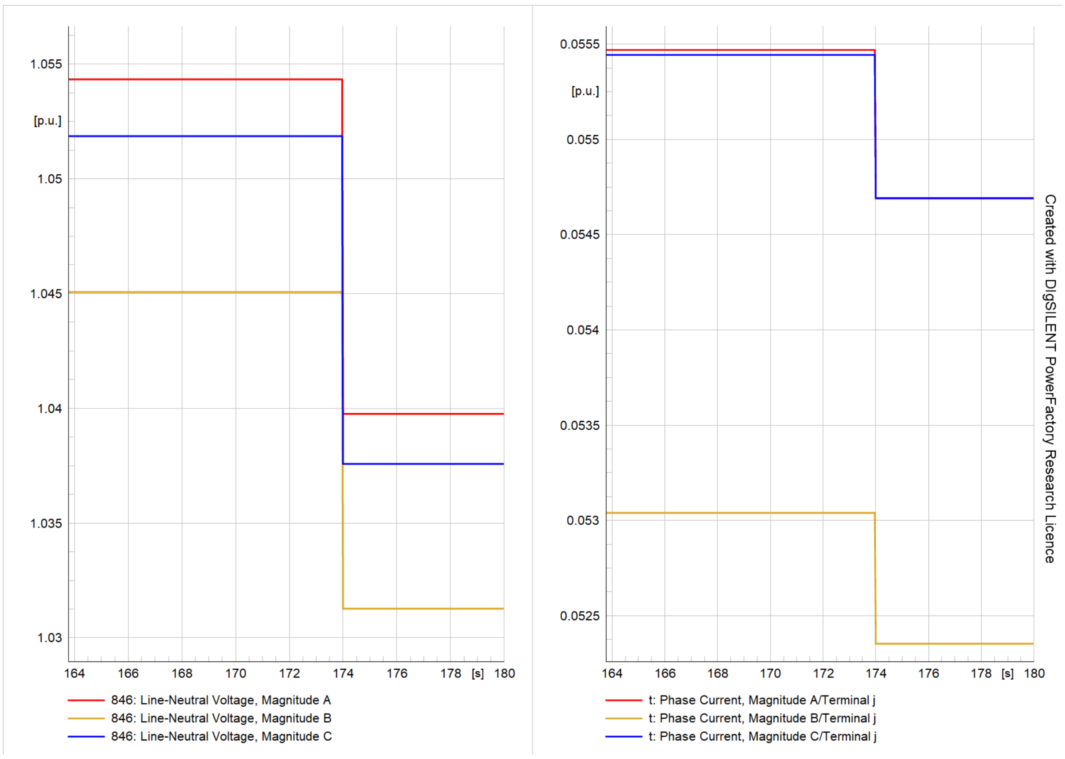


FIGURE 6.3: Capacitor bank switch-off event (μPMU11).

TABLE 6.3: Event category chart and their plots.

Sl. No.	Event Description	Figure Numbers
1	Capacitor Bank Switching	Figures 2–5
2	Circuit Breaker Trip	Figures 6 and 7
3	Circuit Breaker Switching	Figures 8 and 9
4	DG Switching	Figures 10–13
5	DG Trip	Figures 14 and 15
6	Line De-energization	Figures 16 and 17
7	Line Energization	Figures 18 and 19
8	Load switching	Figures 20–23
9	Load trip Event	Figures 24 and 25
10	Open Circuit Fault	Figures 26 and 27
11	Short Circuit Fault	Figures 28 and 29
12	Tap Changer	Figures 30–33
13	Temporary Fault	Figures 34 and 35
14	Transformer Outage	Figures 36 and 37
15	Transformer Energization	Figures 38 and 39
16	Transformer trip	Figures 40 and 41
17	Off Supply Complaint	Figures 42 and 43
18	Unbalance Voltage Complaint	Figures 44 and 45

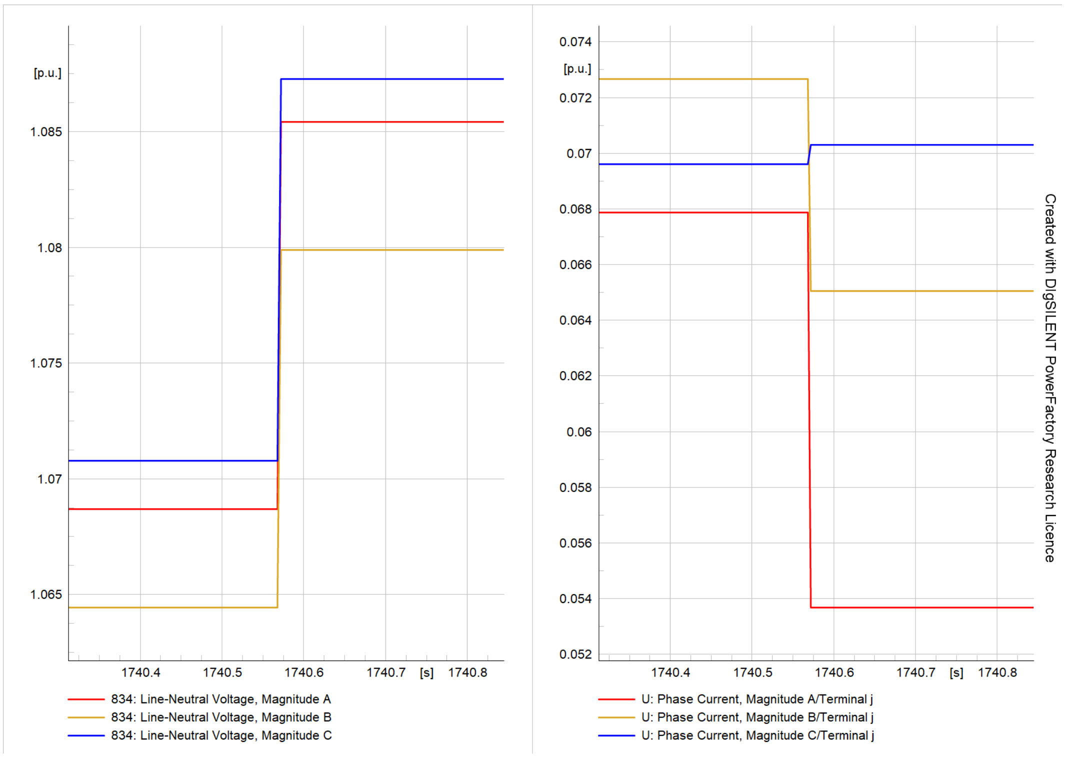


FIGURE 6.4: Capacitor bank switch-on event (µPMU7).

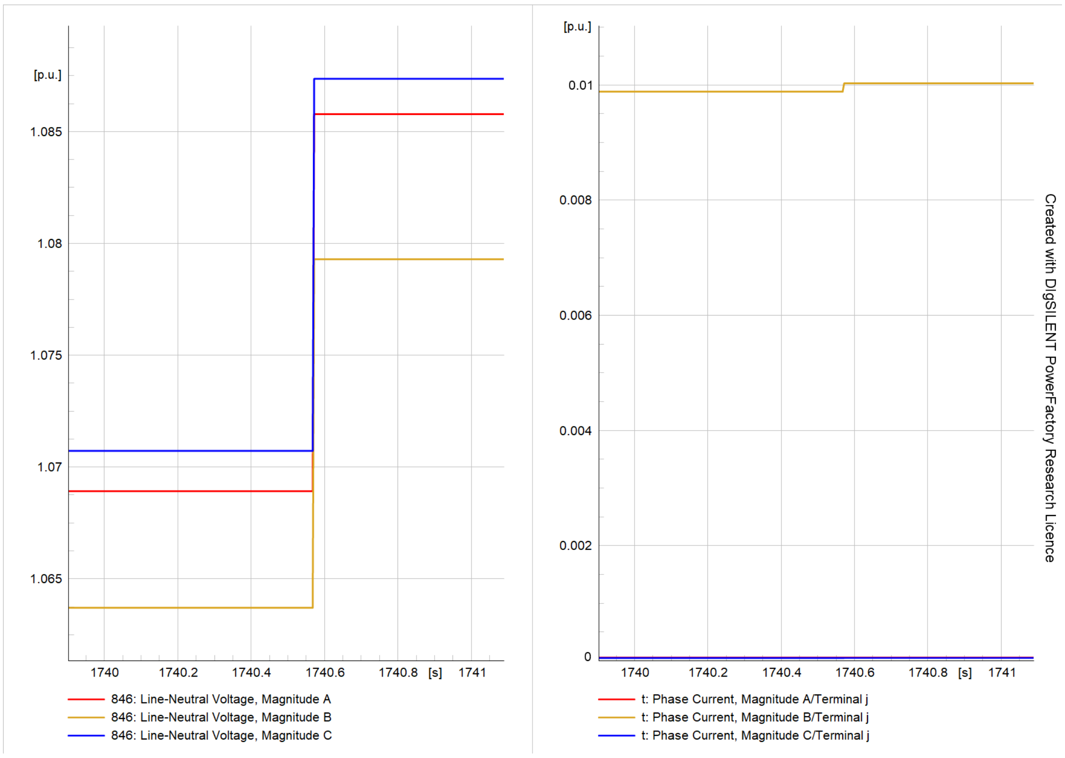


FIGURE 6.5: Capacitor bank switch-on event (μPMU11).

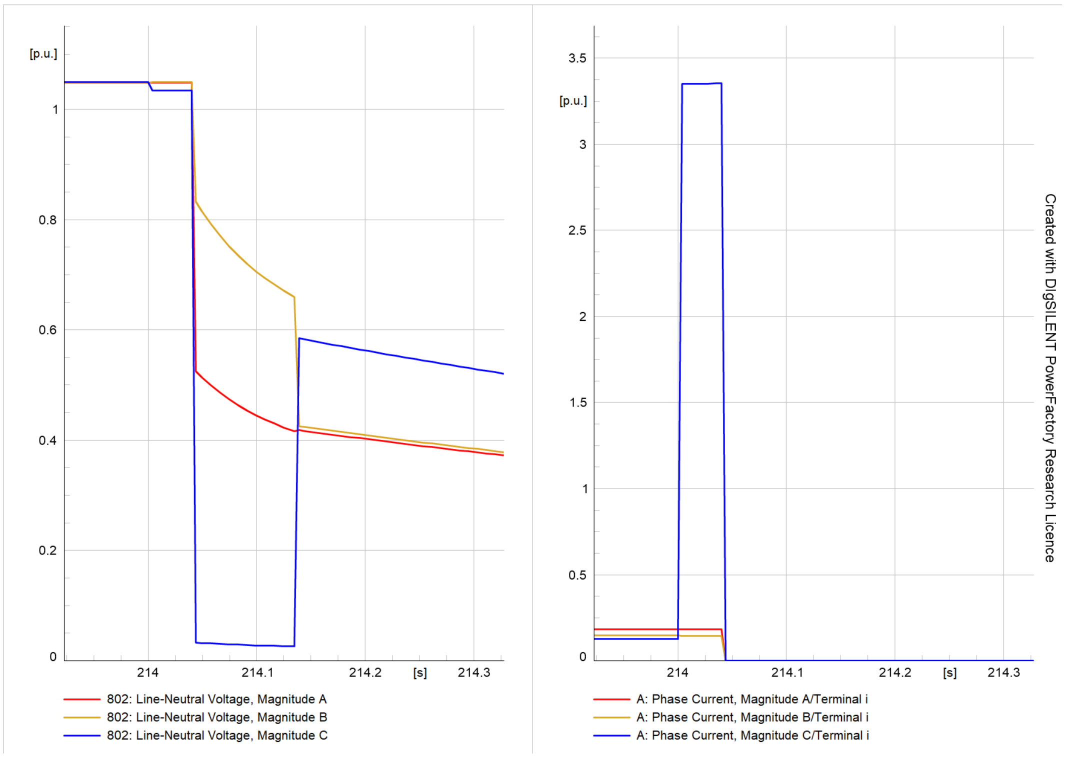


FIGURE 6.6: CB trip event (μPMU1).

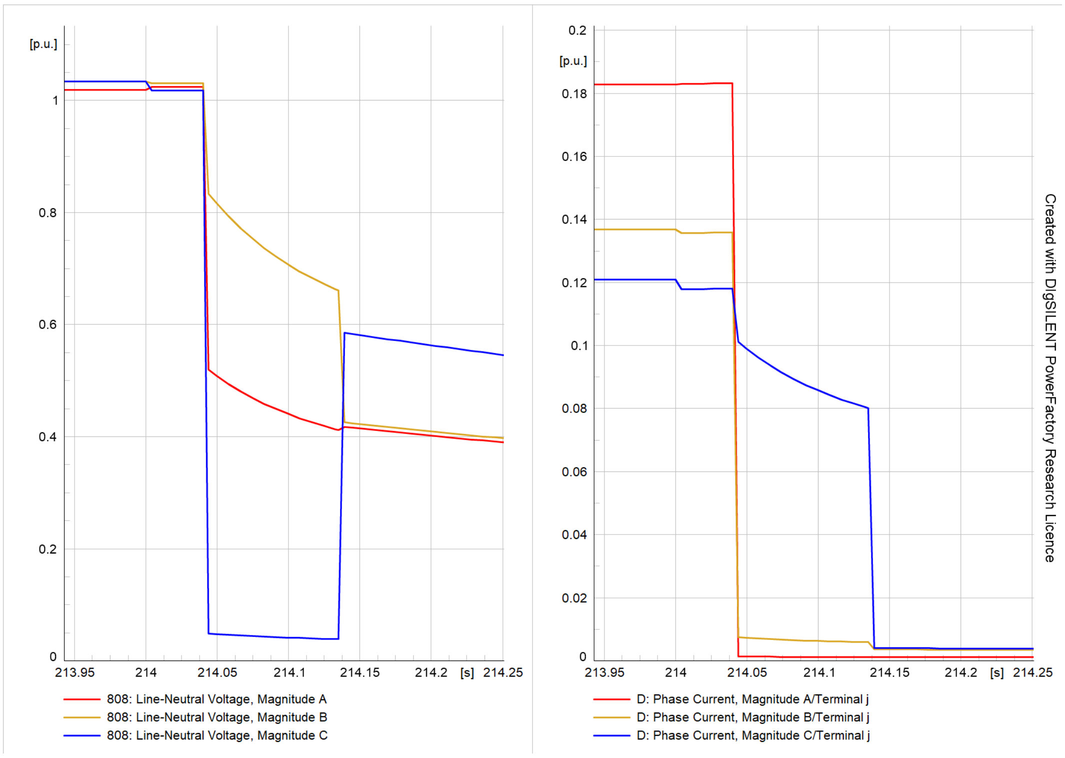


FIGURE 6.7: CB trip event (μPMU2).

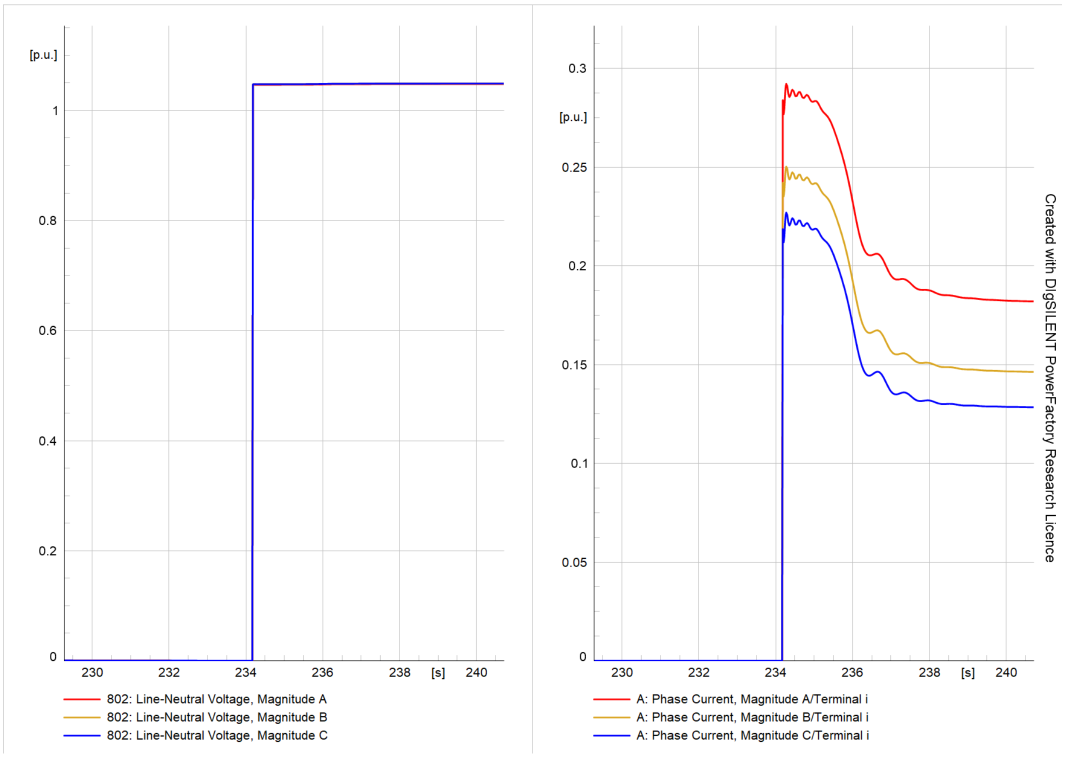


FIGURE 6.8: CB close event (μPMU1).

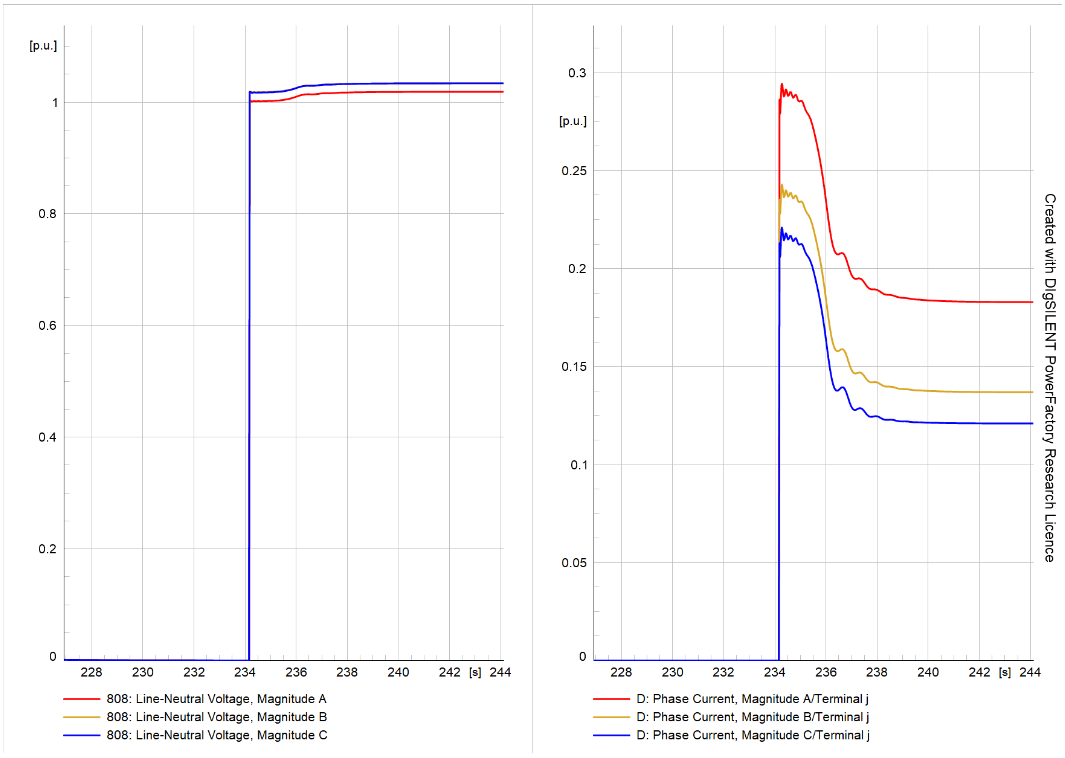


FIGURE 6.9: CB close event (μPMU2).

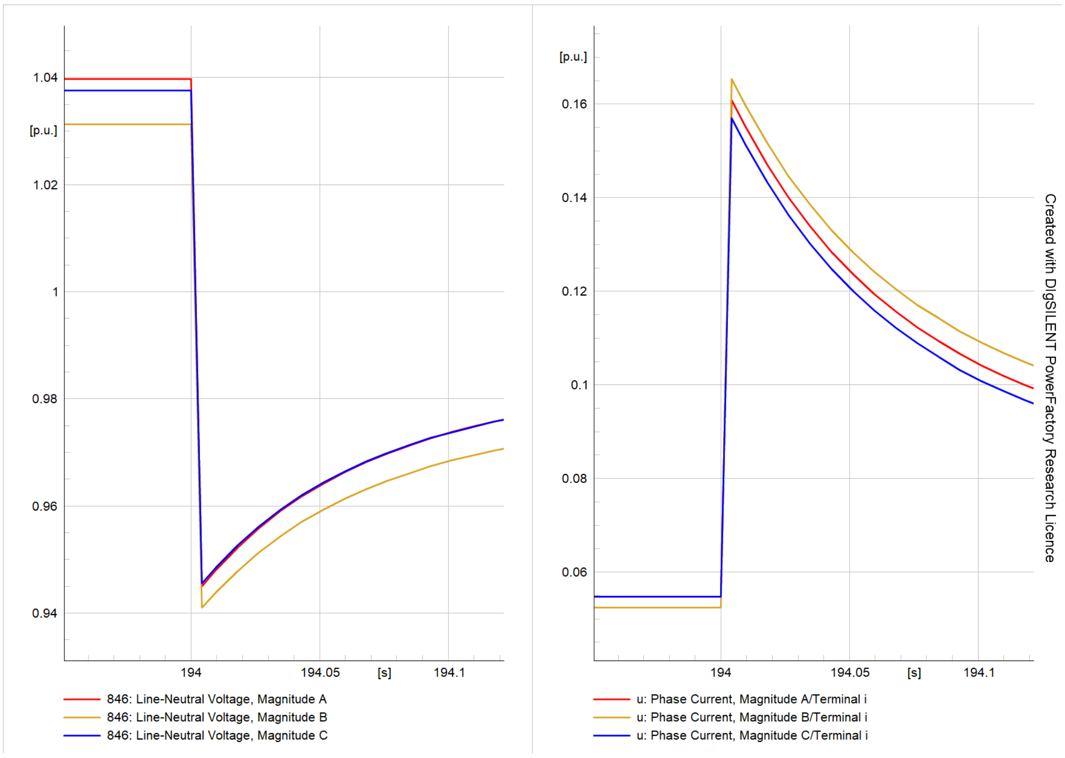


FIGURE 6.10: DG switch-on event (μPMU11).

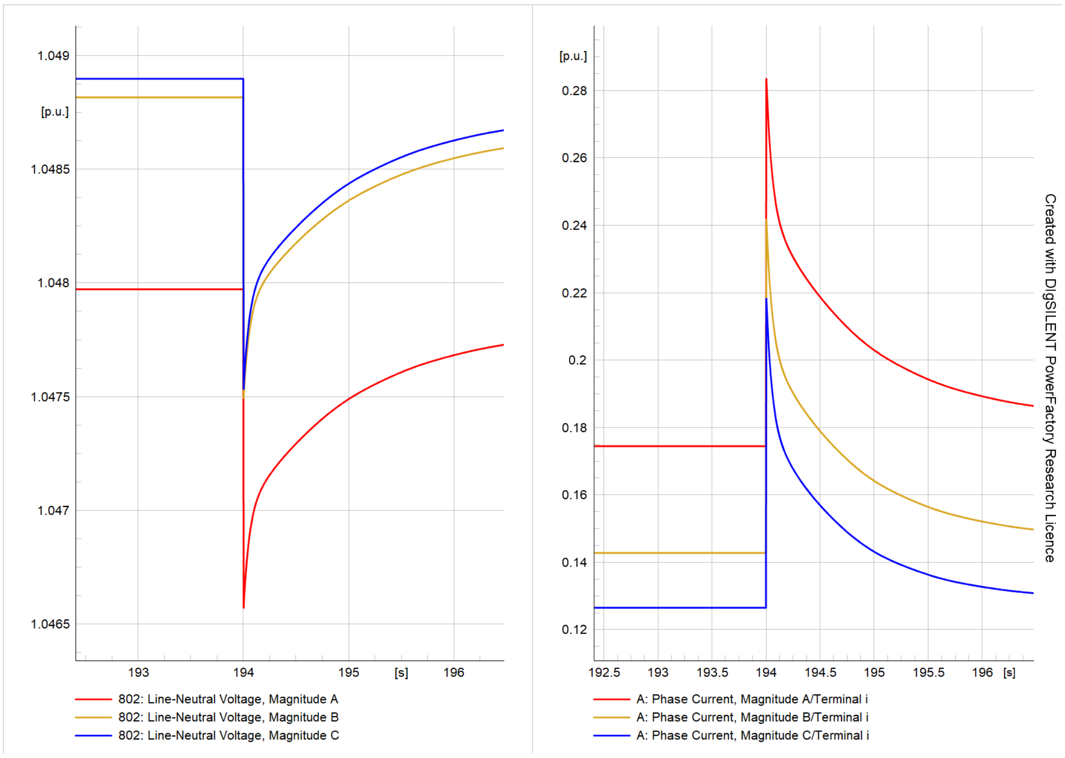


FIGURE 6.11: DG switch-on event (μPMU1).

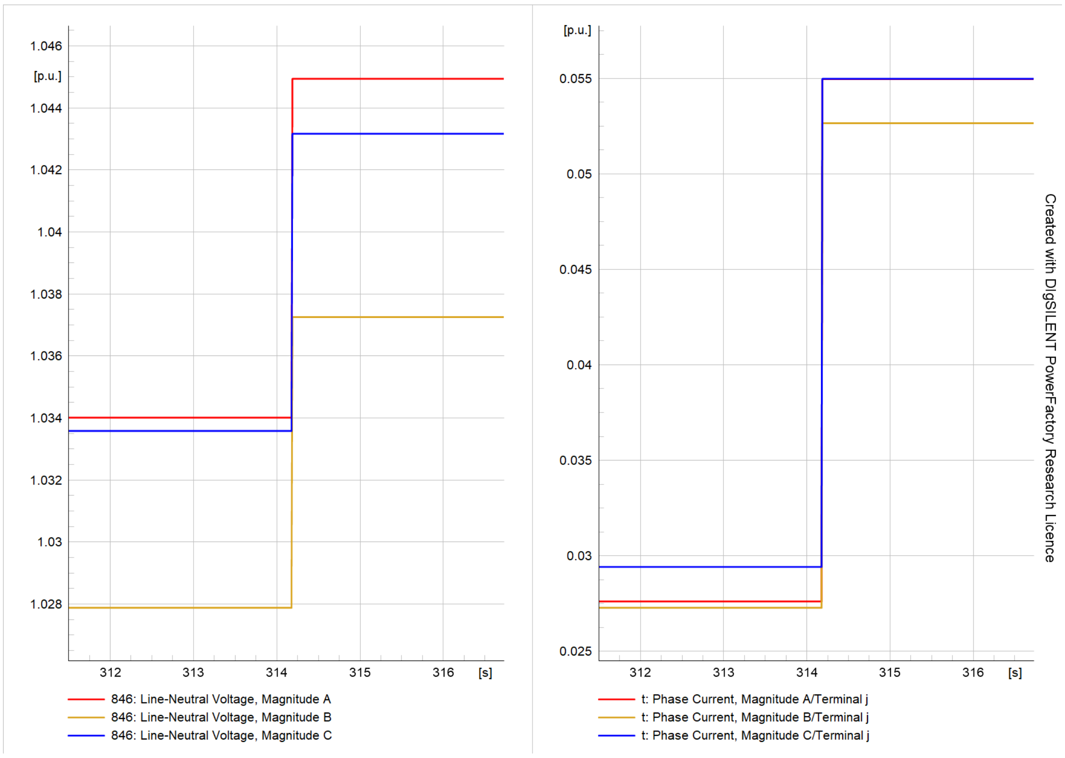


FIGURE 6.12: DG switch-off event (μPMU11).

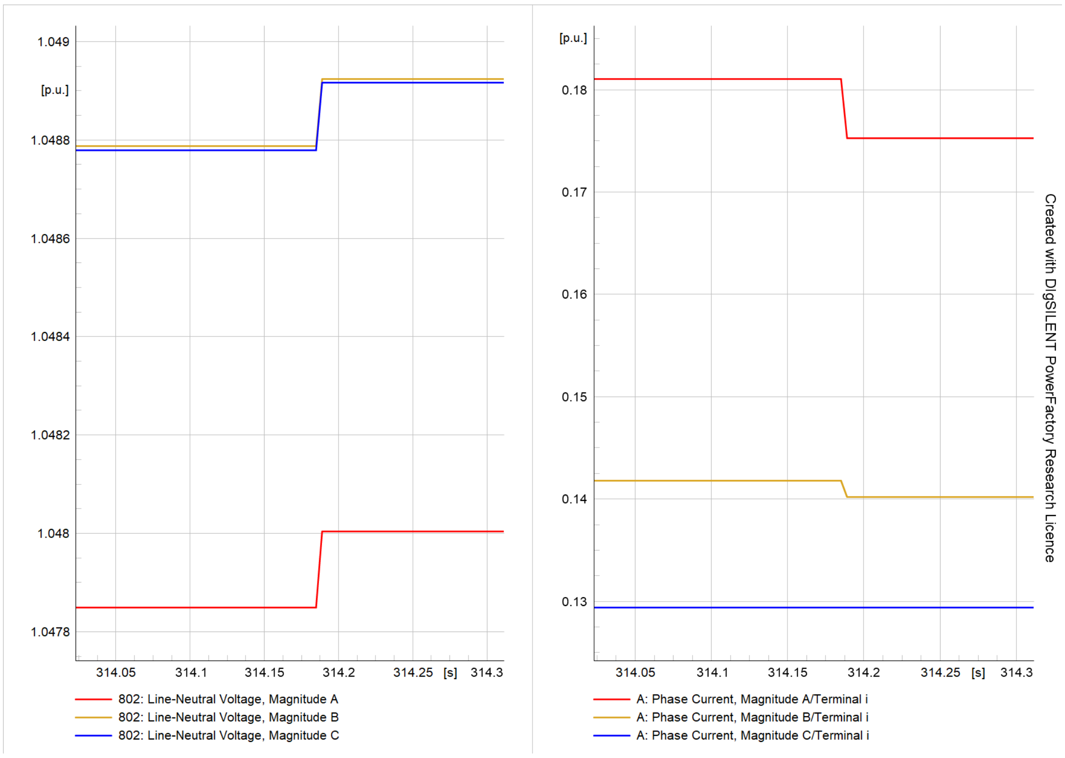


FIGURE 6.13: DG switch-off event (μPMU1).

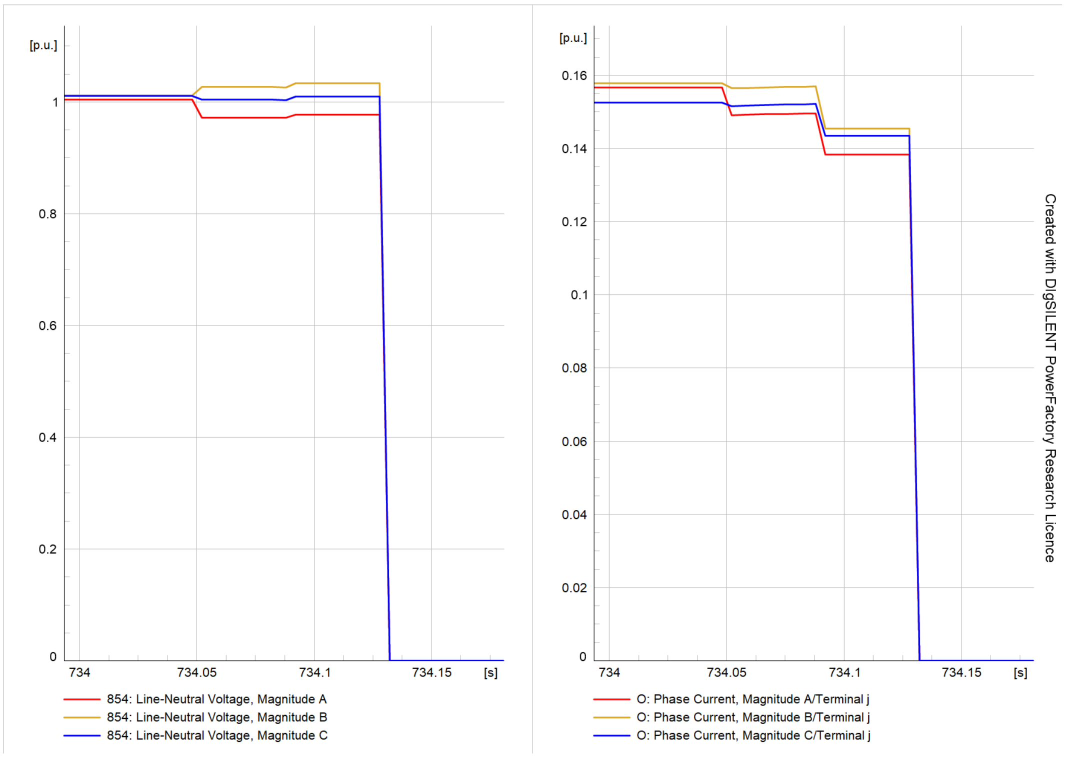


FIGURE 6.14: DG trip event (μPMU5).

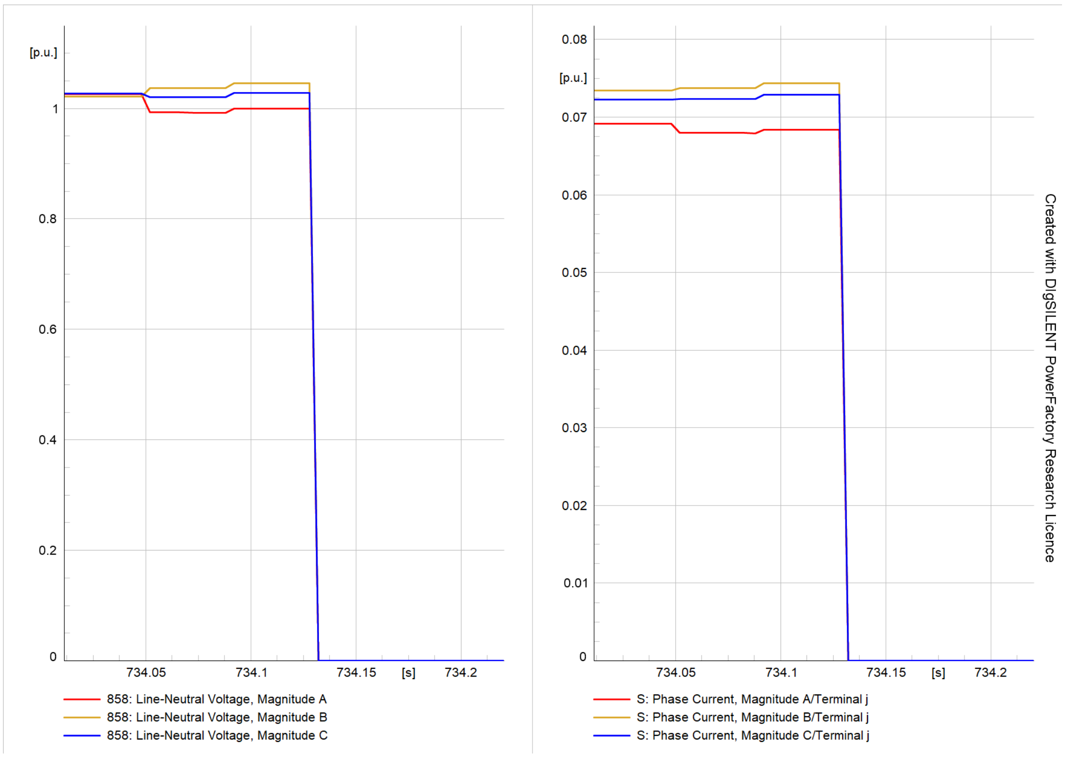


FIGURE 6.15: DG trip event (μPMU6).

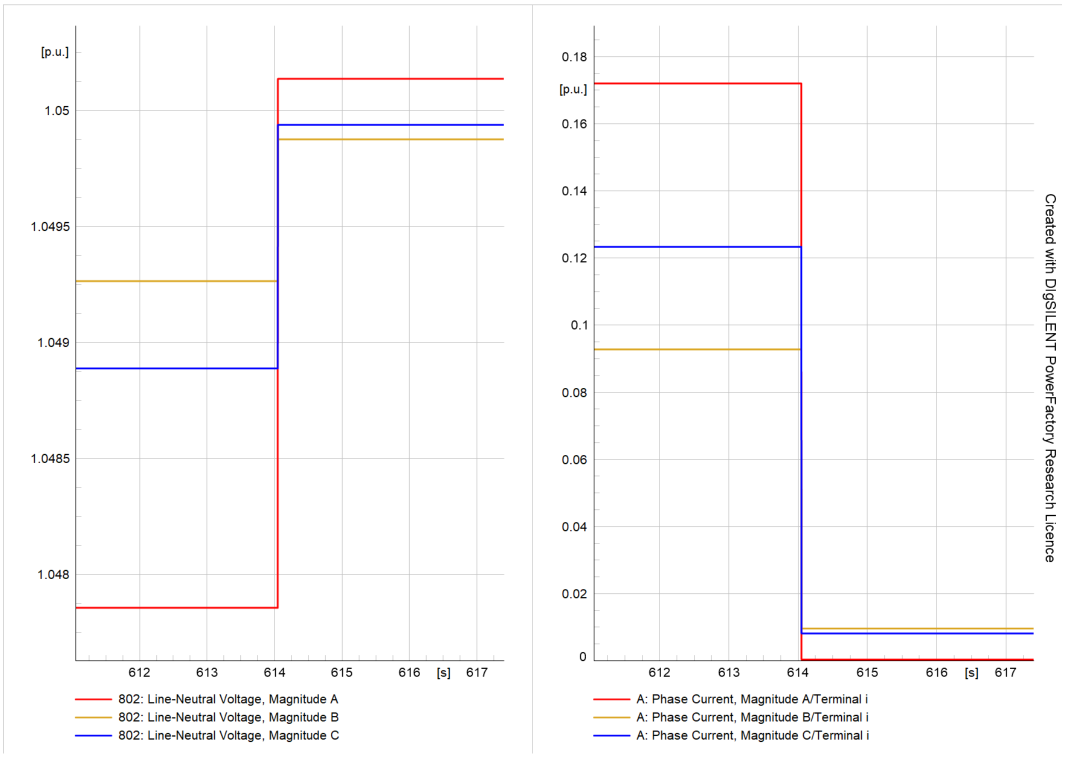


FIGURE 6.16: Line section de-energization (μPMU1).

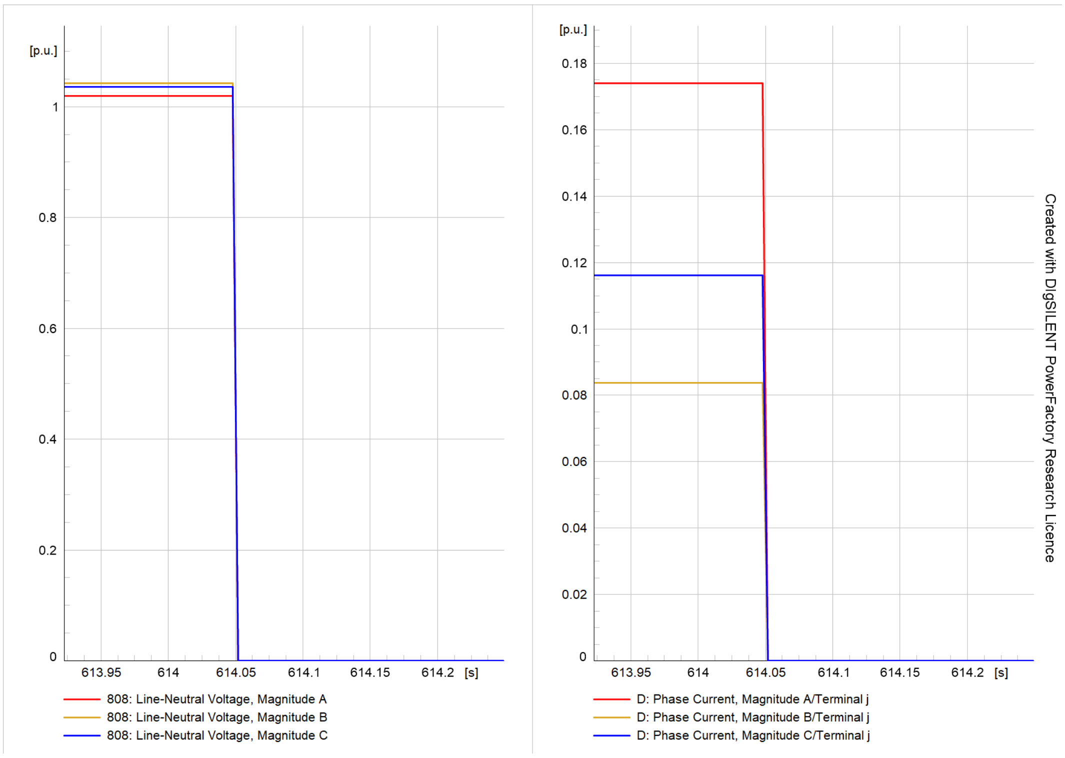


FIGURE 6.17: Line section de-energization (μPMU2).

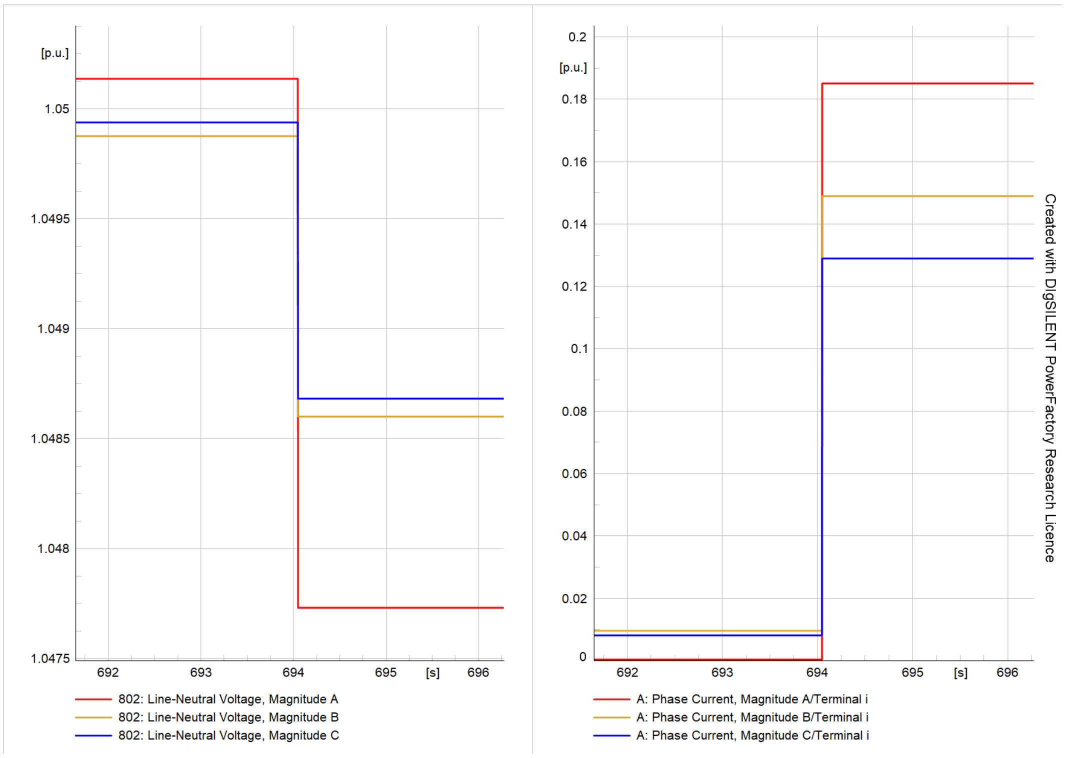


FIGURE 6.18: Line section energization(μPMU1).

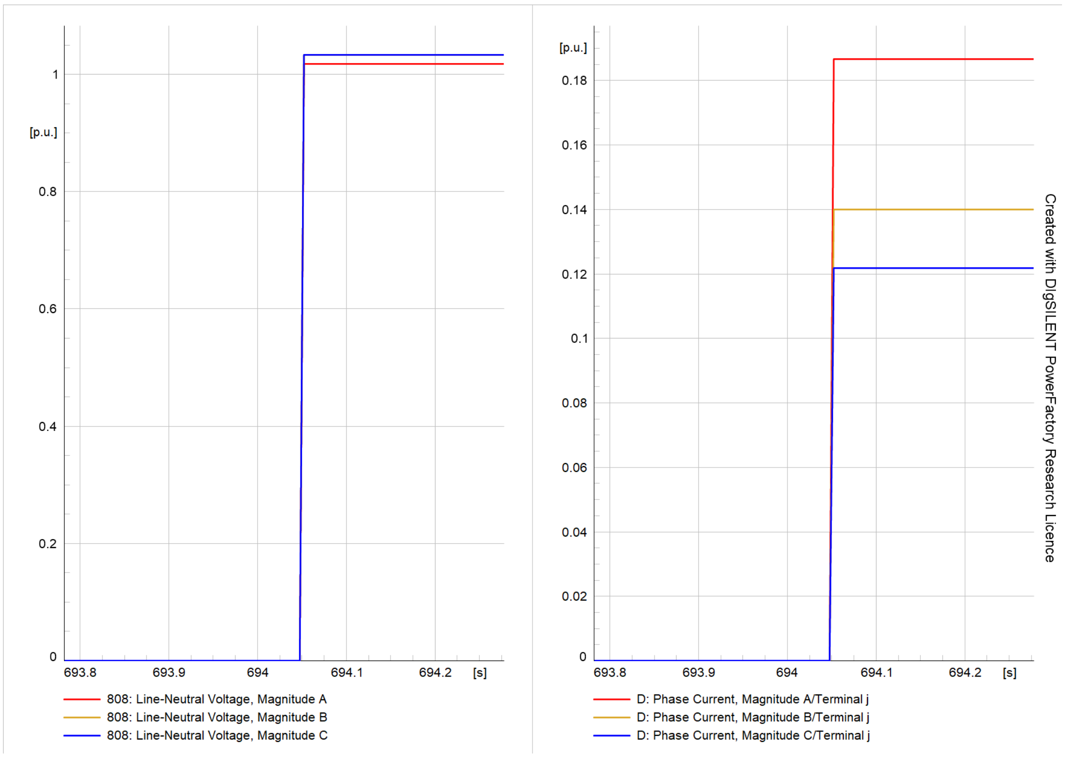


FIGURE 6.19: Line section energization (μPMU2).

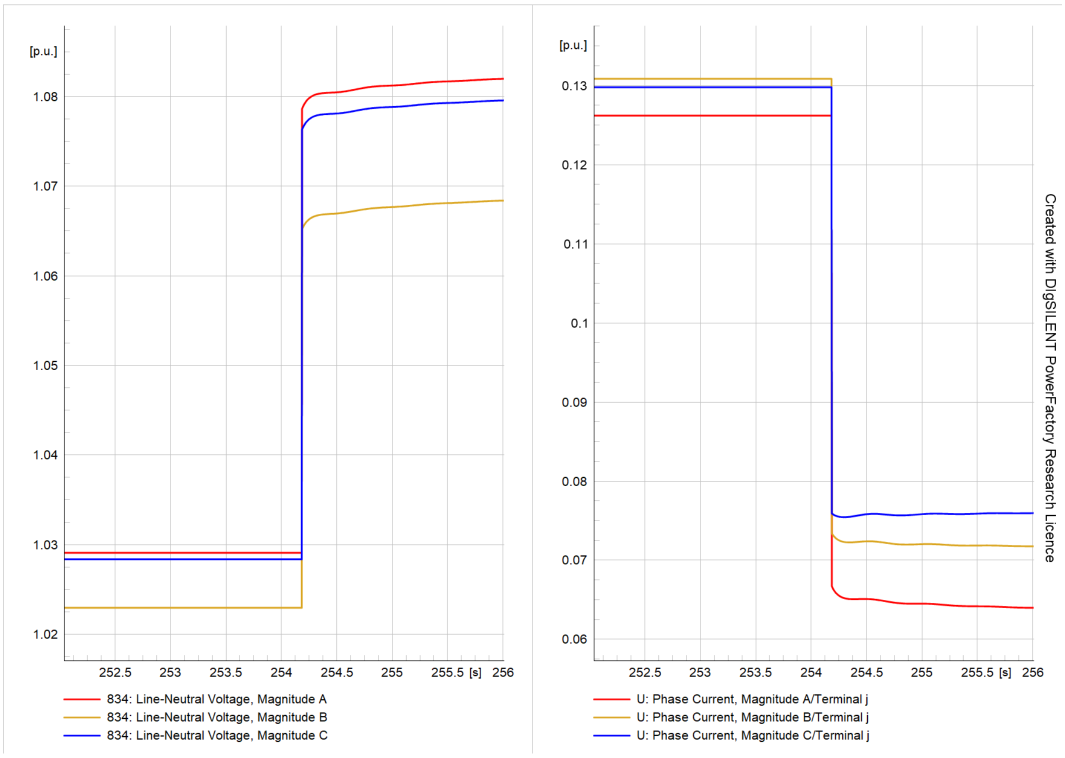


FIGURE 6.20: ABCN load switch-off event (μPMU7).

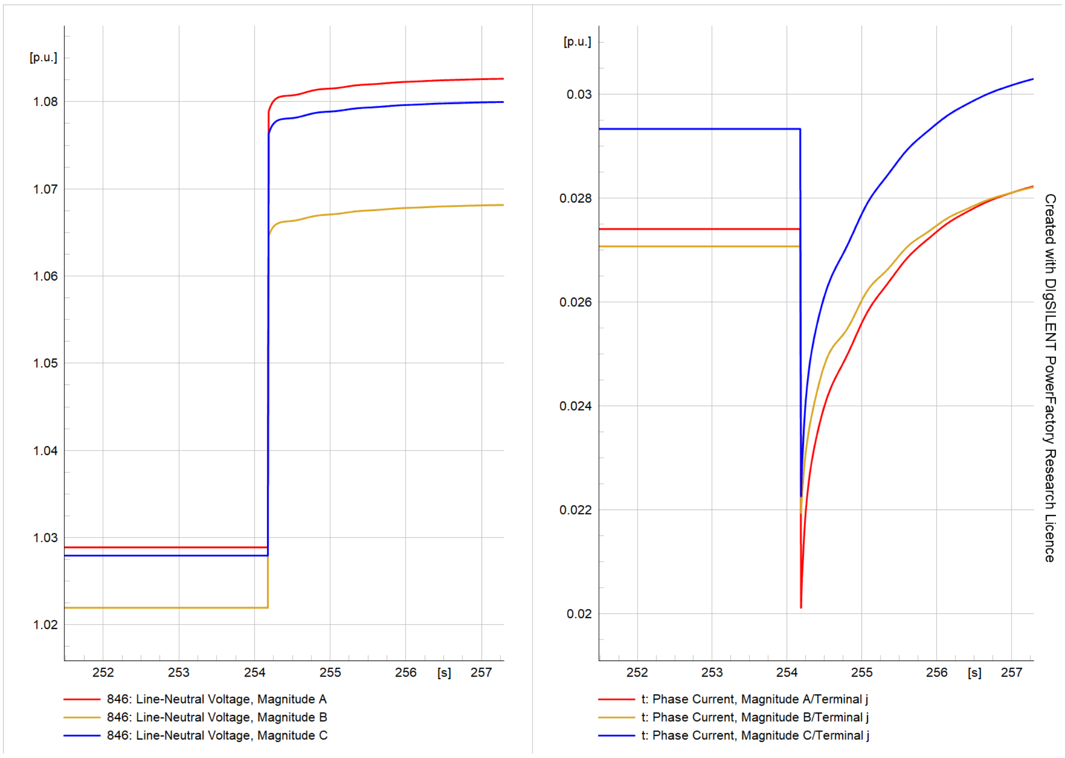


FIGURE 6.21: ABCN load switch-off event (μPMU11).

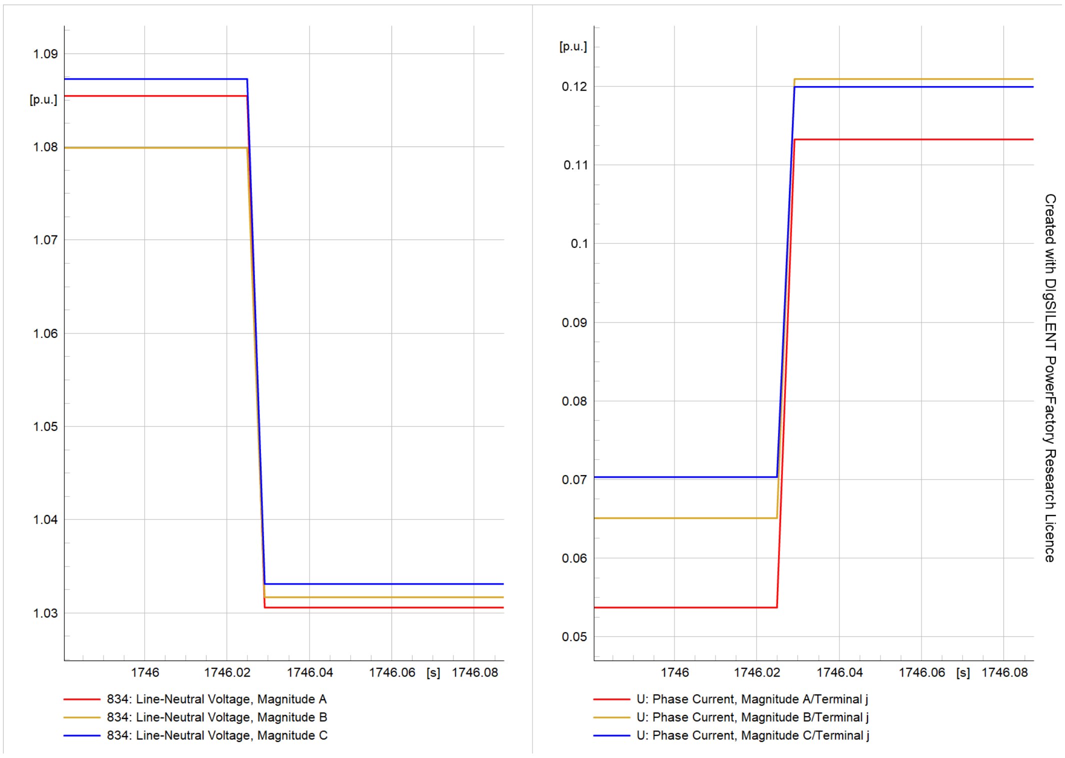


FIGURE 6.22: ABCN load switch-on event (μPMU7).

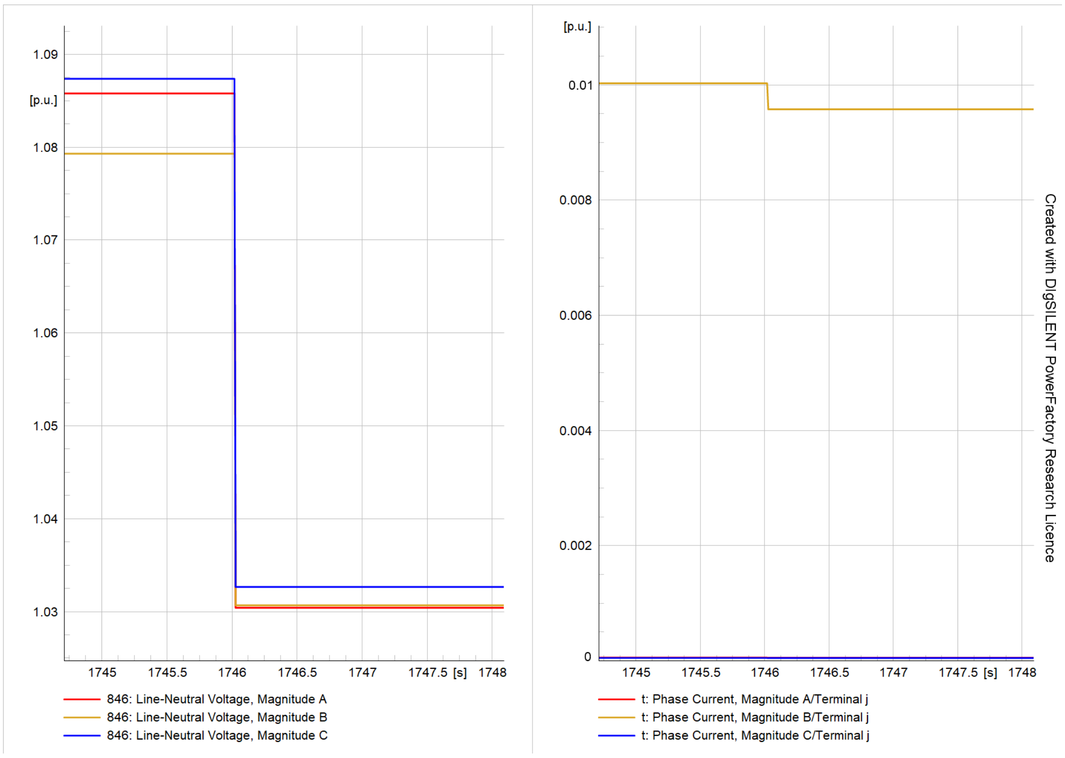


FIGURE 6.23: ABCN load switch-on event (µPMU11).

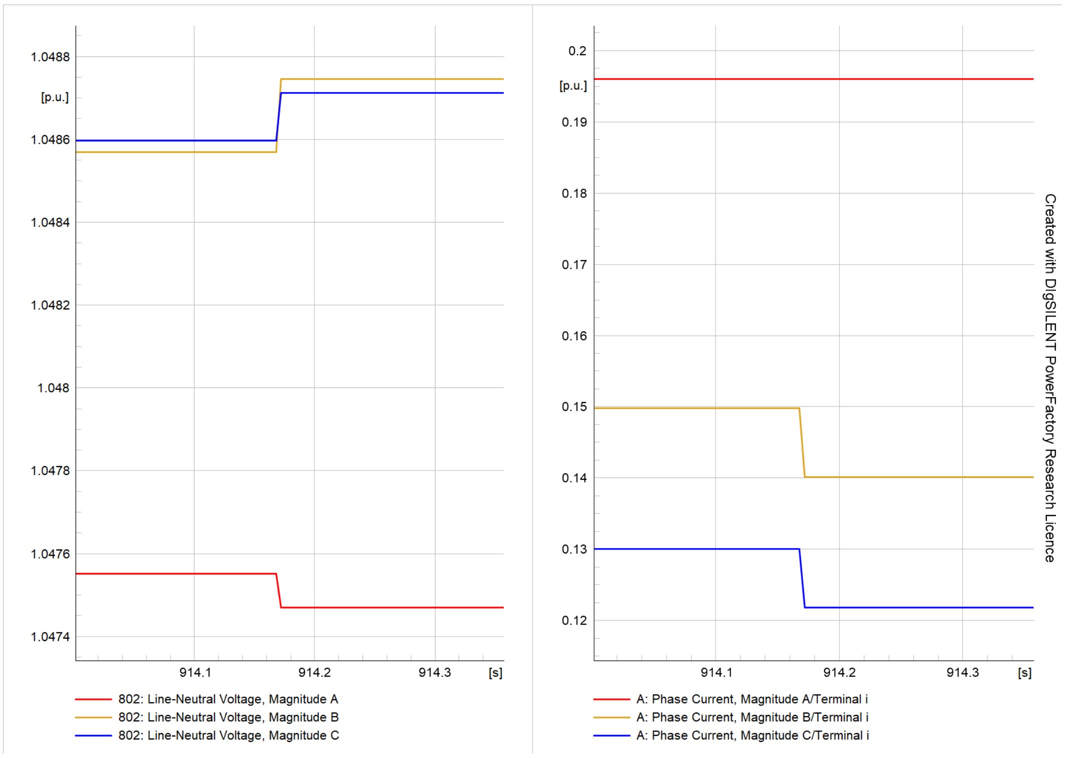


FIGURE 6.24: BCN load trip event (µPMU1).

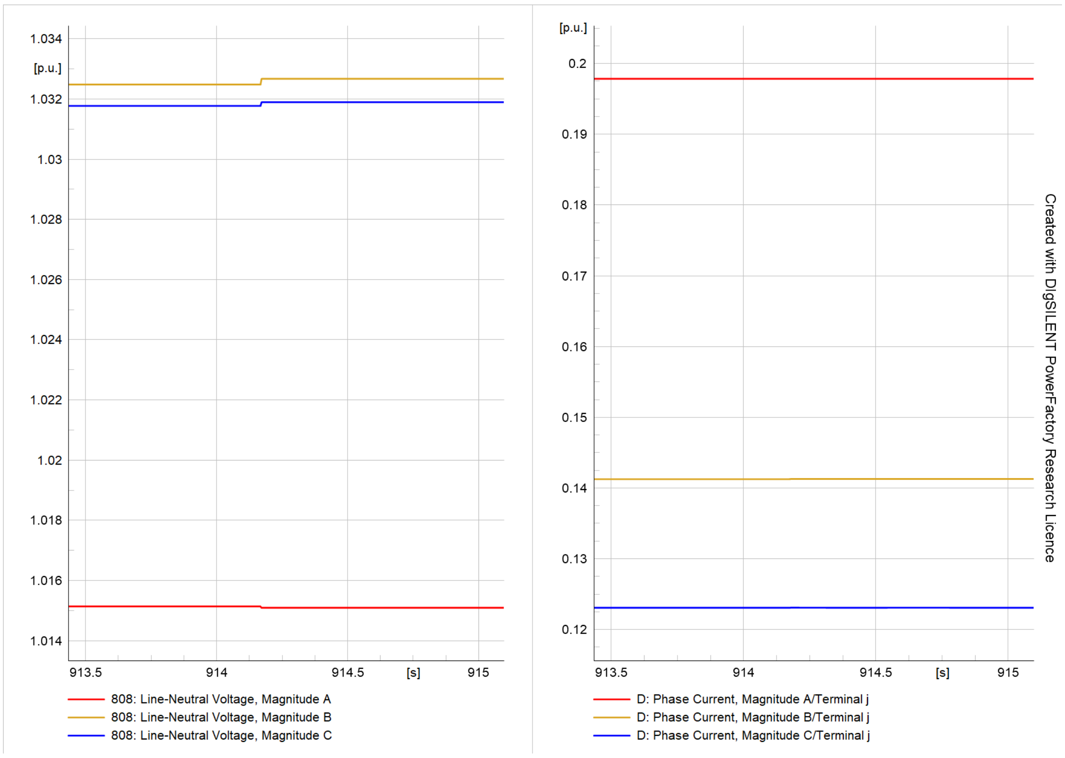


FIGURE 6.25: BCN load Trip Event (μPMU2).

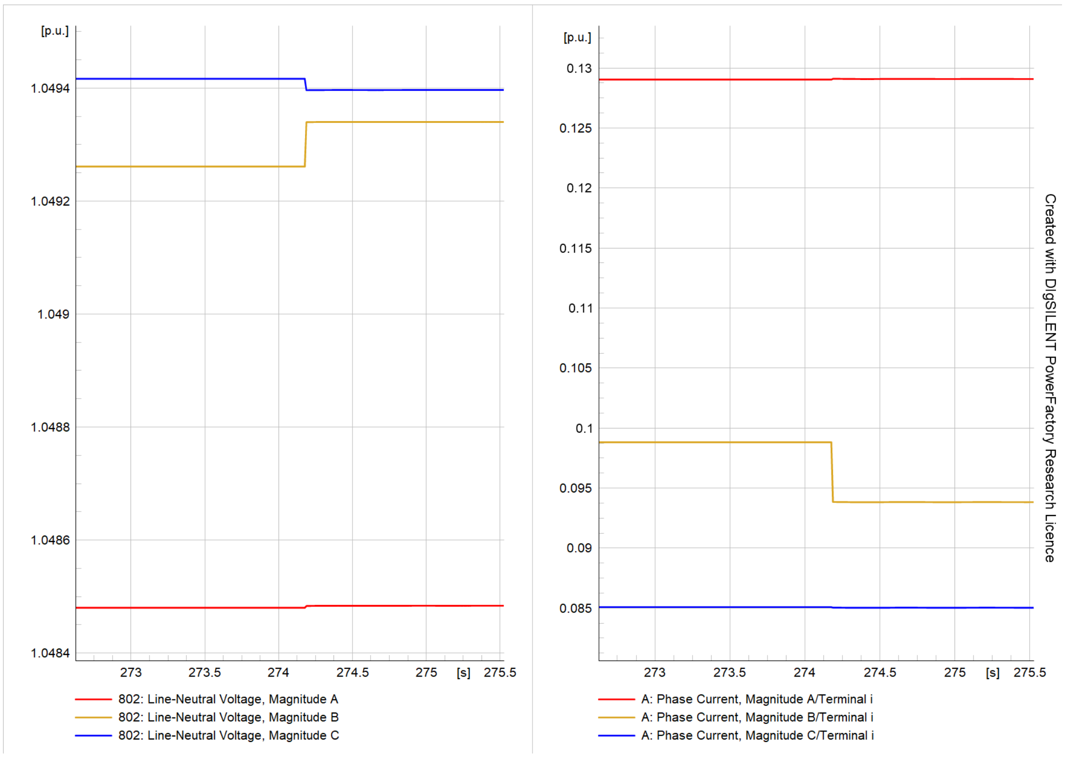


FIGURE 6.26: B-N jumper parted open circuit fault (μPMU1).

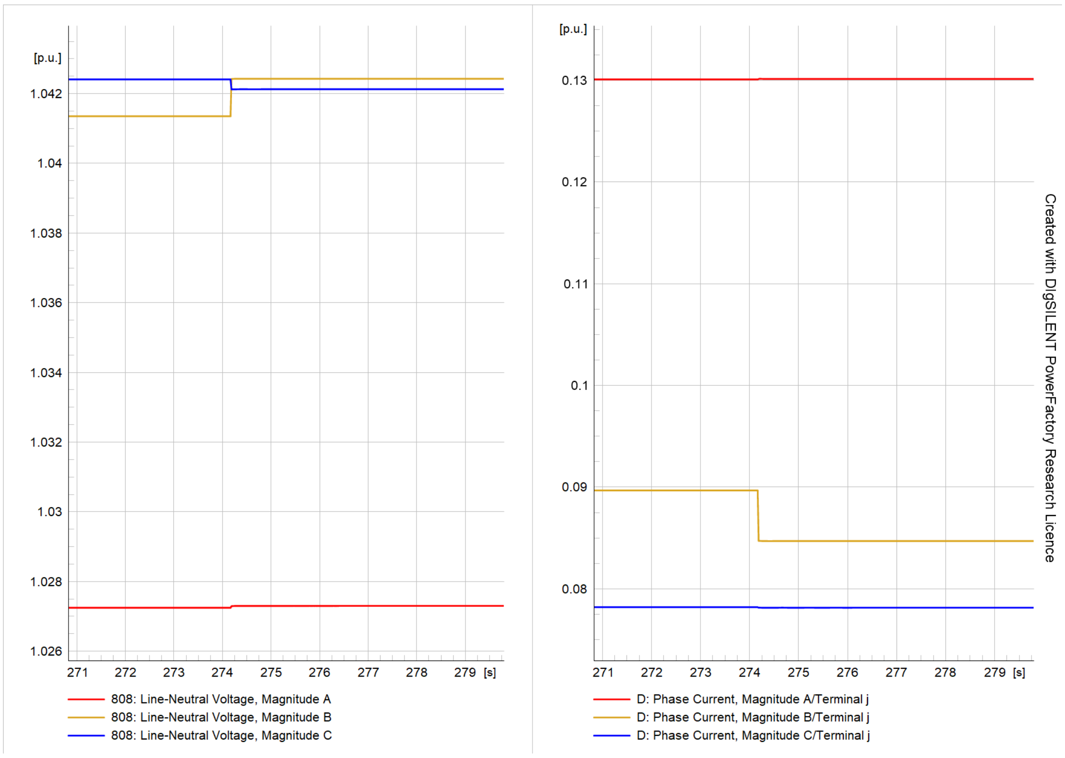


FIGURE 6.27: B-N jumper parted open circuit fault (μPMU2).

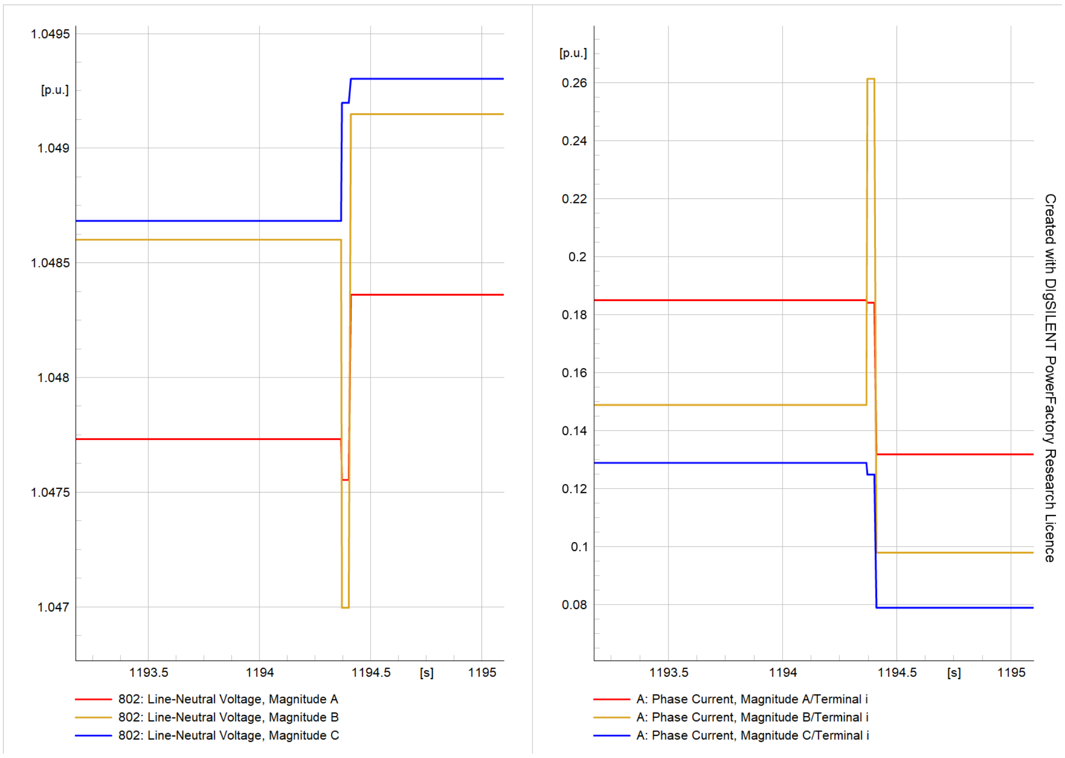


FIGURE 6.28: BG fault event (μPMU1).

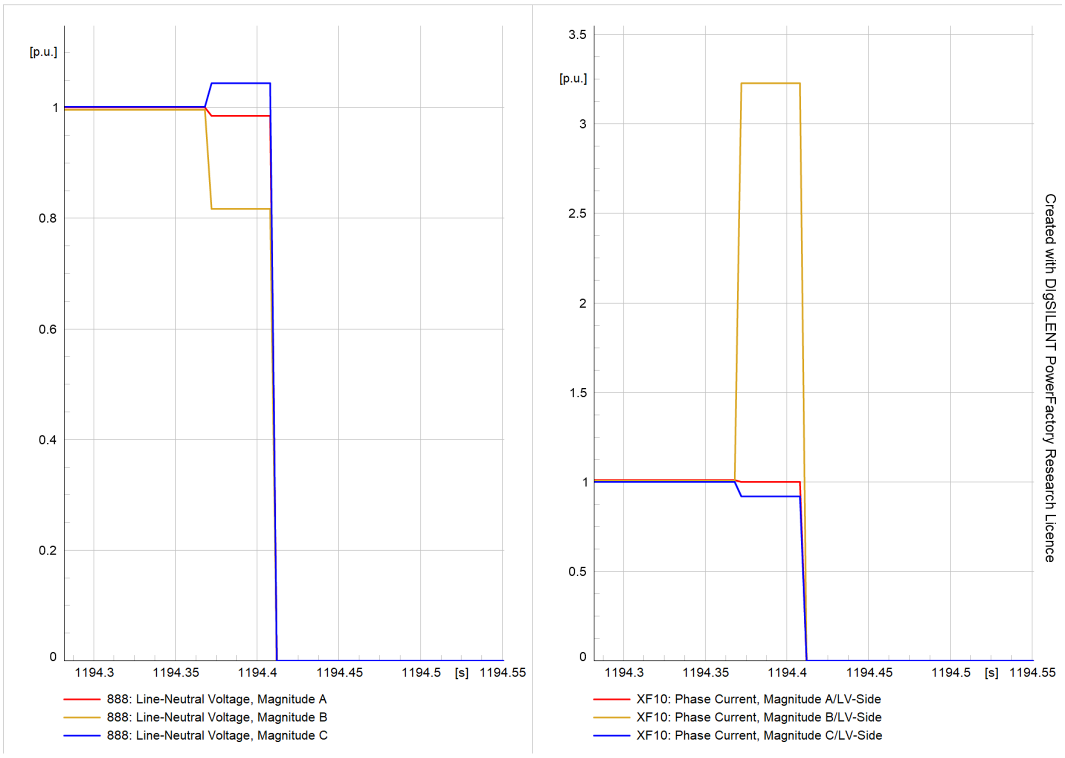


FIGURE 6.29: BG fault event (μPMU2).

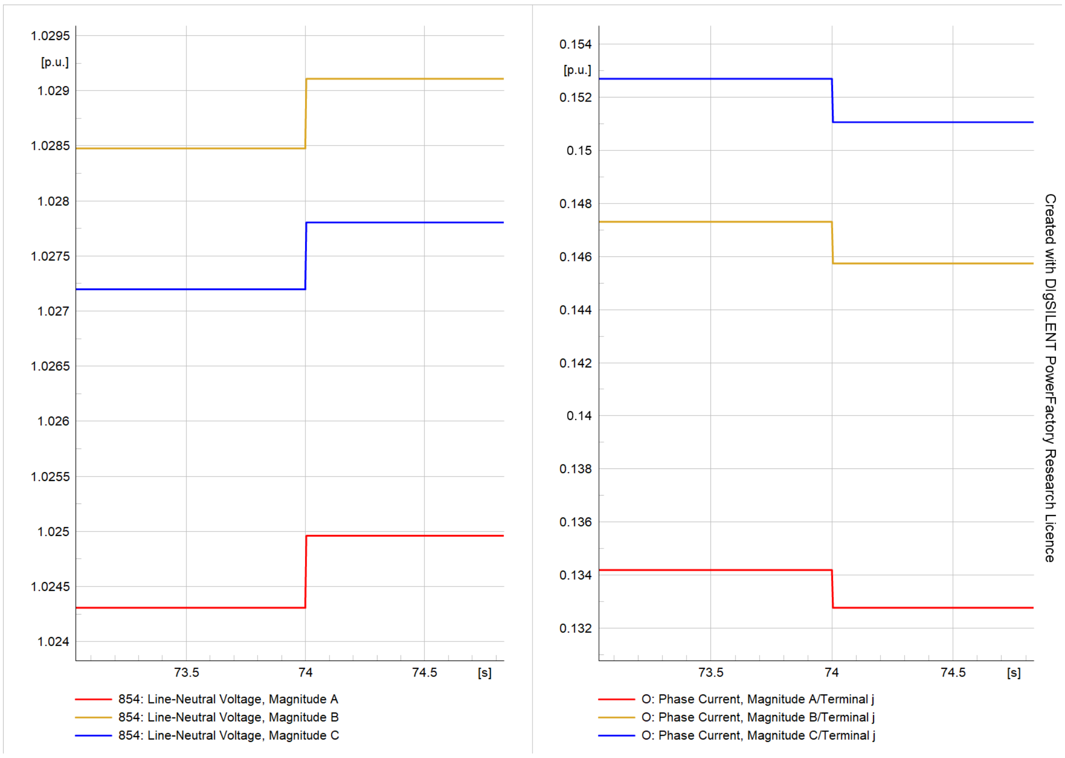


FIGURE 6.30: Tap lowering (μPMU5).

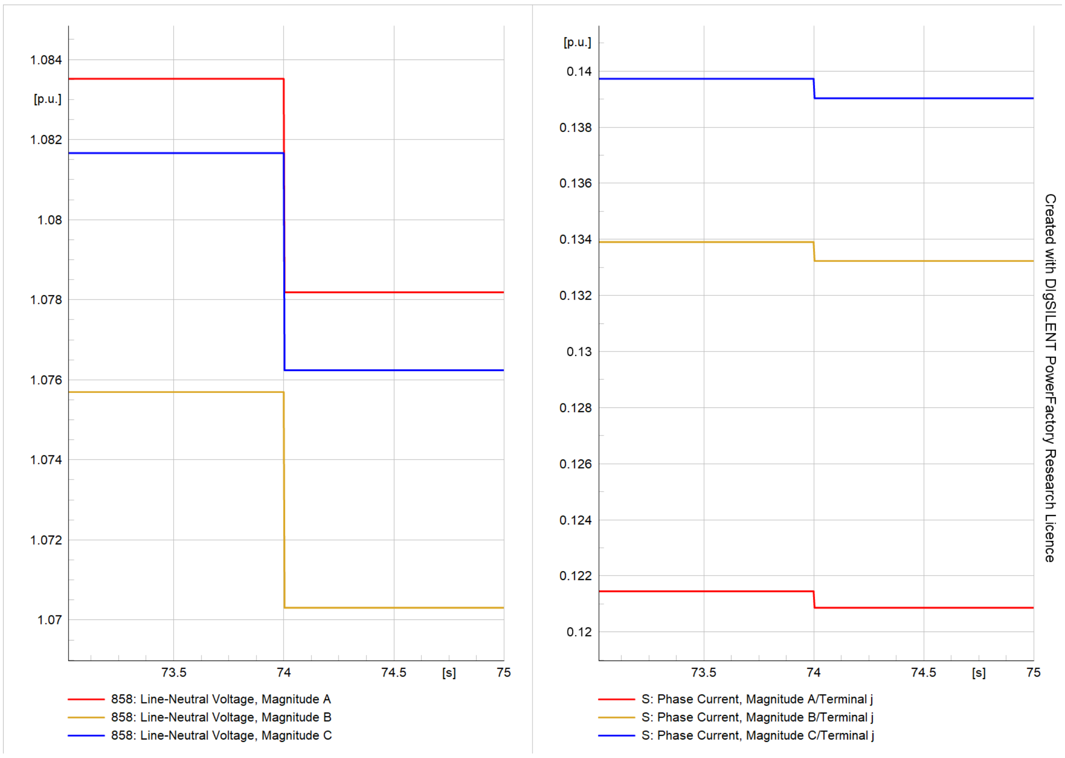


FIGURE 6.31: Tap lowering (μPMU6).

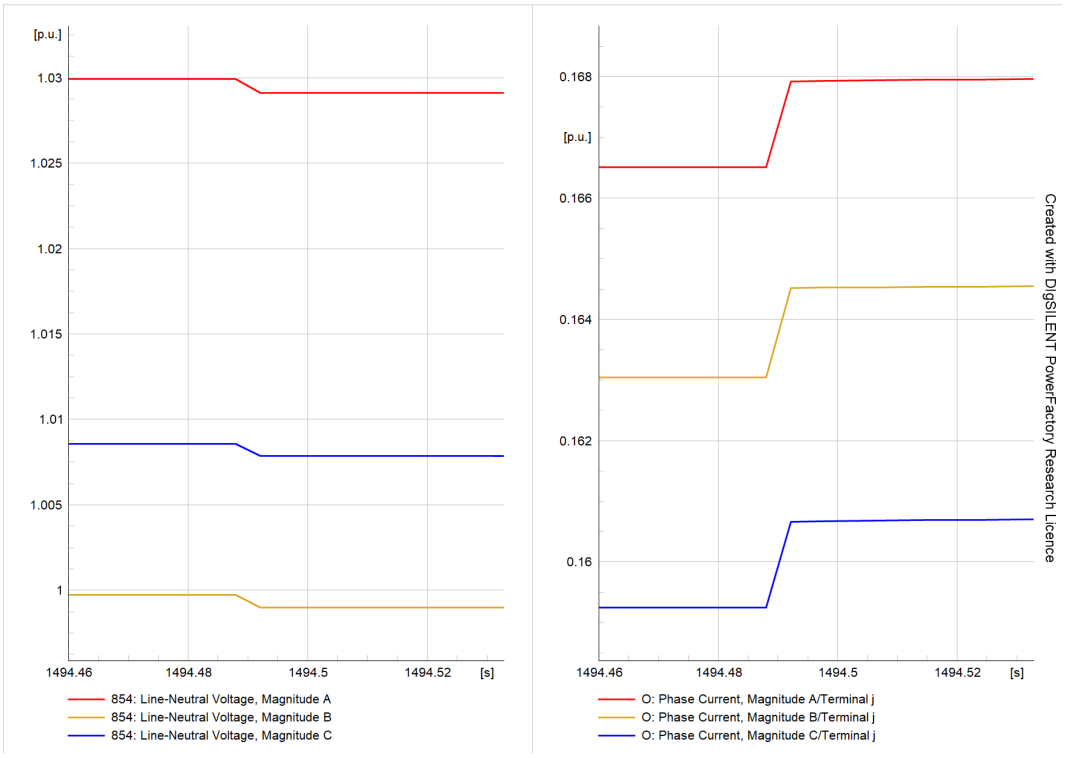


FIGURE 6.32: Tap Raising (μPMU5).

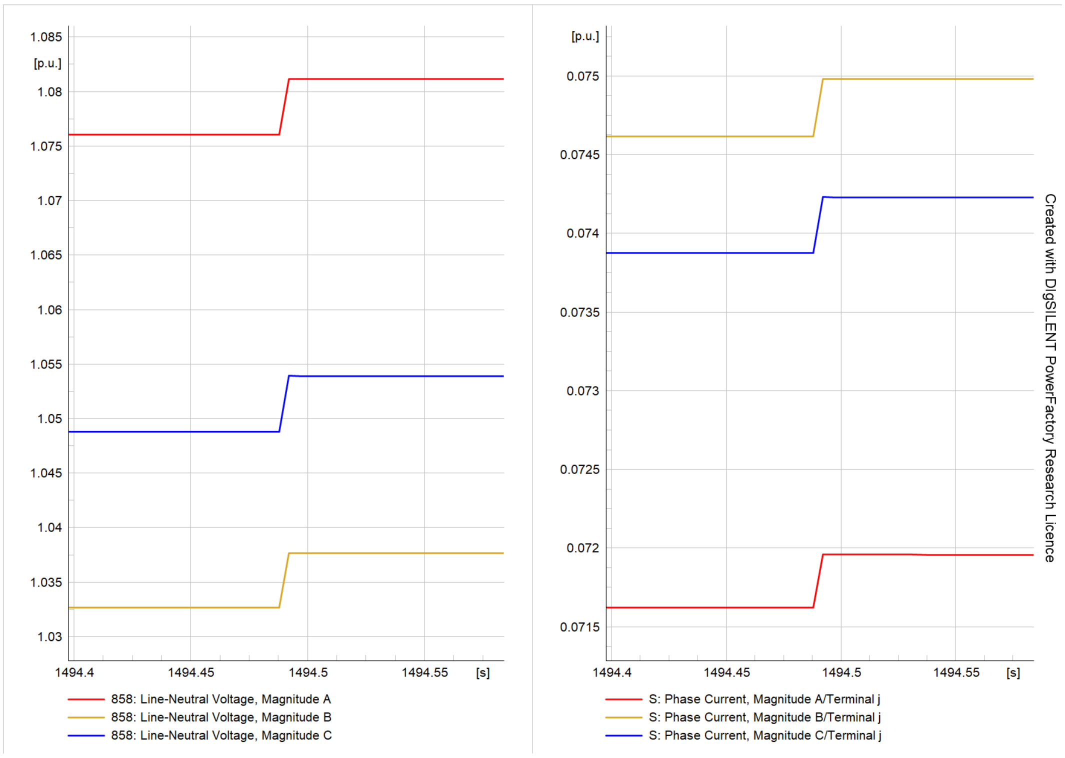


FIGURE 6.33: Tap raising (μPMU6).

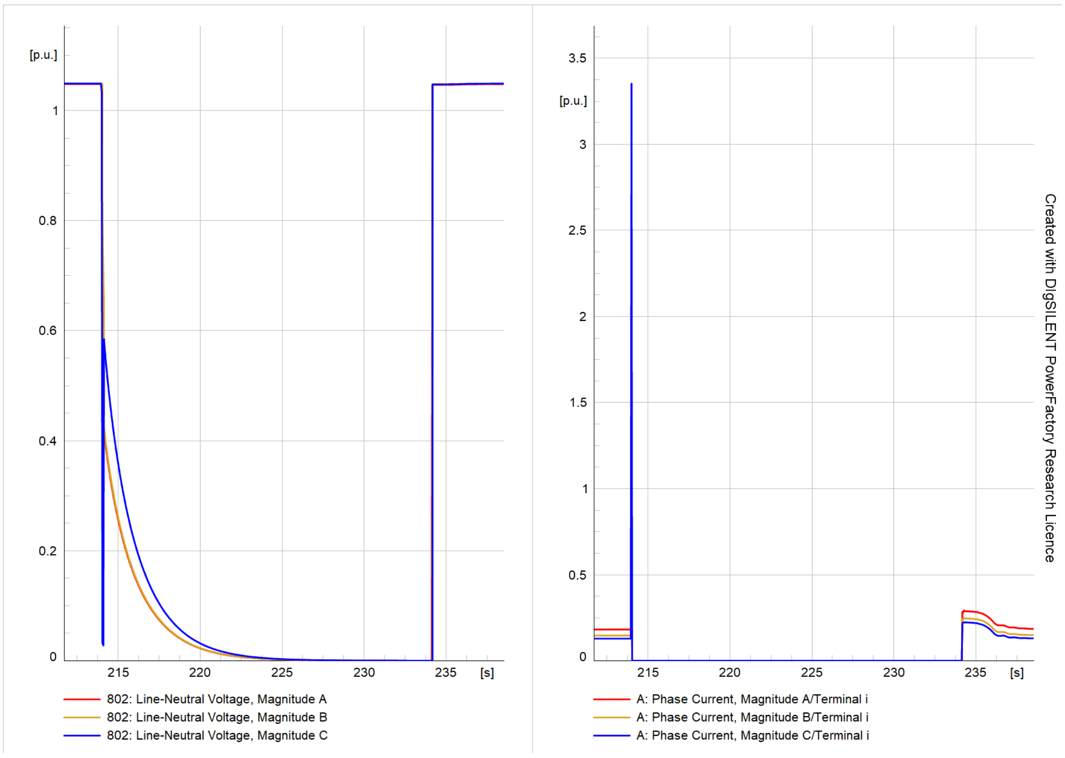


FIGURE 6.34: Temporary fault and reclosing (μPMU1).

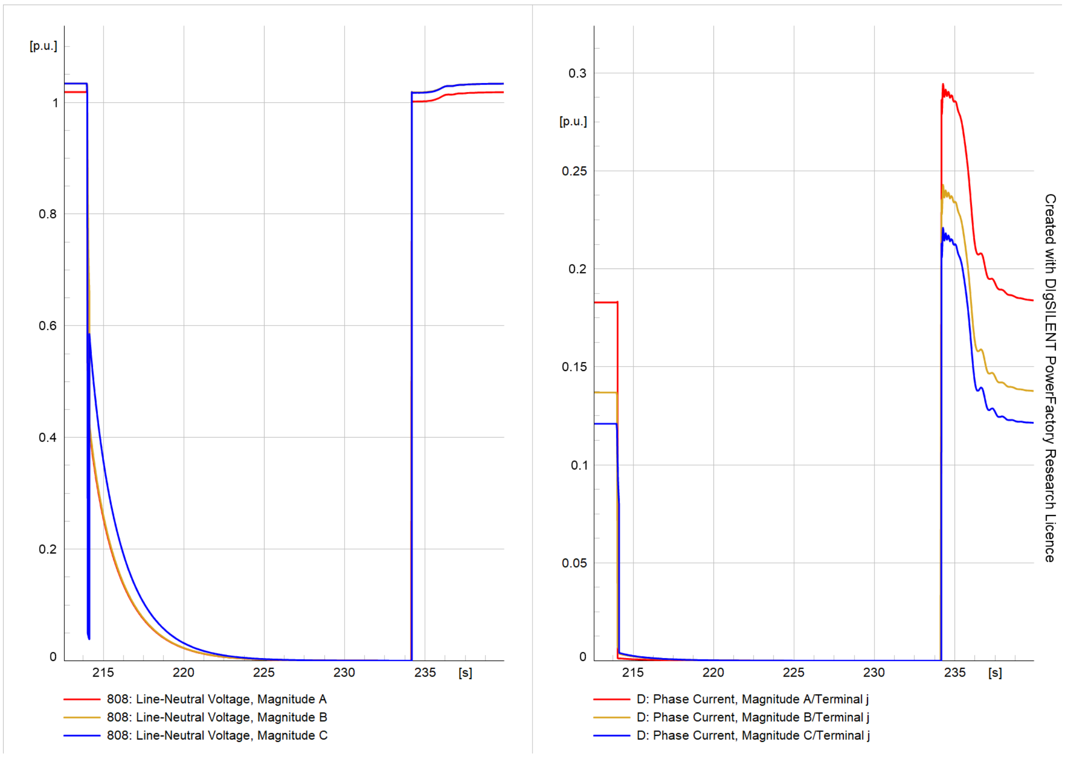


FIGURE 6.35: Temporary fault and reclosing (μPMU2).

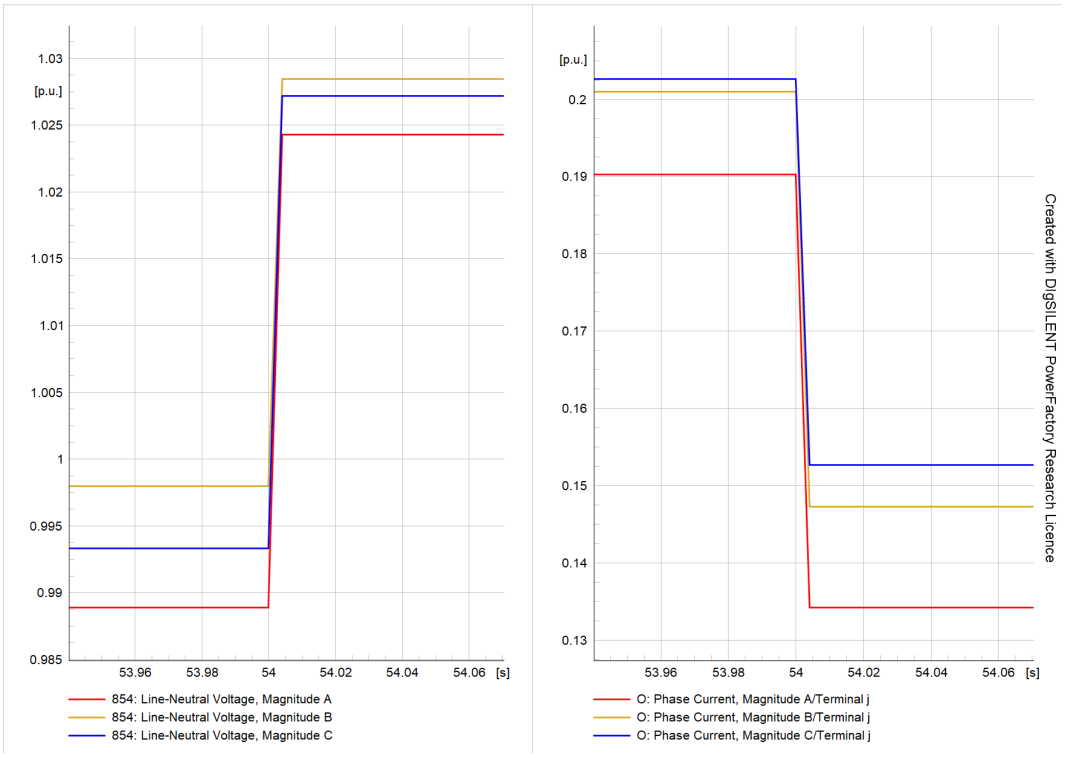


FIGURE 6.36: Transformer outage (μPMU5).

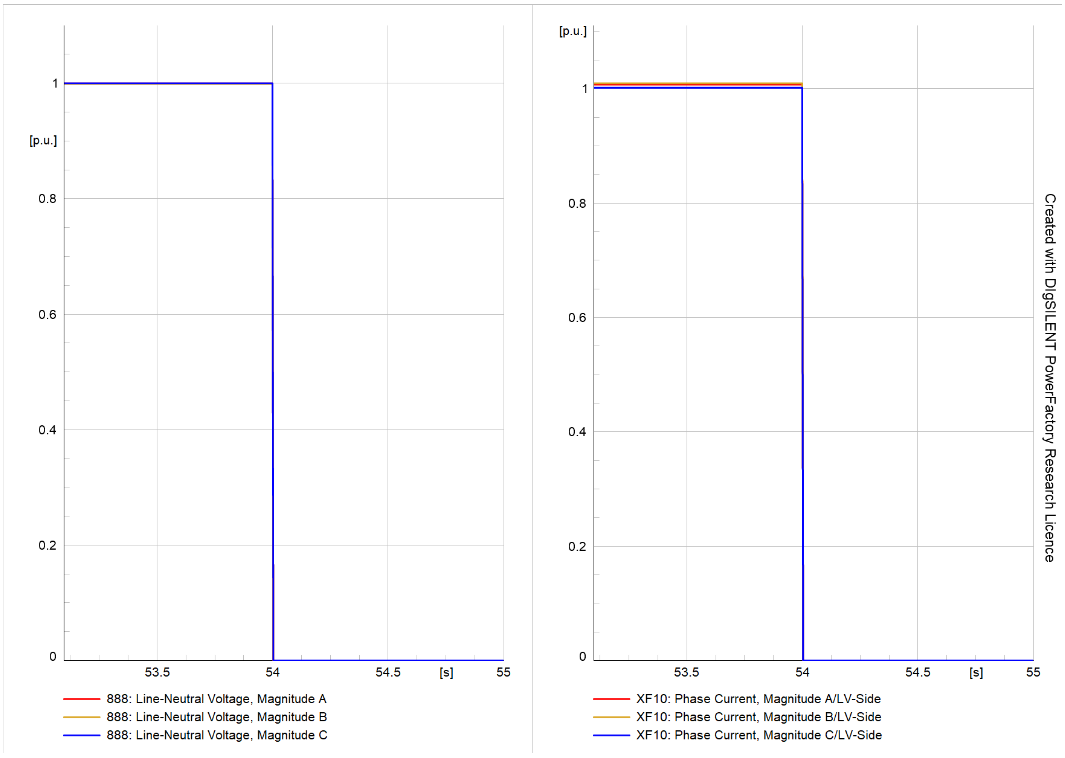


FIGURE 6.37: Transformer outage (μPMU10).

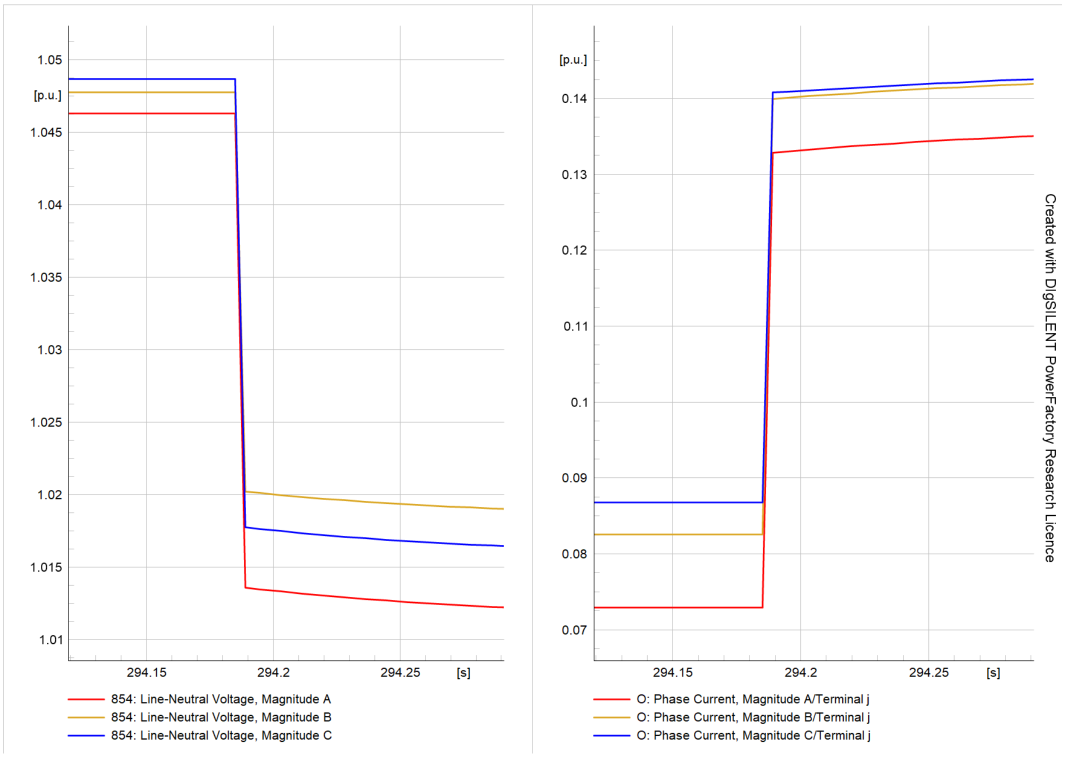


FIGURE 6.38: Transformer energization (μPMU5).

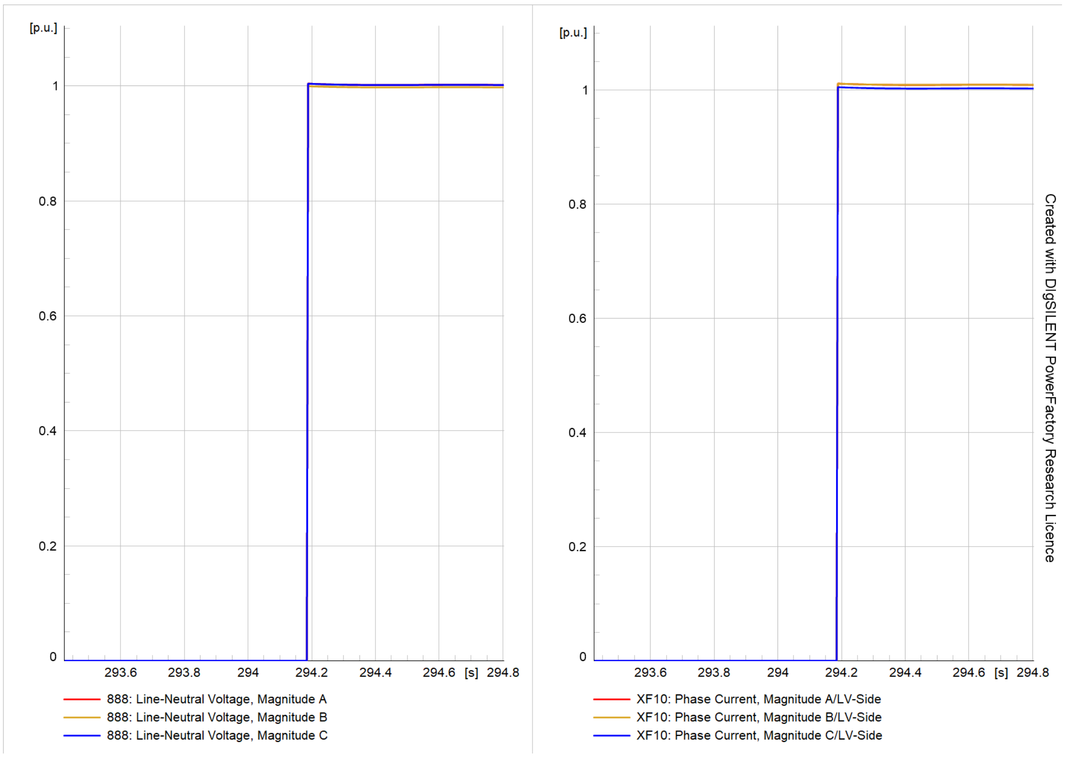


FIGURE 6.39: Transformer energization (μPMU10).

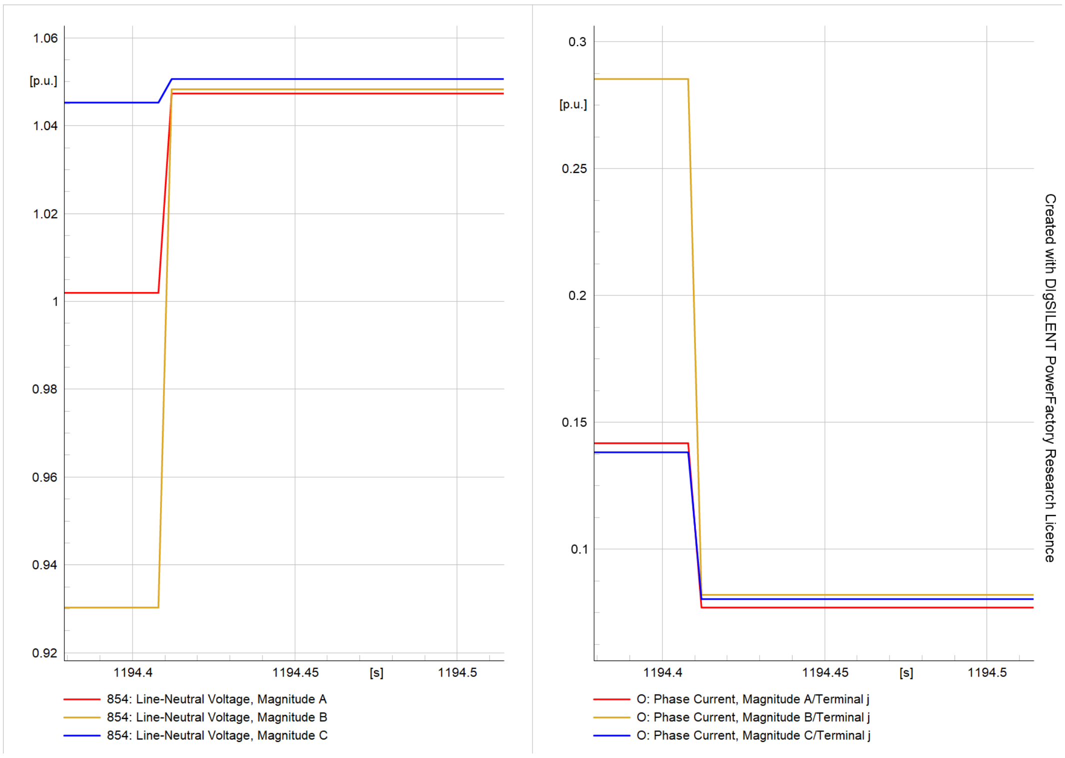


FIGURE 6.40: Transformer trip (μPMU5).

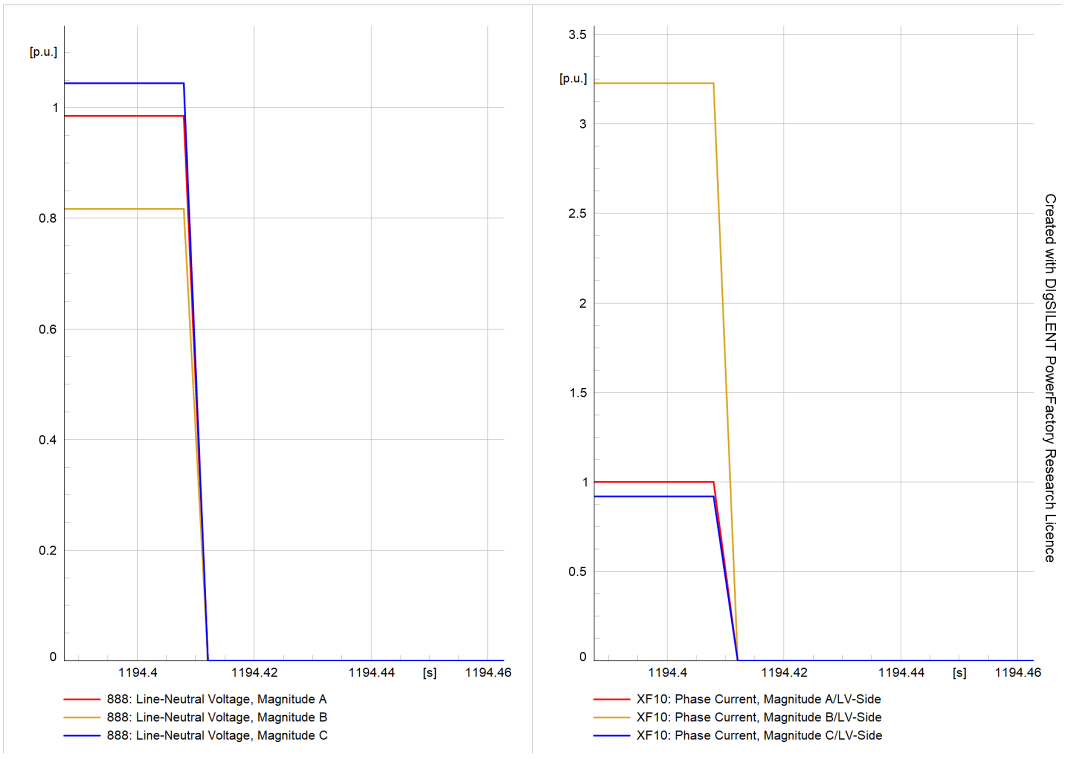


FIGURE 6.41: Transformer trip (μPMU10).

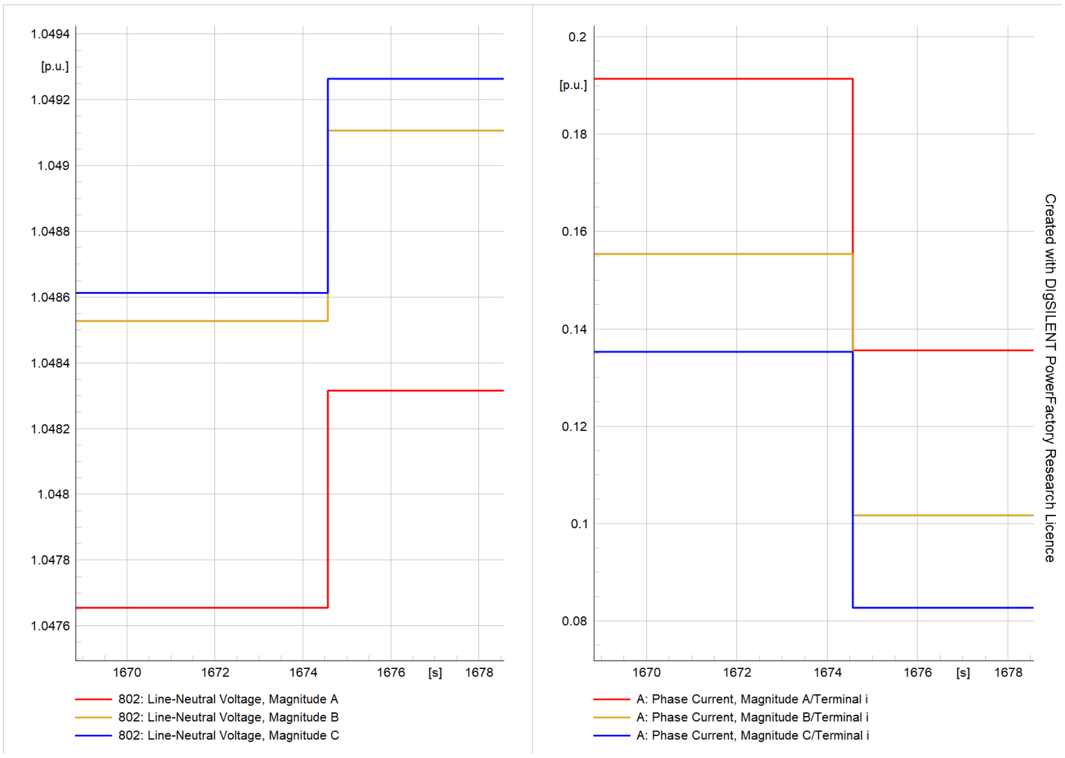


FIGURE 6.42: Off supply complaint (μPMU1).

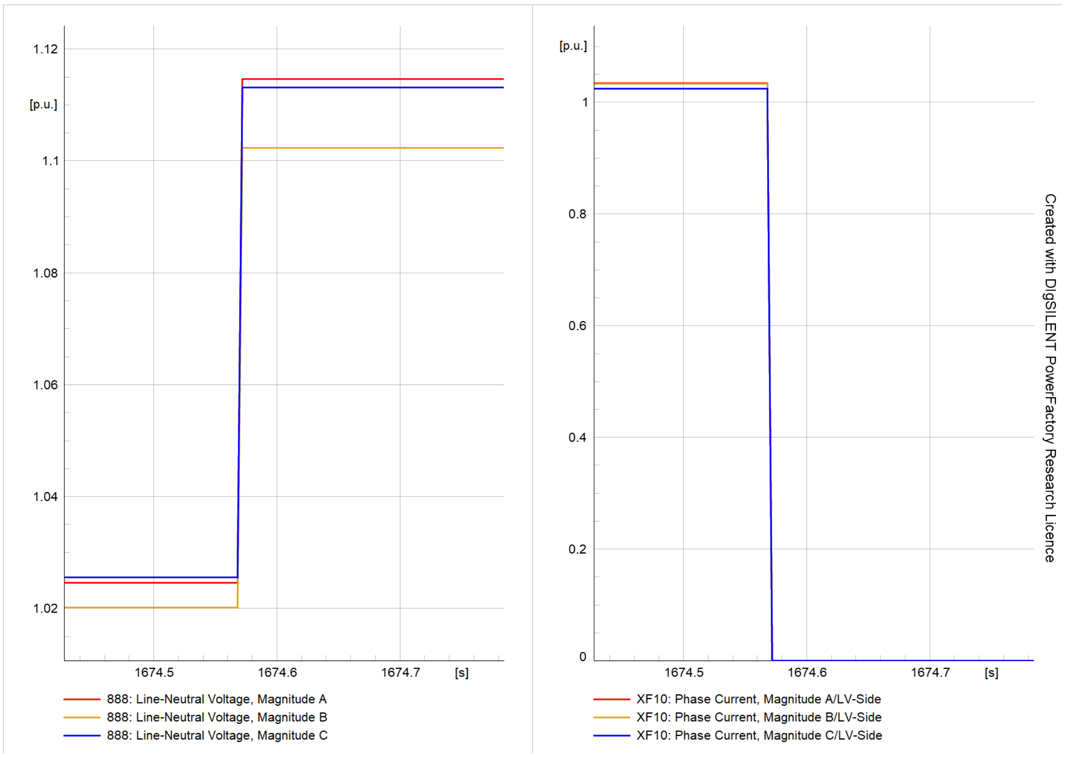


FIGURE 6.43: Off supply complaint (μPMU10).

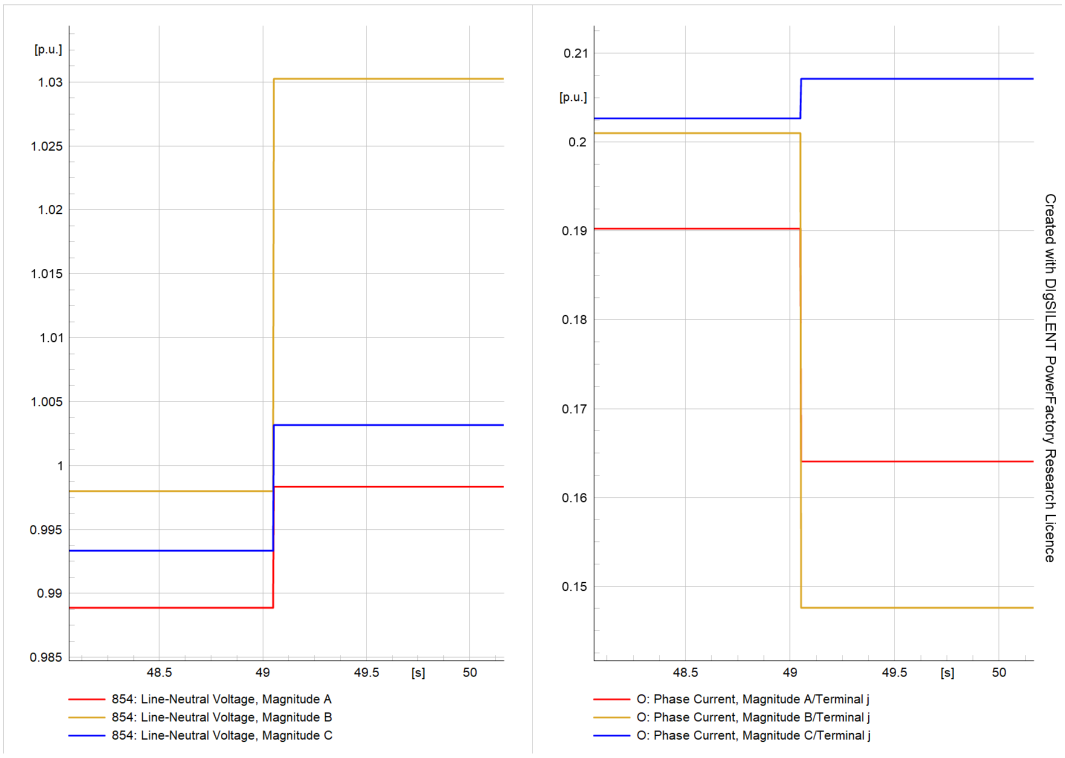


FIGURE 6.44: Unbalance voltage complaint (μPMU5).

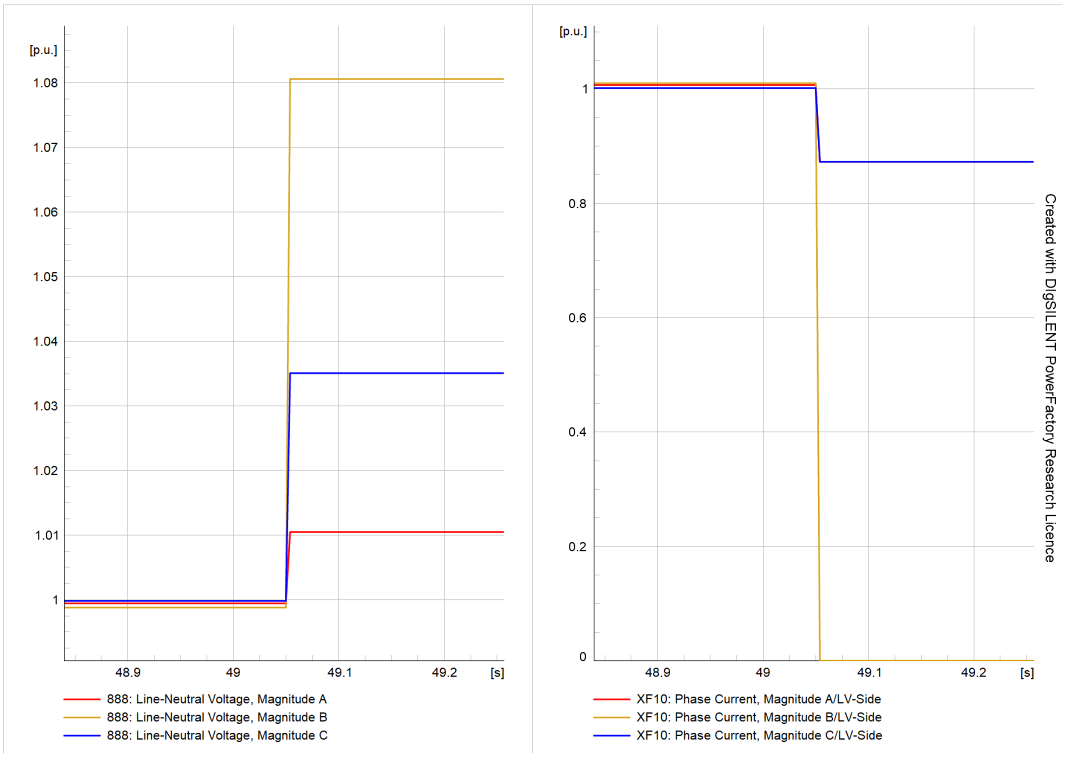


FIGURE 6.45: Unbalance voltage complaint (μPMU10).

6.2.5 Data Validation

The published real-time data from the real DN was used to validate the results obtained for the various real-time events. The generated data are based on a series of planned normal and abnormal events to observe and understand the dynamics created by them, whereas the real-time network data observed by real μPMUs can capture all grid dynamics over time. Because event characteristics are solely determined by the network's initial conditions and other inherent characteristics, validation focuses on the main parameter features of individual events, such as node voltage and line currents and their variations.

The generated μPMU data for real-time events such as capacitor bank switching, fault, CB trip, open, reclosing, and DG switching were validated by comparing it to publicly available real data. Because real-time data for these events is not available in the literature, all other events were validated using the load flow variations at the respective nodes.

6.2.6 Capacitor Bank Switching

The switching of capacitor banks in power systems is referred to as a capacitor-bank-switching event. These occurrences can result in transient and voltage disturbances, which can damage equipment or cause system failure. As a result, detecting and monitoring these events in real-time is critical. This is possible by combining current and voltage sensors with the μPMUs installed in the DN. The sensors detect capacitor-switching events by measuring current and voltage signals.

6.2.6.1 Capacitor Bank Switch-Off Event

When the capacitor bank was turned off, all three-phase voltages decreased from their initial values, but all variations remained within the defined limits. The R-phase current increased, the Y-phase current did not change, and the B-phase current decreased. The generated data voltage and current variations (Figures 6.46 and 6.47) were compared and validated with the real μPMU data observed during the capacitor bank switch-off event (Figure 6.48) published in [127].

6.2.6.2 Capacitor Bank Switch-On Event

The generated data's voltage and current fluctuations shown in Figures 6.49 and 6.51 are as expected. The capacitor bank switch-on event raised the node voltage at all phases, resulting in a reduction in line currents at each phase. The same scenario was compared and validated against the actual μPMU data from [127] (Figure 6.51).

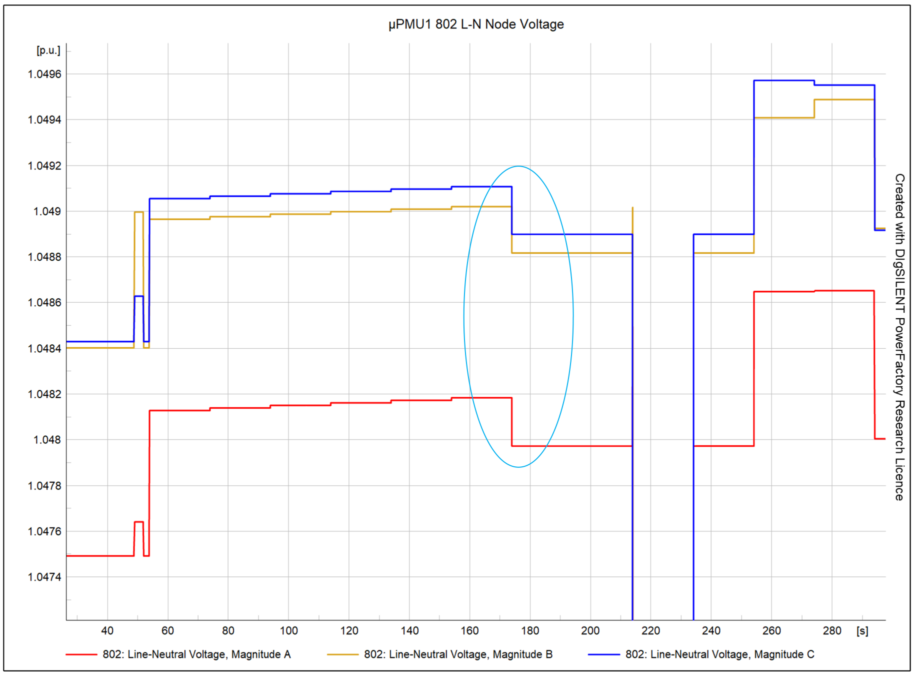


FIGURE 6.46: Capacitor bank switch-off event (voltage variations).

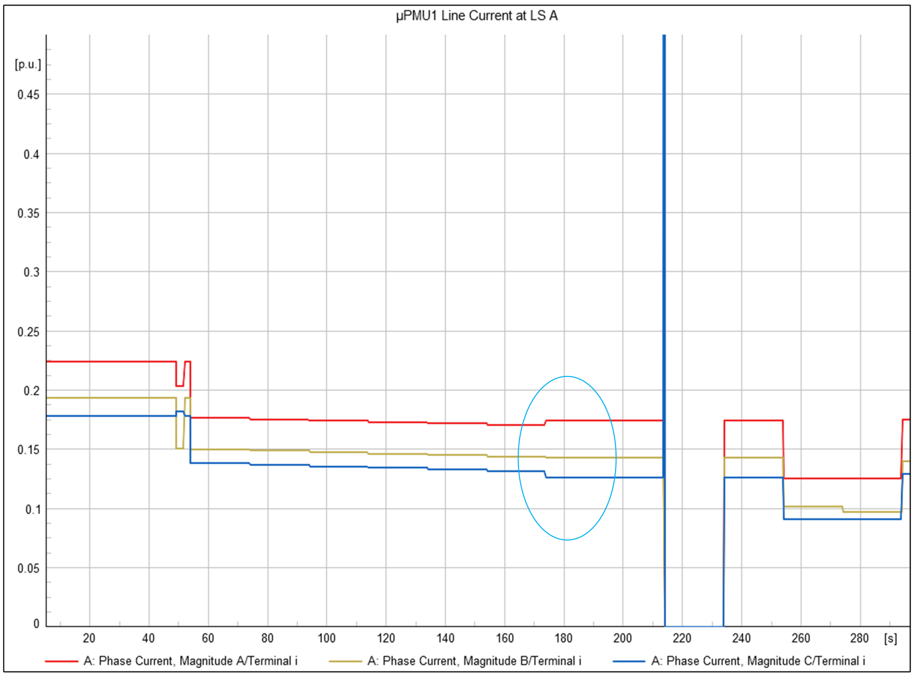


FIGURE 6.47: Capacitor bank switch-off event (current variations).

The three-phase capacitor bank switching study demonstrates that transient currents during switching events are affected by the initial conditions, with the possibility of a rise and fall in current values. Until the parameter studies show that the

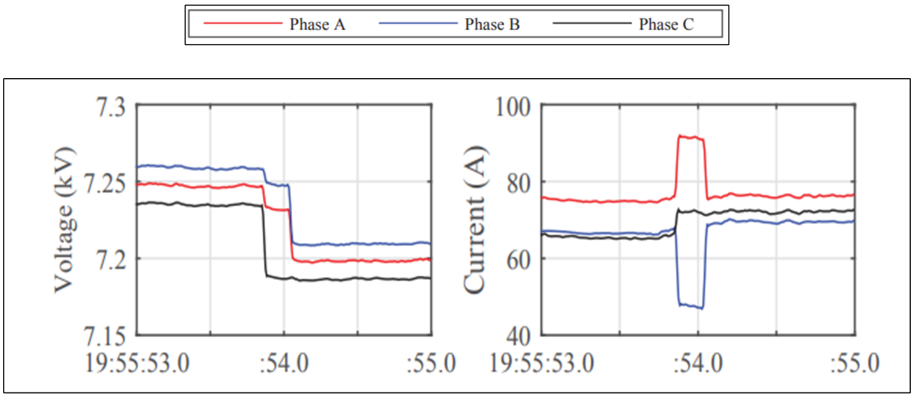


FIGURE 6.48: Capacitor bank switch-off event: voltage and current variations validation using real μPMU data [127].

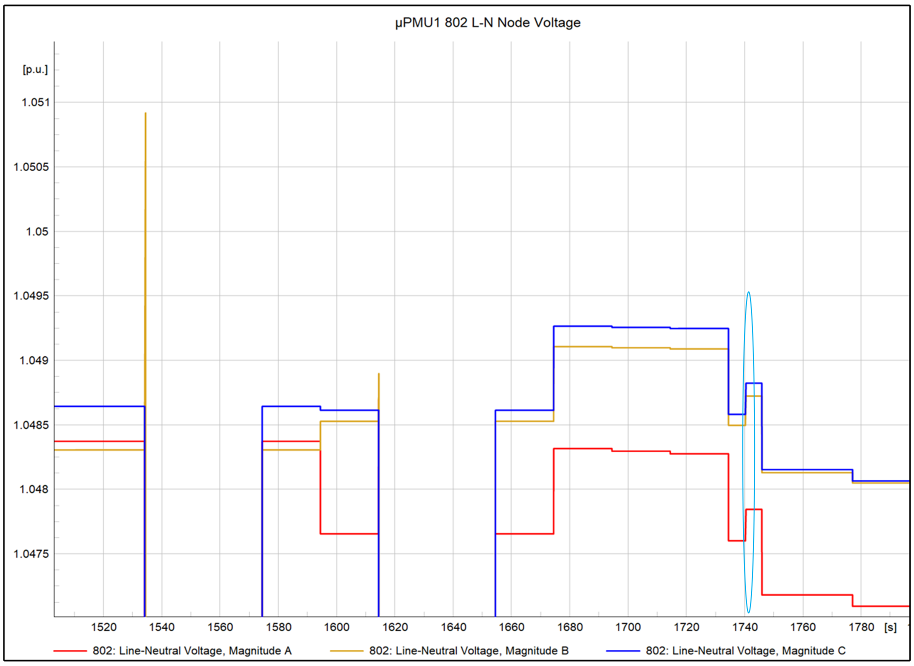


FIGURE 6.49: Capacitor bank switch-on event (voltage magnitude).

system is within the limits, it is considered normal.

6.2.7 Fault, Trip, CB Open, and Reclose Events

Figures 6.52 and 6.53 show the generated event data for the fault, trip, CB open, and reclose events observed by the upstream and downstream μPMUs. These findings are based on a modeled network-generated B-phase-to-ground fault. The real data

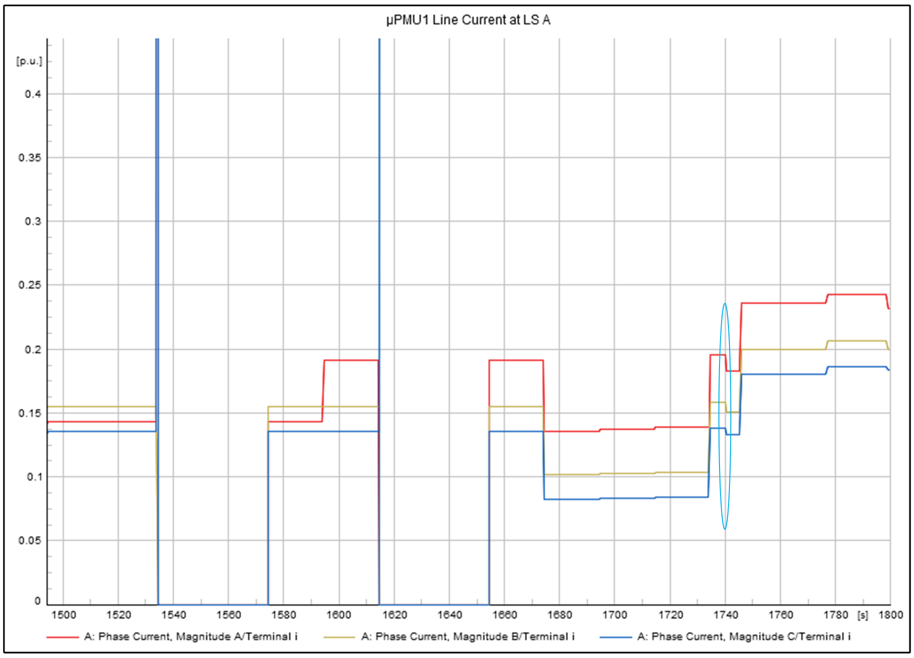


FIGURE 6.50: Capacitor bank switch-on event (current magnitude).

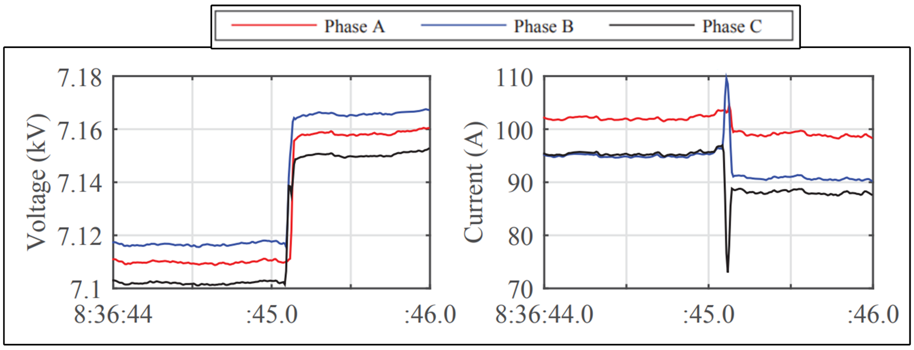


FIGURE 6.51: Capacitor bank switch-on event (voltage and current magnitude) validation using real μPMU data [127].

in [56] are for a B-phase-to-neutral fault, but if the neutral wire in a three-phase distribution system is solidly grounded, a phase-to-neutral fault is a type of phase-to-ground fault. Because the neutral wire in a solidly grounded system is directly connected to the earth, any fault on the neutral wire will cause a current to flow directly to the ground. As a result, even though the fault originated on the neutral wire, it can be classified as a phase-to-ground fault [128]. These events were validated by comparing them to published real data while using the relay settings from [56], as shown in Figure 6.54.

As soon as the fault occurs, the upstream μPMU shows a significant drop in voltage and a rise in B-phase current, with minor changes in other phases. Almost all of the phase voltages show similar values after the breaker trip event, but all of the phase current values reach near zero. When CB completely opens, all phase voltages reach their normal limits, and three-phase currents drop to zero. As the breaker is closed and the loads are immediately connected after the reclose event, all node voltages and line currents return to their pre-fault normal values. This means that the fault was only temporary, and that closing the CB will ensure the network's and components' health.

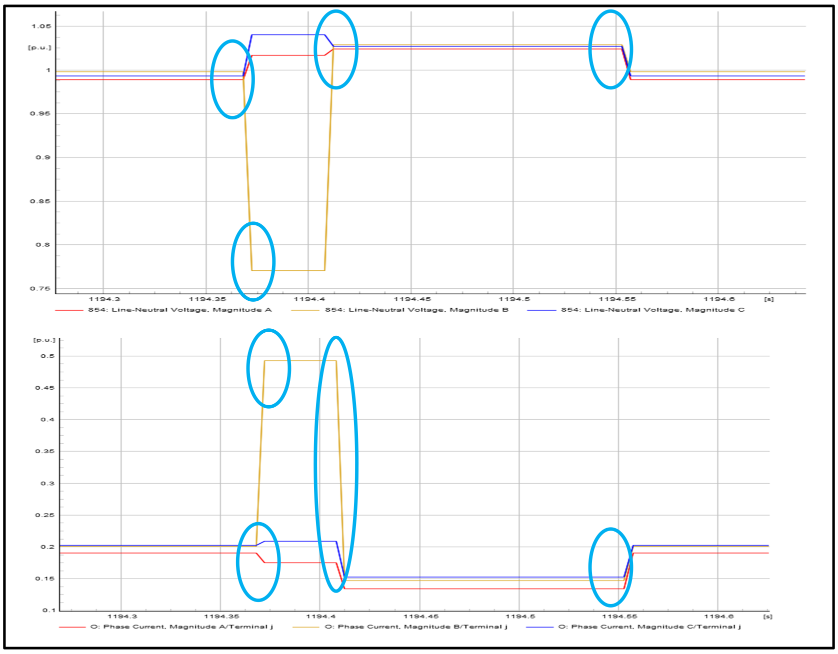


FIGURE 6.52: B-G fault, trip, CB open, and reclose events observed at upstream.

The downstream μPMU observes the same fault and trip events as the upstream μPMU, but right after the CB opens, both voltage and current values of the phases drop to zero. The reclose event observed by this μPMU is consistent with normal pre-fault voltage and current values.

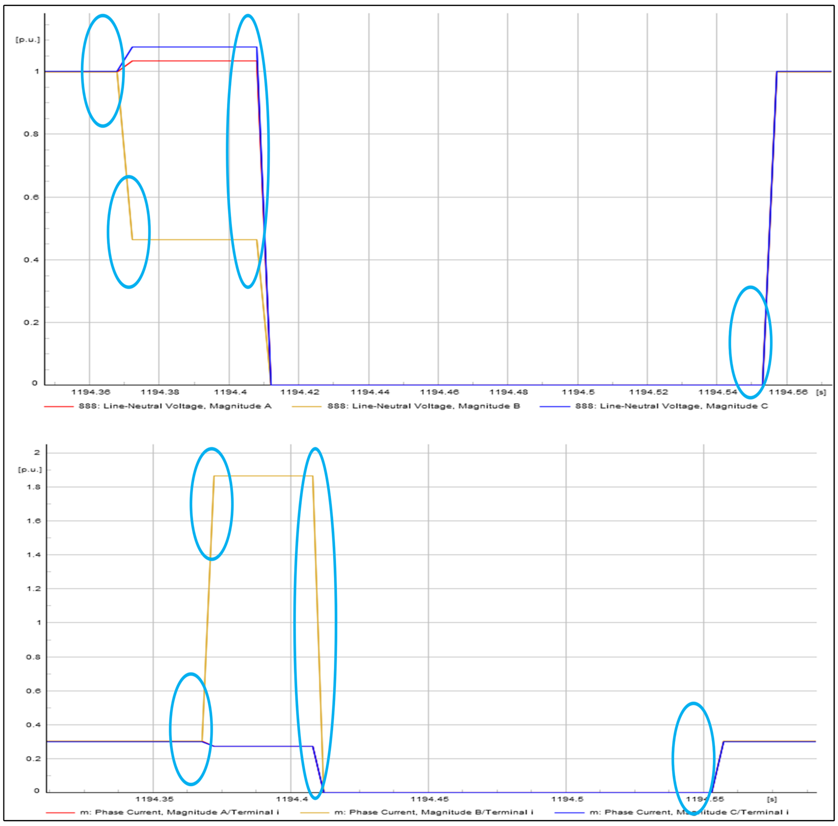


FIGURE 6.53: B-G fault, trip, CB open, and reclose events observed at downstream.

The generated fault event results are comparable to the fault occurrence process dynamics and reclose events presented in [56].

6.2.8 DG-Switching Event

The DG switch-on event is being considered for validation because the real data available in the literature is for this event. The node voltage per phase drops slightly from the initial conditions and settles to a comparatively lower value than the initial values per phase, whereas the currents overshoot to a high value and settle to a slightly higher value than the initial line current magnitude. The DG-switching event generated in Figure 6.55 is validated against the DG-switching event captured

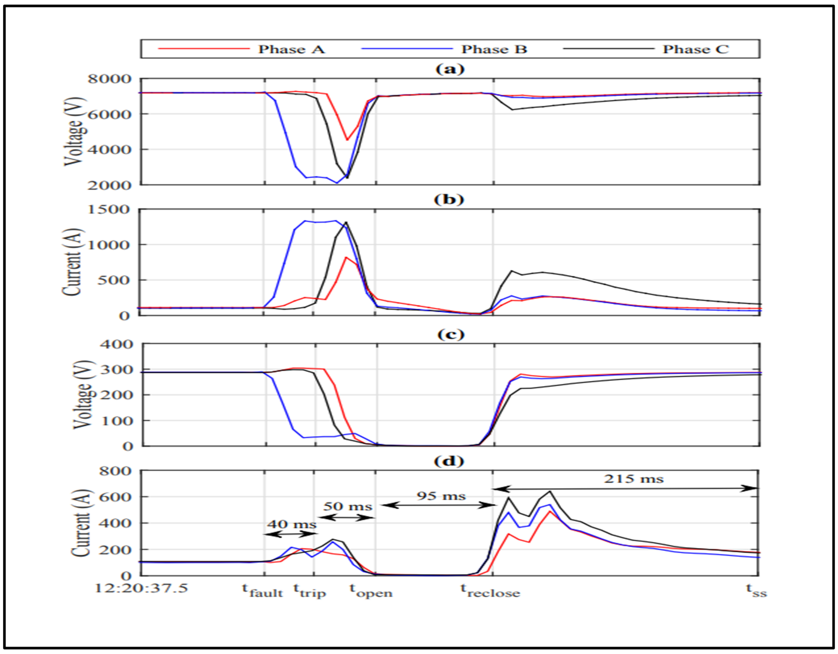


FIGURE 6.54: B-G fault, trip, CB open, and reclose events observed at upstream (Plot a, Plot b) and downstream (Plot c, Plot d) (voltage and current magnitude) [56].

in [129]. Figure 6.56 depicts the actual μPMU observations. The results are roughly comparable to the published real μPMU values.

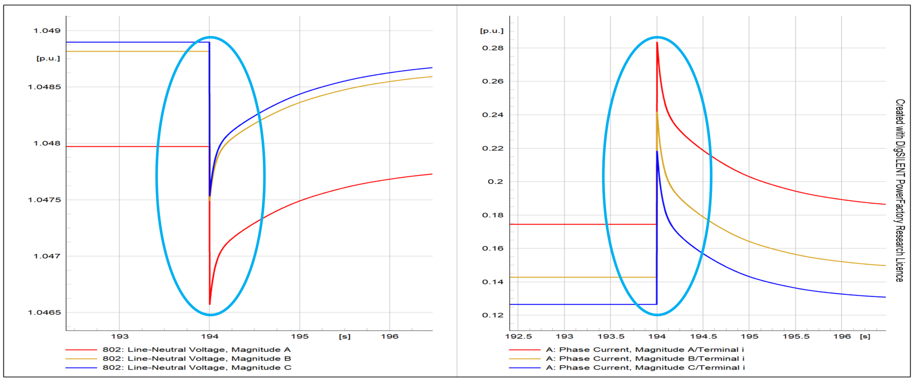


FIGURE 6.55: DG-switching event (voltage and current variations).

6.2.9 Other Events

Because comprehensive observations of the remaining events with regard to measurements of node voltage and line current are not fully captured in the literature,

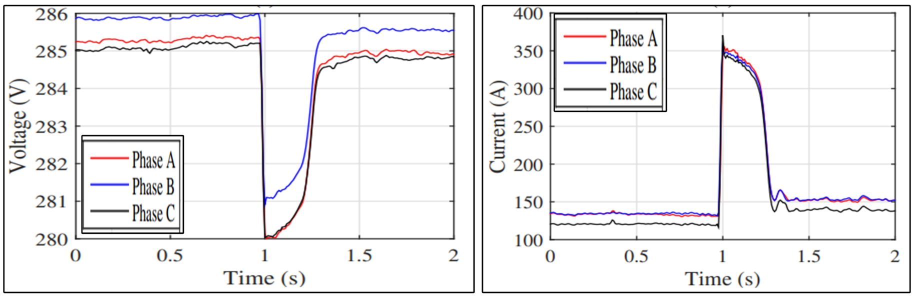


FIGURE 6.56: DG-switching event observed by the real μPMU [129].

the remaining events are validated based on the fluctuations in load flow in the upstream and downstream μPMUs of the respective component. The verified information demonstrates their suitability for use in creating and evaluating specialized real-time DCC operational support applications for event localization, classification, and detection. This will facilitate planned and unforeseen daily operations for DCC operators and raise network reliability metrics.

As this study focused on the fault events, the generated data for different fault classes were mainly investigated and the data variations observed at different μPMUs are taken into consideration for further analysis. The data variations monitored by the master μPMU during the occurrence of the different fault events are listed in table 6.4.

TABLE 6.4: Line currents measured at master μPMU

Fault Classes	**Currents Measured at Master uPMU**		
	I_a(p.u)	**I_b(p.u)**	**I_c(p.u)**
No Fault	0.2243	0.1937	0.1778
a-g	0.2834	0.1939	0.1744
b-g	0.2214	0.2503	0.1771
c-g	0.2239	0.1911	0.2343
a-b	0.31	0.2608	0.1771
b-c	0.2239	0.2767	0.2389
c-a	0.2942	0.1946	0.2616
a-b-g	0.2778	0.2556	0.1739
b-c-g	0.2211	0.2459	0.238
c-a-g	0.288	0.1916	0.2291
a-b-c	0.2828	0.2517	0.2333
a-b-c-g	0.2828	0.2517	0.2333

6.2.10 Experimental Use Case Test

An exploratory experimental study using the most pertinent real-time use case was conducted to show the applicability of generated realistic μPMU data.

Use Case: Event Classification

The classification of an event that occurred in the network is the real-time use case that is being tested in this part. The goal of the experiment is to use the network-collected μPMU data to identify no-fault and fault events. The line currents recorded by the μPMUs are used for this inquiry. The fundamental algorithm listed below is used to categorize the events:

Step 1: Calculate the minimum short circuit currents (MinSCC) of the network per phase.

Step 2: If the line currents measured by the master μPMU (μPMU1) per phase are greater than or equal to the MinSCC of any phase, and if any of the μPMU measures a line current greater than 0.5 p.u. (This is an initial threshold set solely for the purpose of validating the generated data using fault simulation studies. This threshold may change if more scenarios or use cases are added to the analysis while fine-tuning the fault detection algorithm.) for a duration of more than 20 ms or 0.020 s (this time duration is selected for use case test purposes only), then it is a "fault event"; otherwise, it is a "no-fault event".

The MinSCC of phases A, B, and C are 0.2834 p.u., 0.2503 p.u., and 0.2343 p.u., respectively. Three-event data, such as tap changer (VR1), capacitor switching (844), and phase-to-ground fault (at 99.99% of line section "m" with 20 ohms), are used to test the data-driven approach. The results of these tests are shown in Table

6.5. The results show that the per-unit values of the line currents per phase for the tap changer and capacitor-switching events do not satisfy the conditions of the fault event, as the values do not touch the defined thresholds. The generated data was

TABLE 6.5: Use case test results: fault and no-fault event classification.

Tested Data	Event Location	If Master µPMU *Value* ⩾ *MSSC*	If Any µPMU *Value* ⩾ *Threshold*	Classified Event
Tap Lowering	VR1	No	No	No-fault
A-G fault	At 99.99% of line section "m" with 20 ohms	Yes	Yes	Fault
Capacitor Off	844	No	No	No-fault

verified using real-time simulation (RTDS) results. This verification process involved implementing the modified IEEE 34 node feeder in RSCAD, along with strategically positioned software µPMUs and DGs. The Real-time simulator testbed, depicted in Figure 6.57, was utilized for validating the generated data.

FIGURE 6.57: RTDS testbed for genertaed data validation

6.3 Conclusions

DP software was used to achieve realistic μPMU data production for a variety of real-time events in an unbalanced DN. The goals of steady-state and dynamic data creation in an unbalanced benchmark DN were achieved by merging real-time experience and μPMU elements in DP conditions. The generated data include all conceivable real-time events that could occur in the actual DN, and the parameter modifications are seen on their corresponding charts. Due to the difficulty of getting the original μPMU data for a variety of reasons, researchers can utilize this method to generate realistic data by duplicating the μPMU effect on the generated data. This shortens the time needed for research and data collection. Moreover, accurate and practical data that correspond to the duplicated μPMU data are provided. The main objective of this research was to exploit the generated data for several μPMU use cases, such as event detection, categorization, and localization. Future studies will look at a number of studies to improve the usefulness of the data in research projects and incorporate various data quality issues into the generated data.

Chapter 7

I-FDCSI Method Development, Testing and Validation

7.1 Introduction

To ensure the effective operation of power systems, DN must be reliable. The bulk power system is connected to the end consumers through the distribution network, which is the last phase of the power delivery system. There are many different faults that can occur in the distribution network, including short-circuits, open-circuits, and earth faults, which can result in power outages and degrade the quality of the power supply. In order to reduce the impact on the system and restore the power supply, it is crucial to identify and pinpoint distribution network problems as early as feasible. Because of their inherent qualities, DNs, as opposed to transmission networks, are more susceptible to disturbances. Examples include their complex network topology, geographic dispersion over large areas, uneven loading, small amplitude and angle differences between nodes, and faster dynamics (caused by the presence of numerous distributed generations (DG), capacitor banks, autoreclosers, load break switches, fuses, etc.). In power systems, including unbalanced DN, short circuit faults are more frequent than open circuit faults. This is because, unlike open circuit faults, which normally only result from a certain kind of failure, such as a broken conductor or defective switch, short circuit faults can happen for a variety of reasons, including equipment failure, lightning strikes, and other transitory events. As a result, our examination is exclusively concerned with short circuit failures. Analysis of the voltage and current signals at the substation forms the basis of conventional methods for fault identification and classification. These techniques use voltage and current signals to identify and categorize distribution network issues. Nevertheless, the voltage and current data at the substation don't offer enough details to precisely identify and locate the distribution network issues. This is because the network architecture and load changes have an impact on the voltage and current signals at the substation, which can result in false alarms and incorrect fault categorization. μPMU was created to address the shortcomings of the traditional fault detection and classification approaches. The μPMUs are compact devices that are synchronized with the power system frequency and are capable of measuring voltage and current signals with great resolution. To record the dynamic system behavior under fault conditions, the μPMU can be deployed at various points in the distribution network. It is possible to create novel fault detection and classification techniques by using the synchronized data from the μPMU, which can offer more precise information about the position and nature of the issue. Based on the synchronized measurements from the μPMU, novel fault detection and classification algorithms have been developed in a number of research papers. These techniques use high-resolution synchronized readings from the μPMU to identify the problematic area of the distribution network and to detect and classify various fault kinds. Nevertheless, the majority of these techniques rely on machine learning algorithms, which demand a significant quantity of training data and computing power. The caliber and accessibility of the training data has an impact on these methods' success as well. Particularly when noise and measurement errors are present, traditional defect detection and classification approaches sometimes have poor accuracy and lengthy detection times [130]. μPMU have become a promising technology in recent years for enhancing the precision and timeliness of fault detection and location in DN [131]. Recent years have seen a significant amount of study on the application of μPMU for DN defect detection and classification [132]. However, there is still a need for fault detection and classification methods for DN that are more precise and effective, especially when there is noise, measurement error, and distributed energy resources (DERs) present [133]. Since there were no real-world μPMU data, the author created μPMU data that were realistic for a variety of real-time events in an unbalanced distribution network to mimic real grid dynamics [134]. The thresholds for the various algorithms established in this paper were drawn from the dynamics of fault events and line current variations. The integrated fault detection, classification, and section identification (I-FDCSI) approach for real DN using μPMU is proposed in this work. The I-FDCSI approach is based on a set of guidelines created with the help of subject-matter expertise and statistical analysis of the measured data. The suggested method may deliver precise fault detection and classification results with a short response time and does not require a lot of training data or computational resources. The suggested method's effectiveness has been assessed on a benchmark distribution network and contrasted with that of more established methods for section identification and fault classification.

The fault detection, fault classification, and fault section identification techniques are combined in the I-FDCSI approach. According to the flow depicted in Figure 7.1, these algorithms are carried out one by one.

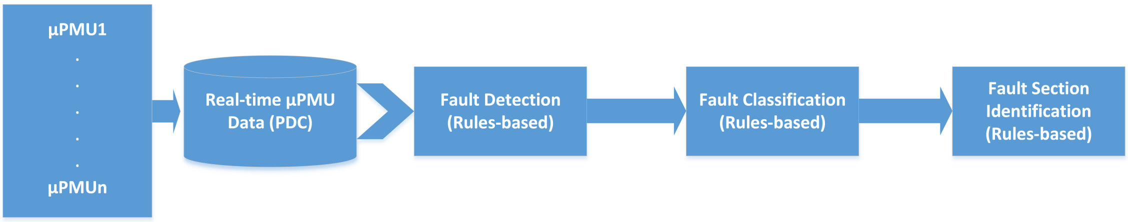


FIGURE 7.1: Block Diagram of I-FDCSI Algorithm.

The real-time data measured and reported by the μPMU deployed at key areas of the DN form the basis for all three rules-based algorithms. The IEEE 34 node test feeder has been chosen as the DN for this study. The components and load flow parameters used for this feeder's modeling and simulation are plainly stated in [134]. Six distributed generations (DG) with a combined capacity of 20% of the feeder load have been inserted into the test feeder. Moreover, 12 μPMUs are installed in the feeder at strategic locations. The locations of the DG and μPMU for the IEEE

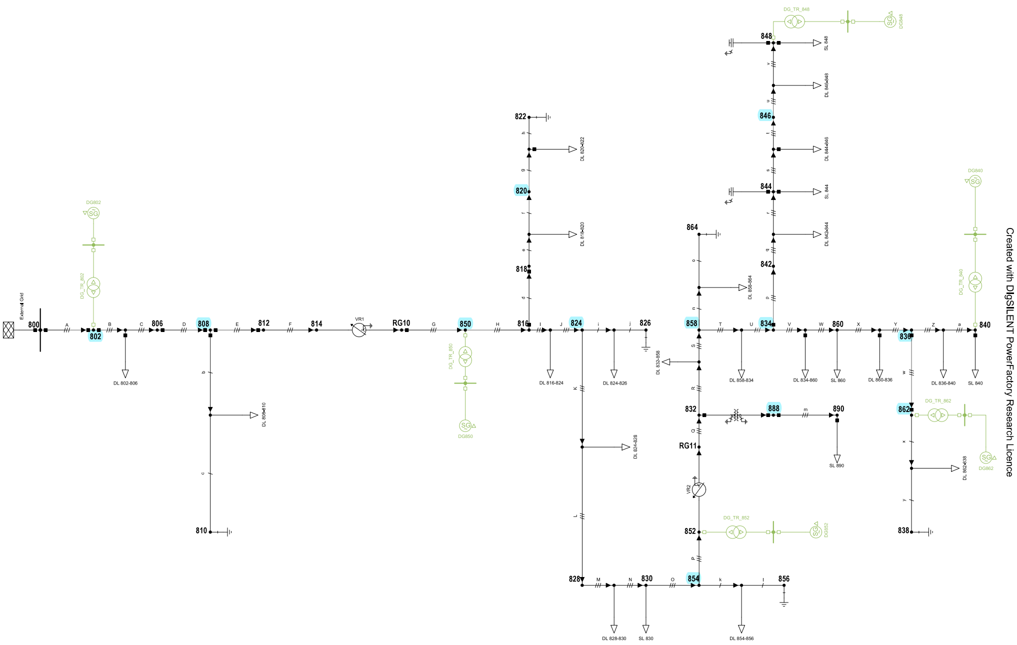


FIGURE 7.2: IEEE 34 node model with DGs and μPMU locations.

34 node test feeder are shown in Figure 7.2. The DG locations, sizes, and μPMU placements are chosen in accordance with [134].

7.2 Calculate the Minimum and Maximum Short Circuit Current Ratio per Phase (Min_{SCCR} and Max_{SCCR}) of the Network

To calculate the Min_{SCCR} per phase, the below steps are followed.

1. Calculate the Line to ground (LG) fault for each line (a–g, b–g and c–g) with a non-zero resistance (resistance kept at 20 ohms for this study) placed at the farthest point (99.99% of the line section) in the eight laterals of the DN including the main feeder [135].

2. Find the lateral with minimum short circuit current in the DN. The lateral with the minimum short circuit current is 800-832-890.

3. The minimum short circuit current per phase (I_{MinSCC}) of the DN without DGs and load switchings measured at the feeding Node (800) reported through the master μPMU (μPMU1) are:

$$I_{aMinSCC} = 0.2834\ p.u, \tag{7.1}$$

$$I_{bMinSCC} = 0.2503\ p.u, \tag{7.2}$$

$$I_{cMinSCC} = 0.2343\ p.u, \tag{7.3}$$

4. The minimum short circuit currents per phase (I_{MinSCC}) of the DN with DGs (in this study, one DG is switched on at a time with 20% capacity of the total feeder load) measured at the feeding node (800) reported through the master μPMU (μPMU1) are:

$$I_{aMinSCC} = 0.2346\ p.u, \tag{7.4}$$

$$I_{bMinSCC} = 0.2046\ p.u, \tag{7.5}$$

$$I_{cMinSCC} = 0.1898\ p.u, \tag{7.6}$$

5. The minimum short circuit currents per phase (I_{MinSCC}) of the DN with load switchings (in this study, the maximum spot load and maximum distributed load of the DN is kept off simultaneously to calculate the minimum short circuit and fine tune the algorithm) measured at the feeding node (800) reported through the master μPMU (μPMU1) are:

$$I_{aMinSCC} = 0.2008\ p.u, \tag{7.7}$$

$$I_{bMinSCC} = 0.2084\ p.u, \tag{7.8}$$

$$I_{cMinSCC} = 0.1982\ p.u, \tag{7.9}$$

6. The minimum short circuit current ratio per phase (Min_{SCCR}) is the ratio of measured line currents (I_{Meas}) to the minimum short circuit current. Equations (7.4)–(7.9) are used to find the minimum short circuit current per phase.

$$Min_{SCCR_a} = I_{aMeas}/I_{aMinSCC} \tag{7.10}$$

$$Min_{SCCR_b} = I_{bMeas}/I_{bMinSCC} \tag{7.11}$$

$$Min_{SCCR_c} = I_{cMeas}/I_{cMinSCC} \tag{7.12}$$

where, I_{aMeas}, I_{bMeas}, and I_{cMeas} are line currents measured by the master μPMU1 per phase and $I_{aMinSCC}$, $I_{bMinSCC}$, and $I_{cMinSCC}$ are the minimum short circuit current of the network per phase. The Min_{SCCR} is calculated very accurately to investigate the high impedance faults in the network. During the high impedance faults, the current magnitude will be much less compared to the low and medium impedance faults.

7. Calculate the minimum fault current threshold for the installed μPMUs without DGs and load switching: this is performed by simulating all the fault types in the farthest point (at section "m") of lateral with minimum short circuit current which can be observed by the installed nearby μPMU10. From all the simulated fault types, L-L-G faults give the minimum values of the short circuit currents per phase per μPMUs (I_{Measi}). The values obtained from simulations are:

$$I_{aMeasi} = 0.6138\ p.u, \tag{7.13}$$

$$I_{bMeasi} = 0.6246\ p.u, \tag{7.14}$$

$$I_{cMeasi} = 0.6166\ p.u, \tag{7.15}$$

$$I_{\mu PMU_t} = (I_{aMeasi} + I_{bMeasi} + I_{cMeasi})/3 = 0.6183\ p.u, \tag{7.16}$$

where $i = 1, 2, ..., 12$ (number of μPMUs).

8. Calculate the minimum fault current threshold for the installed μPMUs with DG connection: this is performed by simulating all the fault types in the farthest point (at section "m") of lateral with minimum short circuit current which can be observed by the installed nearby μPMU10. From all the simulated fault types, L-L-G faults give the minimum values of the short circuit currents per phase per μPMUs (I_{Measi}). The values obtained from simulations are:

$$I_{aMeasi} = 0.6031 \; p.u, \tag{7.17}$$

$$I_{bMeasi} = 0.6111 \; p.u, \tag{7.18}$$

$$I_{cMeasi} = 0.6045 \; p.u, \tag{7.19}$$

$$I_{\mu PMU_t} = (I_{aMeasi} + I_{bMeasi} + I_{cMeasi})/3 = 0.6062 p.u, \tag{7.20}$$

where i = 1, 2, ..., 12 (number of μPMUs).

9. Calculate the minimum fault current threshold for the installed μPMUs with load switchings: This is carried out by simulating all the fault types in the farthest point (at section "m") of lateral with minimum short circuit current which can be observed by the installed nearby μPMU10 keeping the maximum spot load and maximum distributed load in off mode simultaneously. From all the simulated fault types, L-L-G faults give the minimum values of the short circuit currents per phase per μPMUs (I_{Measi}). The values obtained from simulations are:

$$I_{aMeasi} = 0.4349 \; p.u, \tag{7.21}$$

$$I_{bMeasi} = 0.4182 \; p.u, \tag{7.22}$$

$$I_{cMeasi} = 0.4229\ p.u, \tag{7.23}$$

$$I_{\mu PMU_t} = (I_{aMeasi} + I_{bMeasi} + I_{cMeasi})/3 = 0.4253\ p.u, \tag{7.24}$$

where $i = 1, 2, ..., 12$ (number of μPMUs).

10. Calculate the maximum short circuit current that can be monitored by all the installed μPMUs: this is basically calculated by simulating a three-phase fault at the closest point (at 0.001% of the line section) of the immediate downstream line section of each μPMUs with a 0 Ω (p.u) fault resistance [135]. For the μPMUs installed at the single phase to neutral laterals, a line-to-ground fault simulation is carried out instead of a three-phase fault. The maximum short circuit current per phase of all the installed μPMUs is shown in Table 7.1. The accuracy and quality of the data generated by micro-PMUs can be affected by various factors. This can make it challenging to accurately identify and diagnose faults in real-time. So for this study, lower and upper thresholds are set for each μPMUs based on the calculated minimum and maximum short circuit current ratio per phase. During the data processing, the values outside these thresholds are filtered out before applying to the algorithms.

7.3 Fault Detection Algorithm

To detect the fault in the DN with strategically placed μPMUs, a real-time measurement rules-based algorithm is implemented. Fault to trip duration settings(40ms) were adapted from a real-world μPMU data analysis carried out in [56].The flow chart of the algorithm using these rules is shown in Figure 7.3. The FD algorithm uses the rules 7.25, 7.26, and 7.27.

TABLE 7.1: Maximum short circuit currents that can be monitored by each μPMU.

µPMU No.	Ia_Max_SCC (p.u)	Ib_Max_SCC (p.u)	Ic_Max_SCC (p.u)
µPMU 1 (Master µPMU)	89.63	93.76	86.48
µPMU 2	6.7	7.07	6.5
µPMU 3	2.81	3.09	2.84
µPMU 4	2.5	2.74	2.53
µPMU 5	2.04	2.22	2.05
µPMU 6	1.39	1.52	1.41
µPMU 7	1.35	1.47	1.36
µPMU 8	1.31	1.43	1.32
µPMU 9	0	1.02	0
µPMU 10	3.69	3.84	3.69
µPMU 11	1.31	1.42	1.32
µPMU 12	1.53	NA	NA

7.3.1 Rules for Fault Detection without DG and Load Switching

If

$(SCCR_{amin} \geq 1)$ `or` $(SCCR_{bmin} \geq 1)$ `or` $(SCCR_{cmin} \geq 1\ )$ & $(I_{Meas_i} < 0.6183)$

$for\ a\ time, t = 1\ to\ 40ms$

then, "**Fault Detected at first stream before the first microPMU**".

else if

$(SCCR_{amin} \geq 1)$ `or` $(SCCR_{bmin} \geq 1)$ `or` $(SCCR_{cmin} \geq 1\ )$ & $(I_{Meas_i} \geq 0.6183)$

$for\ a\ time, t = 1\ to\ 40ms$

then, "**Fault Detected**".

else

"**Fault Not Detected**".

(7.25)

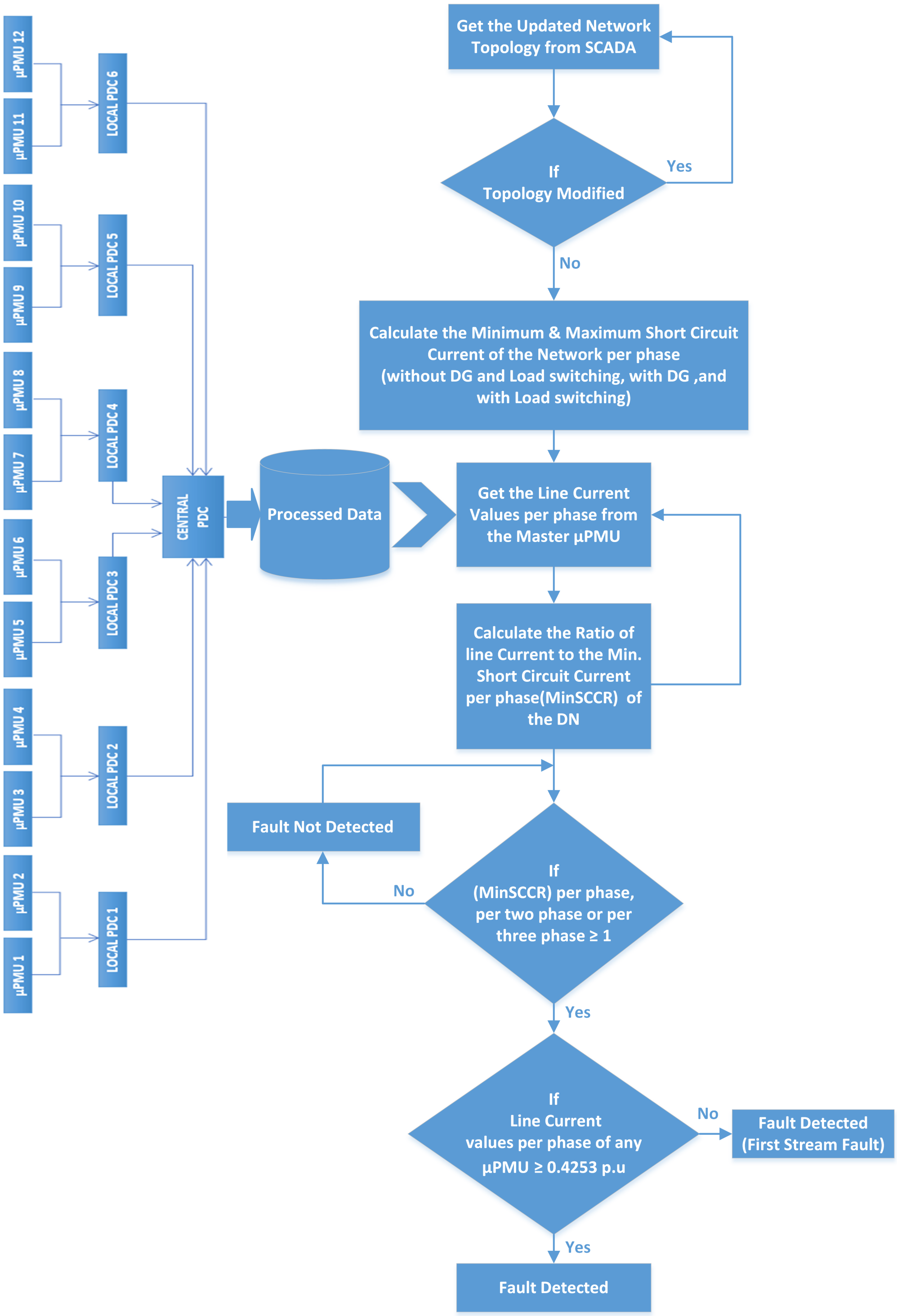


FIGURE 7.3: Fault detection flow chart.

7.3.2 Rules for Fault Detection with DG

$$
\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \texttt{or}\ (SCCR_{bmin} \geq 1)\ \texttt{or}\ (SCCR_{cmin} \geq 1\ )\ \&\ (I_{Meas_i} < 0.6062)\\
&\ for\ a\ time, t = 1\ to\ 40ms\\
&\text{then, ``}\textbf{Fault Detected at first stream before the first microPMU}''.\\
&\text{else if}\\
&(SCCR_{amin} \geq 1)\ \texttt{or}\ (SCCR_{bmin} \geq 1)\ \texttt{or}\,(SCCR_{cmin} \geq 1\ )\ \&\ (I_{Meas_i} \geq 0.6062)\\
&\ for\ a\ time, t = 1\ to\ 40ms\\
&\text{then, ``}\textbf{Fault Detected}''.\\
&\text{else}\\
&\text{``}\textbf{Fault Not Detected}''.
\end{aligned}
\tag{7.26}
$$

7.3.3 Rules for Fault Detection with Load Switching

$$
\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \texttt{or}\ (SCCR_{bmin} \geq 1)\ \texttt{or}\ (SCCR_{cmin} \geq 1\ )\ \&\ (I_{Meas_i} < 0.4253)\\
&\ for\ a\ time, t = 1\ to\ 40ms\\
&\text{then, ``}\textbf{Fault Detected at first stream before the first microPMU}''.\\
&\text{else if}\\
&(SCCR_{amin} \geq 1)\ \texttt{or}\ (SCCR_{bmin} \geq 1)\ \texttt{or}\,(SCCR_{cmin} \geq 1\ )\ \&\ (I_{Meas_i} \geq 0.4253)\\
&\ for\ a\ time, t = 1\ to\ 40ms\\
&\text{then, ``}\textbf{Fault Detected}''.\\
&\text{else}\\
&\text{``}\textbf{Fault Not Detected}''.
\end{aligned}
\tag{7.27}
$$

7.4 Fault Classification Algorithm

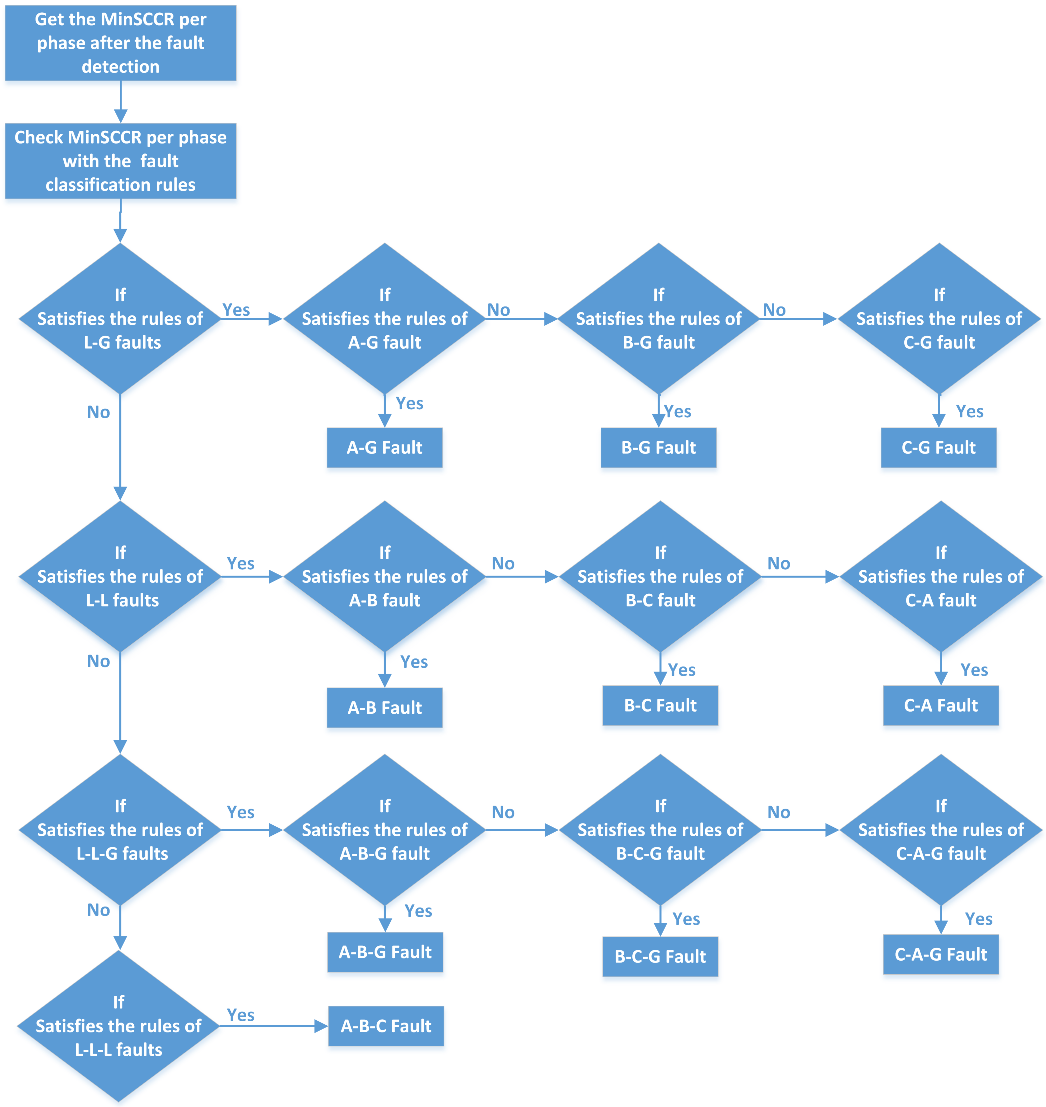


FIGURE 7.4: Fault classification flow chart.

The detected faults in the system are classified by establishing distinct rules for various classes of faults. These rules are formulated through a thorough investigation of all possible fault combinations. Each fault class is assigned specific criteria to determine its classification. The algorithm follows a flow chart, depicted in Figure 7.4, which outlines the sequence of steps based on these rules.

7.4.1 Rules for Line to Ground Faults (L-G)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \texttt{or}\ (SCCR_{bmin} \geq 1)\ \texttt{or}\ (SCCR_{cmin} \geq 1\ )\\
&\text{then, ``}\mathbf{L-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ L-G\ Fault}\text{''.}
\end{aligned} \tag{7.28}$$

7.4.1.1 Rules for A-G Fault

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \&\ (SCCR_{bmin} < 1)\ \&\ (SCCR_{cmin} < 1\ )\\
&\text{then, ``}\mathbf{A-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ A-G\ Fault}\text{''.}
\end{aligned} \tag{7.29}$$

7.4.1.2 Rules for B-G Fault

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} < 1)\ \&\ (SCCR_{bmin} \geq 1)\ \&\ (SCCR_{cmin} < 1\ )\\
&\text{then, ``}\mathbf{B-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ B-G\ Fault}\text{''.}
\end{aligned} \tag{7.30}$$

7.4.1.3 Rules for C-G Fault

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} < 1)\ \&\ (SCCR_{bmin} < 1)\ \&\ (SCCR_{cmin} \geq 1\ )\\
&\text{then, "}\mathbf{C-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{"}\mathbf{Not\ C-G\ Fault}\text{''.}
\end{aligned} \tag{7.31}$$

7.4.2 Rules for Line to Line Faults (L-L)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \&\ (SCCR_{bmin} \geq 1)\ \ \texttt{or}\\
&(SCCR_{bmin} \geq 1)\ \&\ (SCCR_{cmin} \geq 1)\ \ \texttt{or}\\
&(SCCR_{cmin} \geq 1)\ \&\ (SCCR_{amin} \geq 1)\\
&\text{then, "}\mathbf{L-L\ Fault}\text{''.}\\
&\text{else}\\
&\text{"}\mathbf{Not\ L-L\ Fault}\text{''.}
\end{aligned} \tag{7.32}$$

7.4.2.1 Rules for Line to Line Faults (A-B)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \&\ (SCCR_{bmin} \geq 1)\ \ \&\\
&(SCCR_{cmin} < 1)\\
&\text{then, "}\mathbf{A-B\ Fault}\text{''.}\\
&\text{else}\\
&\text{"}\mathbf{Not\ A-B\ Fault}\text{''.}
\end{aligned} \tag{7.33}$$

7.4.2.2 Rules for Line to Line Faults (B-C)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{bmin} \geq 1)\ \&\ (SCCR_{cmin} \geq 1)\ \ \&\\
&(SCCR_{amin} < 1)\\
&\text{then, ``}\mathbf{B-C\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ B-C\ Fault}\text{''.}
\end{aligned} \tag{7.34}$$

7.4.2.3 Rules for Line to Line Faults (C-A)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{cmin} \geq 1)\ \&\ (SCCR_{amin} \geq 1)\ \ \&\\
&(SCCR_{bmin} < 1)\\
&\text{then, ``}\mathbf{C-A\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ C-A\ Fault}\text{''.}
\end{aligned} \tag{7.35}$$

7.4.3 Rules for Line to Line to Ground Faults (L-L-G)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq .97)\ \&\ (SCCR_{bmin} \geq .97)\ \ \texttt{or}\\
&(SCCR_{bmin} \geq .97)\ \&\ (SCCR_{cmin} \geq .97)\ \ \texttt{or}\\
&(SCCR_{cmin} \geq .97)\ \&\ (SCCR_{amin} \geq .97)\\
&\text{then, ``}\mathbf{L-L-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ L-L-G\ Fault}\text{''.}
\end{aligned} \tag{7.36}$$

7.4.3.1 Rules for Line to Line Faults (A-B-G)

$$\begin{aligned}
&\text{If}\\
&(.98 \geq SCCR_{amin} < 1)\ \&\ (SCCR_{bmin} \geq 1)\ \ \&\\
&(.74 \geq SCCR_{cmin} < 1)\\
&\text{then, ``}\mathbf{A-B-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ A-B-G\ Fault}\text{''.}
\end{aligned} \tag{7.37}$$

7.4.3.2 Rules for Line to Line Faults (B-C-G)

$$\begin{aligned}
&\text{If}\\
&(.78 \geq SCCR_{amin} < 1)\ \&\ (.98 \geq SCCR_{bmin} < 1)\ \ \&\\
&(SCCR_{cmin} \geq 1)\\
&\text{then, ``}\mathbf{B-C-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ B-C-G\ Fault}\text{''.}
\end{aligned} \tag{7.38}$$

7.4.3.3 Rules for Line to Line Faults (C-A-G)

$$\begin{aligned}
&\text{If}\\
&(SCCR_{amin} \geq 1)\ \&\ (.76 \geq SCCR_{bmin} < 1)\ \ \&\\
&(.97 \geq SCCR_{cmin} < 1)\\
&\text{then, ``}\mathbf{C-A-G\ Fault}\text{''.}\\
&\text{else}\\
&\text{``}\mathbf{Not\ C-A-G\ Fault}\text{''.}
\end{aligned} \tag{7.39}$$

7.4.4 Rules for Three Phase Faults (A-B-C)

$$
\begin{aligned}
&\text{If} \\
&(SCCR_{amin} \geq 1)\ \&\ (SCCR_{bmin} \geq 1)\ \ \& \\
&(SCCR_{cmin} \geq 1) \\
&\text{then, ``}\mathbf{A - B - C\ Fault}\text{''.} \\
&\text{else} \\
&\text{``}\mathbf{Not\ A - B - C\ Fault}\text{''.}
\end{aligned}
\tag{7.40}
$$

7.5 Fault Section Identification Algorithm

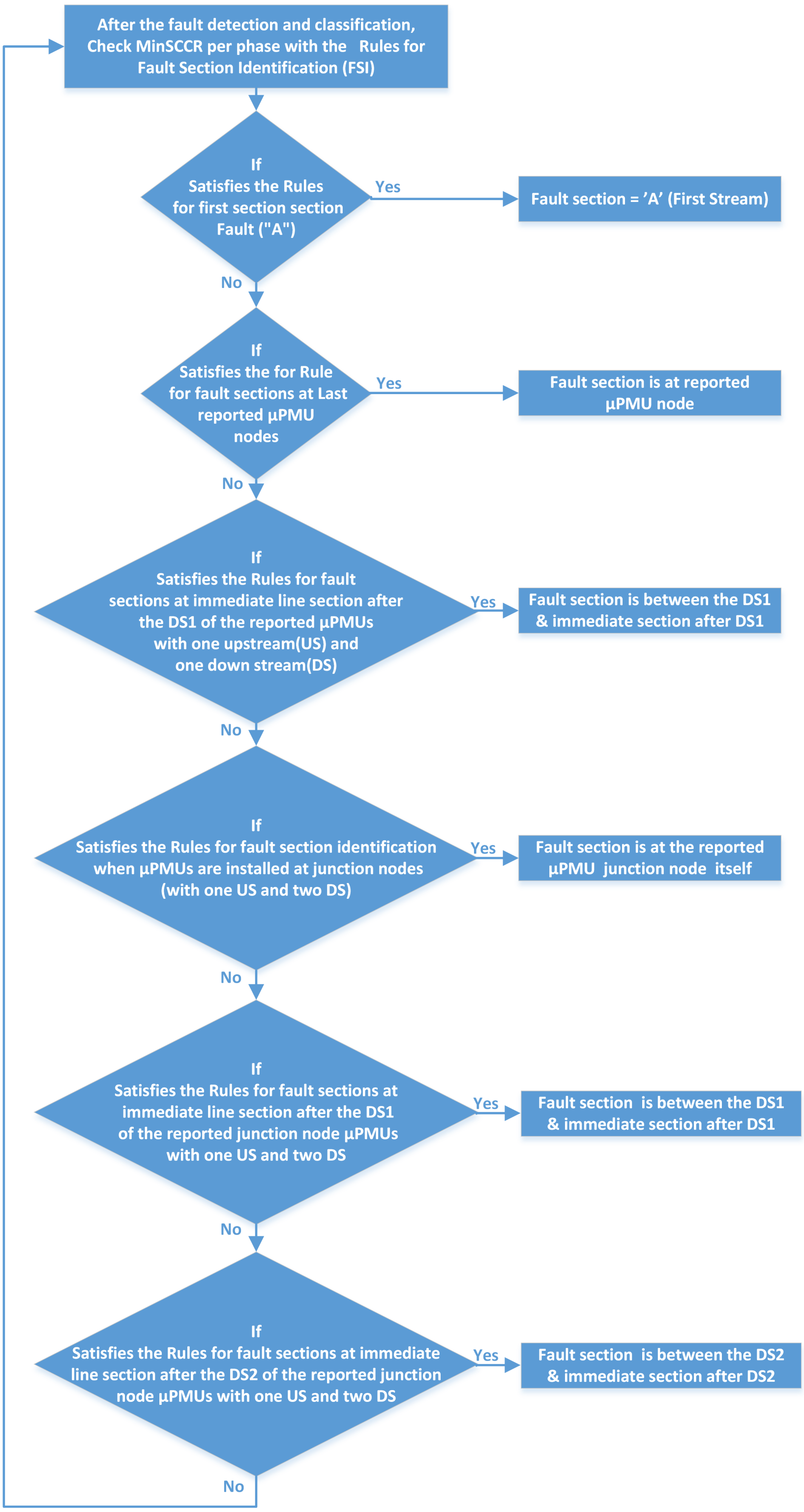


Figure 7.5: Fault section identification flow chart.

Fault section is usually identified in radial DN between the last reported and first not reported μPMU. The flow chart of the algorithm using these rules is shown in Figure 7.5.

7.5.1 Rules for First Line Section ("A") Fault

$$\begin{aligned}
&\text{If} \\
&(The\ fault\ is\ detected)\ \& \\
&(\ None\ of\ the\ microPMUs\ reported\ SCCR_{min}\ threshold\ triggers\ per\ phase) \\
&\\
&\text{then, "}\mathbf{fault\ has\ happened\ before\ the\ first\ microPMU,\ ie,\ FS = \ 'A'}\text{".} \\
&\text{else} \\
&\text{"}\mathbf{Not\ First\ Section\ Fault}\text{".}
\end{aligned} \tag{7.41}$$

7.5.2 Rules for Rule for Fault Sections at MicroPMU Nodes

$$\begin{aligned}
&\text{If} \\
&(The\ fault\ is\ detected)\ \& \\
&(US\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \ \geq\ SCCR_{min})\ \& \\
&(DS1\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \ <\ SCCR_{min}) \\
&\\
&\text{then, "}\mathbf{fault\ has\ happened\ at\ the\ reported\ microPMU\ Node,\ itself}\text{".} \\
&\text{else} \\
&\text{"}\mathbf{Fault\ Section\ is\ Not\ at\ microPMU\ Nodes}\text{".}
\end{aligned} \tag{7.42}$$

7.5.3 Rules for Fault Sections at Immediate Line Section after the DS1 of the Reported MicroPMUs with One Upstream (US) and One Down Stream (DS)

$$
\begin{aligned}
&\text{If}\\
&(The\ fault\ is\ detected)\ \&\\
&(US\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})\ \&\\
&(DS1\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})\\
&\text{then, “}\textbf{FS is between the DS1 \& immediate section after DS1}\text{”.}\\
&\text{else}\\
&\text{“}\textbf{Fault Section is Not between the DS1 \& immediate section after DS1}\text{”.}
\end{aligned}
\tag{7.43}
$$

7.5.4 Rules for Fault Section Identification When MicroPMUs are Installed at Junction Nodes (with One US and Two DS)

Here, stream leading to the main feeder line from the junction node is considered as DS1 and the stream leading to the laterals are considered as DS2.

$$
\begin{aligned}
&\text{If}\\
&(The\ fault\ is\ detected)\ \&\\
&(\ US\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})\ \&\\
&(DS1\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ <\ SCCR_{min})\ \&\\
&(DS2\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ <\ SCCR_{min})\\
&\text{then, “}\textbf{fault has happened at the reported microPMU Junction node, itself}\text{”.}\\
&\text{else}\\
&\text{“}\textbf{Fault Section is Not at microPMU junction Nodes}\text{”.}
\end{aligned}
\tag{7.44}
$$

7.5.5 Rules for Fault Sections at Immediate Line Section after the DS1 of the Reported Junction Node MicroPMUs with One US and Two DS

If

$(The\ fault\ is\ detected)$ &

$(\ US\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})$ &

$(DS1\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})$ &

$(DS2\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ <\ SCCR_{min})$

then, "**FS is between the DS1** & **immediate section after DS1**".

else

"**Fault Section is Not between the DS1** & **immediate section after DS1**". (7.45)

7.5.6 Rules for Fault Sections at Immediate Line Section after the DS2 of the Reported Junction Node MicroPMUs with One US and Two DS

If

$(The\ fault\ is\ detected)$ &

$(\ US\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})$ &

$(DS1\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ <\ SCCR_{min})$ &

$(DS2\ Line\ current\ per\ phase\ of\ the\ last\ reported\ uPMU\ \geq\ SCCR_{min})$

then, "**FS is between the DS2** & **immediate section after DS2**".

else

"**Fault Section is Not between the DS2** & **immediate section after DS2**". (7.46)

By developing separate dedicated algorithms for fault detection, classification, and section identification, power distribution networks can be optimized to address specific scenarios effectively. Scenario-specific rule sets and thresholds can be established within each algorithm, ensuring robust performance across diverse operating conditions, including scenarios with and without load and distributed generation switchings. This modular approach enables easy adaptation and customization of algorithms to suit evolving network requirements and emerging challenges associated with load dynamics and distributed generation integration.

7.6 Integration of FDCSI Algorithm

Figure 7.6 shows the integrated algorithm for fault detection, classification, and section identification. This task is performed by combining the different algorithms step-by-step to ensure that all the steps are followed in order to meet the objectives of the algorithm process.

The integration of the Fault Detection, Classification, and Section Identification (FDCSI) Algorithm offers a compelling technical solution for expediting service restoration in real-time distribution networks. By consolidating fault detection, classification, and section identification into a unified framework, the FDCSI Algorithm enables rapid and precise fault localization, minimizing downtime and enhancing network reliability. This integration streamlines decision-making processes by providing comprehensive insights to network operators, facilitating quicker responses to faults. Additionally, the FDCSI Algorithm optimizes resource allocation by accurately identifying the affected network section, ensuring efficient deployment of maintenance crews and resources. Furthermore, it enhances situational awareness

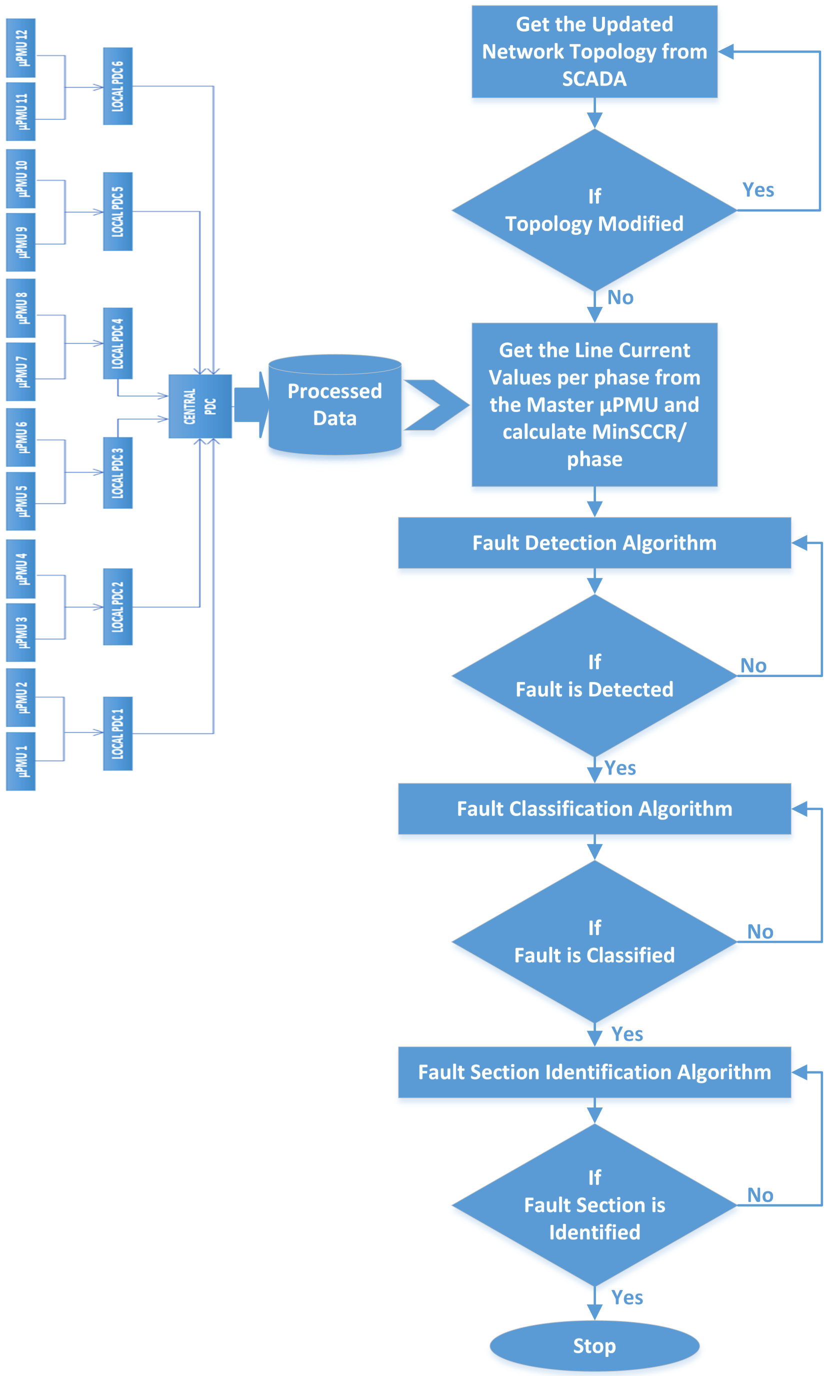


FIGURE 7.6: I-FDCSI Flow Chart.

by offering a holistic view of network status in real-time, allowing operators to prioritize restoration efforts effectively. The adaptability of the FDCSI Algorithm to dynamic network conditions, including load variations and distributed energy resource integration, ensures consistent and reliable performance across diverse operating scenarios. Overall, the integration of the FDCSI Algorithm represents a valuable advancement in enhancing the resilience, reliability, and efficiency of real-time distribution networks, ultimately leading to improved service quality and customer satisfaction.

7.7 Testing and Validation of Algorithms

The validation of the individual algorithms and integrated algorithms is performed by the proposed rules-based I-FDCSI method for real distribution networks using μPMU. The method was tested and validated using data from a real benchmark distribution network using RTDS Simulator. The rules-based algorithms were subjected to validation using the RTDS test bed, shown in figure 7.7.

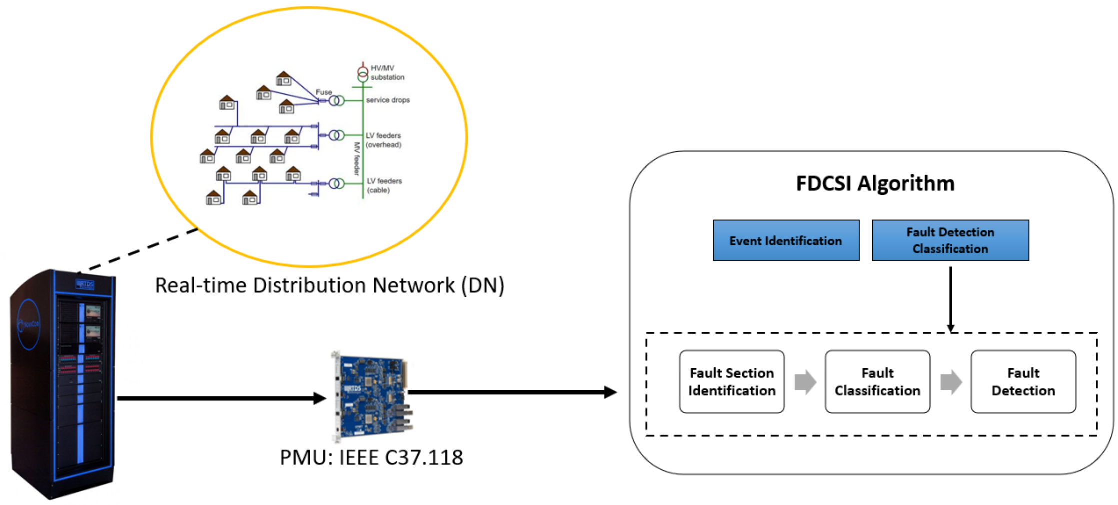


FIGURE 7.7: RTDS testbed for I-FDCSI Algorithm validation

The method was tested on all the possible faults with different % of sections ranging from 0.001% to 99.99% and with different fault resistances (0.01 Ω, 1 Ω, 2.5 Ω, 5 Ω, 10 Ω, 15 Ω, and 20 Ω) and was able to successfully detect, classify, and sectionalise faults with a high degree of accuracy. For all the classes and sections of faults, the algorithm is giving highly accurate results for both simulated data and the generated realistic μPMU data. Additionally, the method was able to accurately estimate the fault when the fault occurs at the nodes, which is important for the isolation of the faulted section from the healthy portion of the network and restoration of service. Overall, the testing and validation results demonstrate the effectiveness and accuracy of the proposed I-FDCSI method for fault detection, classification, and section identification in real distribution networks using μPMU.

7.7.1 Fault Detection Test

The developed algorithm was tested with different events such as load switching, DG switching, tap change event, capacitor switching and fault events and the results of non-fault events and fault event detection are plotted in Table 7.2.

TABLE 7.2: Fault detection algorithm test results.

Events Tested	Test Location	Event Description	Fault Detected as
Load switching	844	3 Phase SL844 OFF	Not Detected
DG Switching	850	20% DG850 ON	Not Detected
Tap Change event	VR1	Tap lowered at VR1	Not Detected
Capacitor switching	CAP848	Cap 848 OFF	Not Detected
Fault	A	A-G at 0.001% (LS), 1 ohm	First stream fault
Fault	b	B-G at 50% (LS), 1 ohm	Fault
Fault	846	A-B at node 846, 20 ohm	Fault
Fault	834	C-G at node 834, 15 ohm	Fault
Fault	P	B-C at 75% (LS), 10 ohm	Fault
Fault	E	C-A at 99.99% (LS), 0.1 ohm	Fault
Fault	m	A-B-C at 99.99% (LS), 20 ohm	Fault
Fault	u	A-B-G at 30% (LS), 5 ohm	Fault
Fault	K	B-C-G at 75% (LS), 15 ohm	Fault
Fault	D	C-A-G at 50% (LS), 5 ohm	Fault

7.7.1.1 No-Fault Event Test

All the non-fault events tested using the FD algorithm were not detected as "fault". The events include load switching (Figure 7.8), DG switching event (Figure 7.9), tap changer event (Figure 7.10), and capacitor switching event (Figure 7.11).

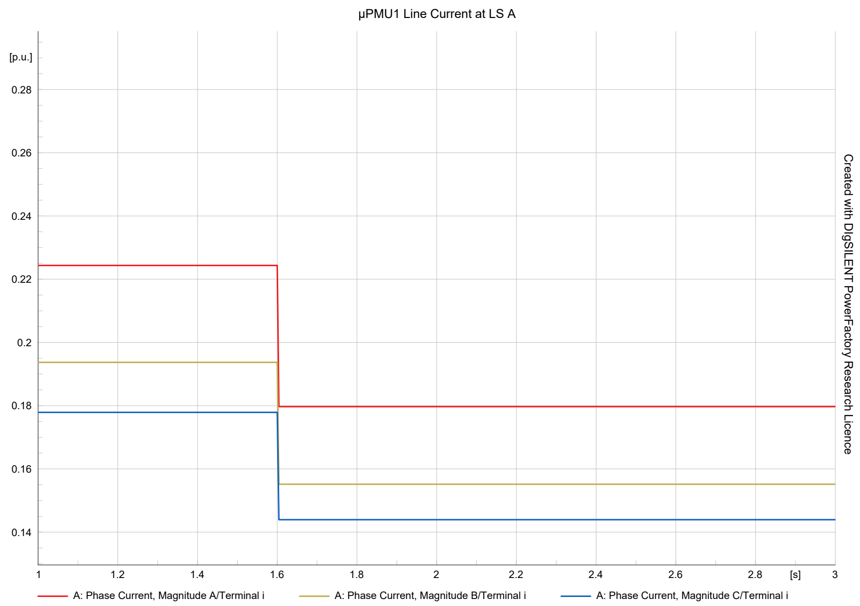


FIGURE 7.8: Load switching event results from master μPMU.

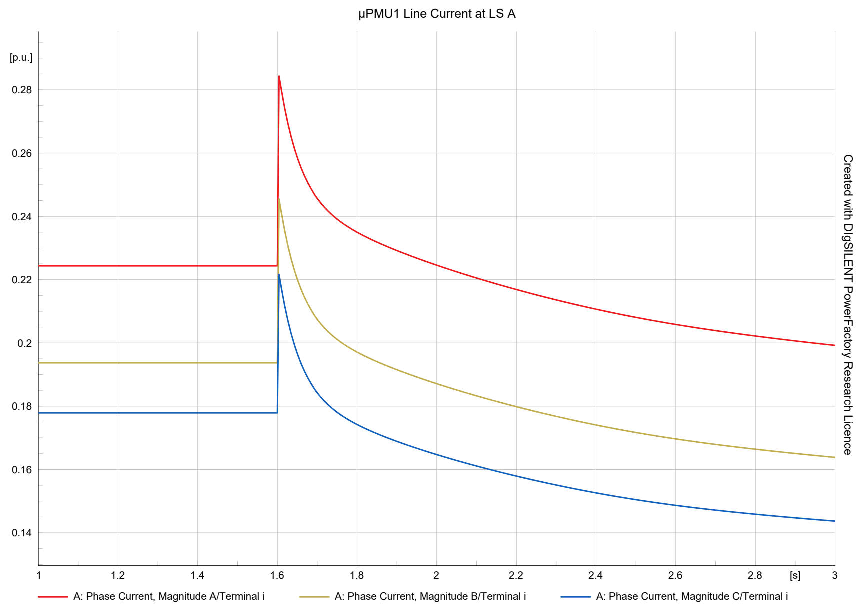


FIGURE 7.9: DG switching event simulation results from master μPMU.

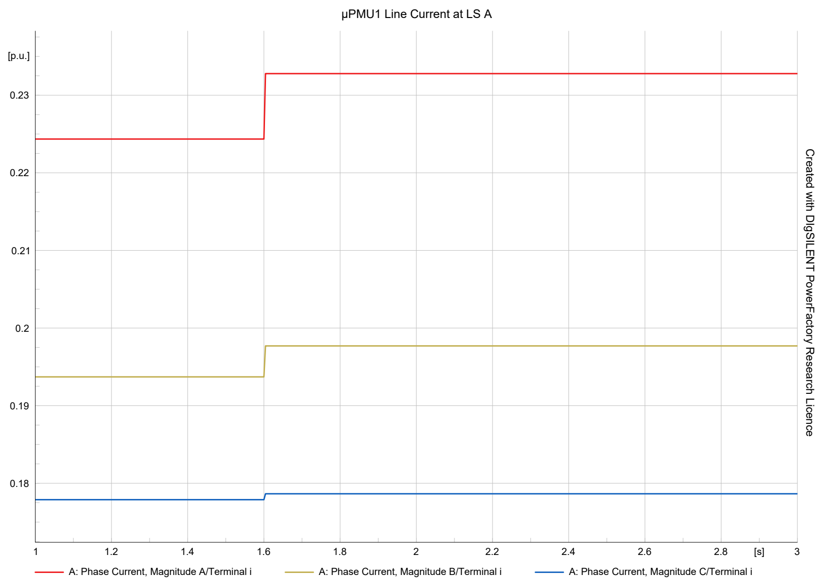


FIGURE 7.10: Tap change event simulation results from the master μPMU.

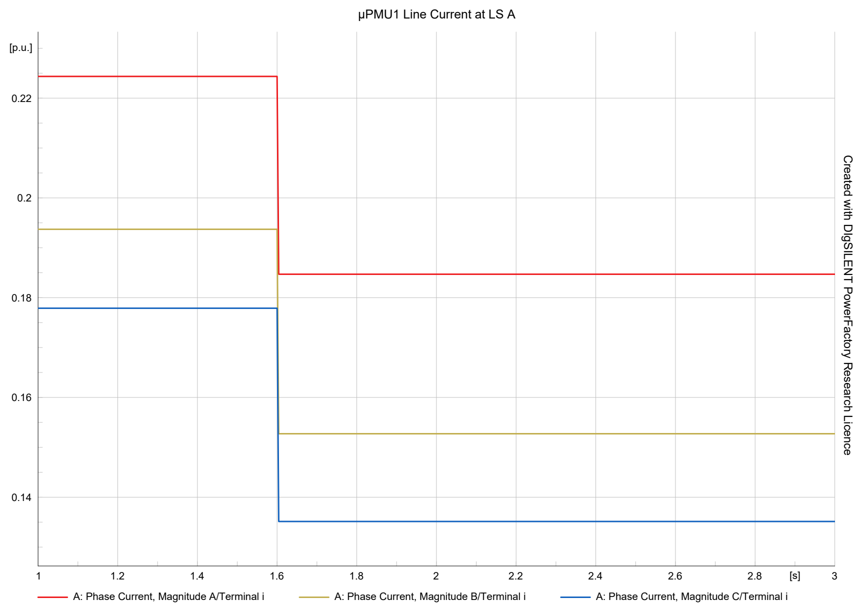


FIGURE 7.11: Capacitor switching simulation results from master μPMU.

None of these events were detected as faults because these events are not satisfying the defined FD algorithm conditions.

7.7.1.2 Fault Event Test

All the fault events tested crossed the thresholds of at least one phase to satisfy the fault detection rules. The thresholds are set after fine-tuning the line currents during the fault with respect to the maximum impedance location of the network or the farthest point from the main feeder.

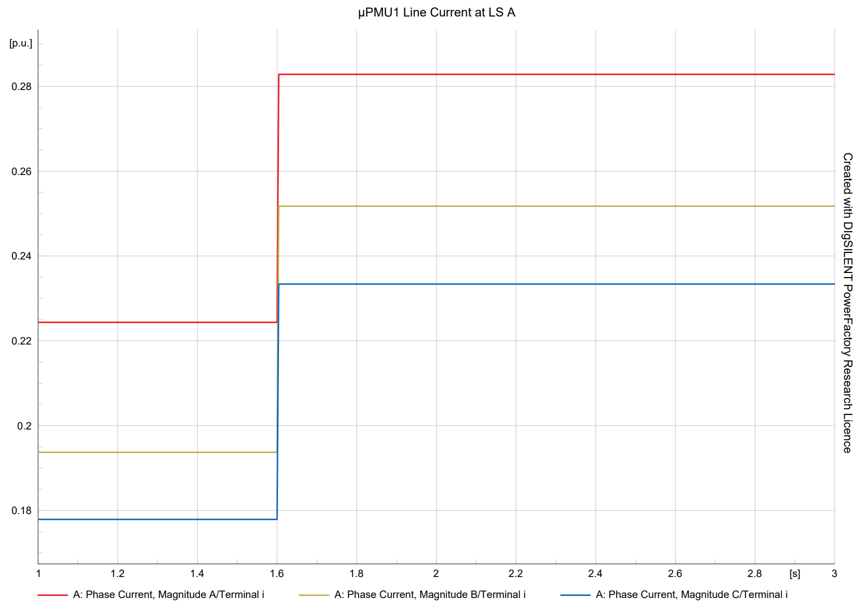


FIGURE 7.12: A-B-C fault detection simulation results from the master μPMU.

Even though the unbalanced loads are showing frequent variations in the line currents per phase, all the tested fault events met at least one phase threshold to detect the fault. The A-B-C fault detection simulation results from the master μPMU and nearest μPMU are shown in Figures 7.12 and 7.13 respectively. The results cross the threshold values and conditions of the FD algorithm. Hence, the fault is detected. The fault detection algorithm test results are shown in Table 7.2. Out of the tested events, almost all the fault events with different types of faults worked perfectly using the developed algorithm. The first stream fault tested at line section 'A' was also detected by the algorithm.

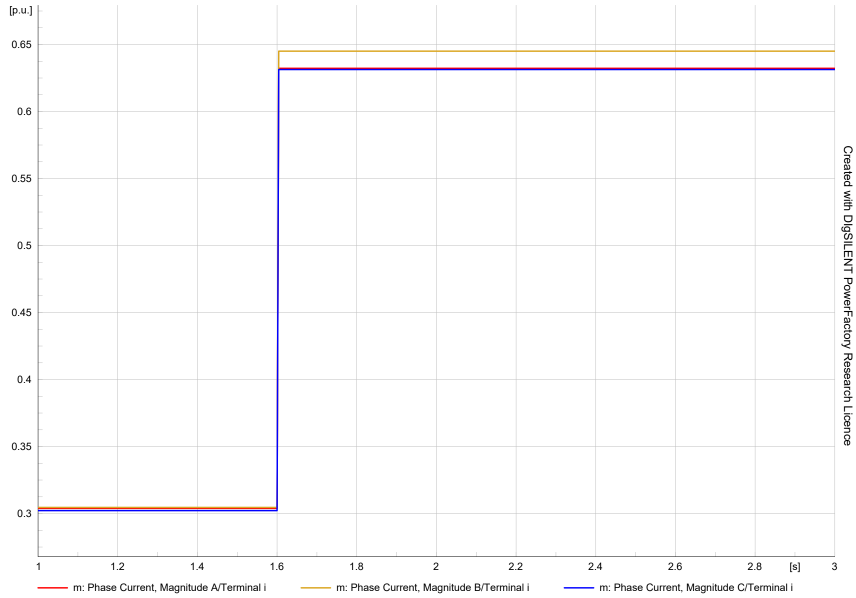


FIGURE 7.13: A-B-C fault detection simulation results from the nearest μPMU.

7.7.2 Fault Classification Test

The developed algorithm was tested with different classes of faults such as LG, LL, LLG, and LLL. Their simulation results are plotted below figures and their summary is listed in Table 7.3. All the classes of faults at different locations and fault resistances (0 Ω , 0.001 Ω, 0.01 Ω , 1 Ω, 5 Ω, 10 Ω , 15 Ω, and 20 Ω). A total of 24,480 simulations with all the possible fault classes were carried out to test the classification algorithm with real-time time fault scenarios.

7.7.2.1 LG Fault

Figure 7.14 shows the results of L-G fault classification through the measurement observed by the master μPMU. The result of L-G fault classification through the measurement observed by the μPMU near the fault is shown in Figure 7.15.

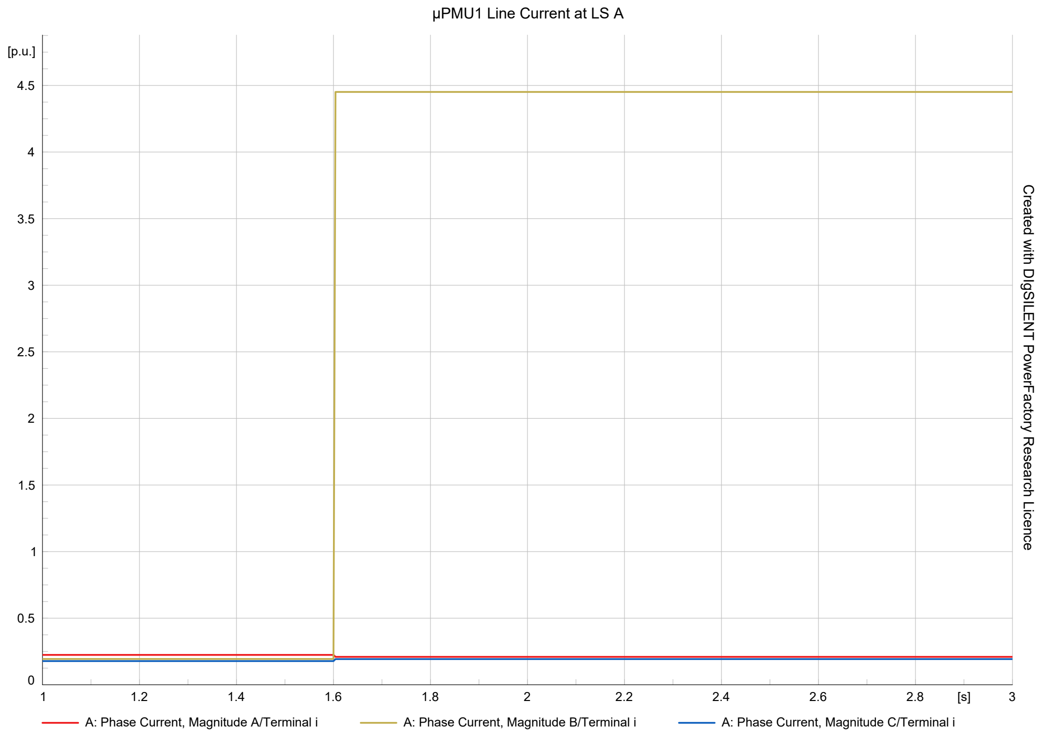


FIGURE 7.14: LG fault classification simulation results from the master μPMU.

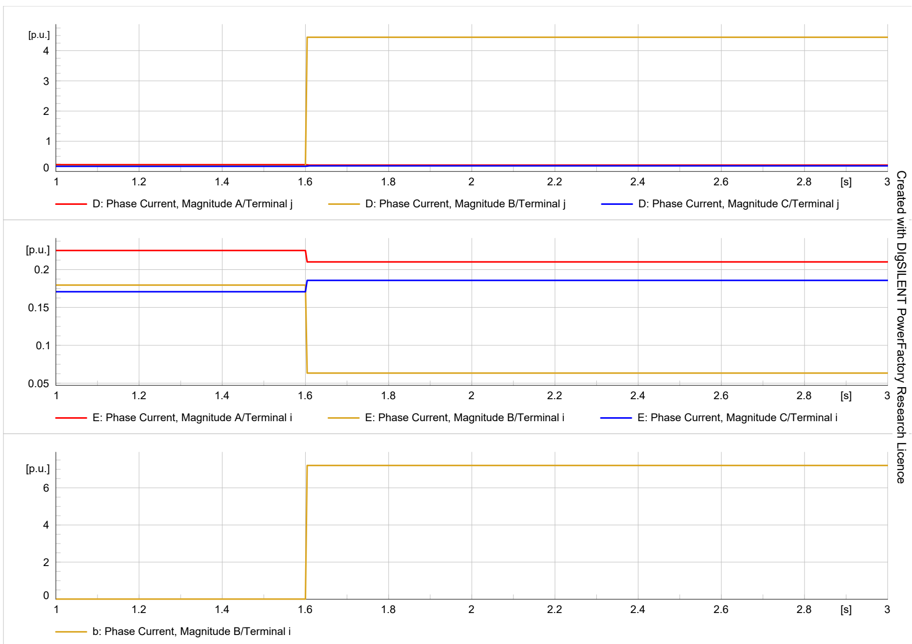


FIGURE 7.15: LG fault classification simulation results from the nearest μPMU.

7.7.2.2 LL Fault

The line currents variations observed by the master μPMU and the nearest μPMU during the LL fault are shown in Figures 7.16 and 7.17, respectively.

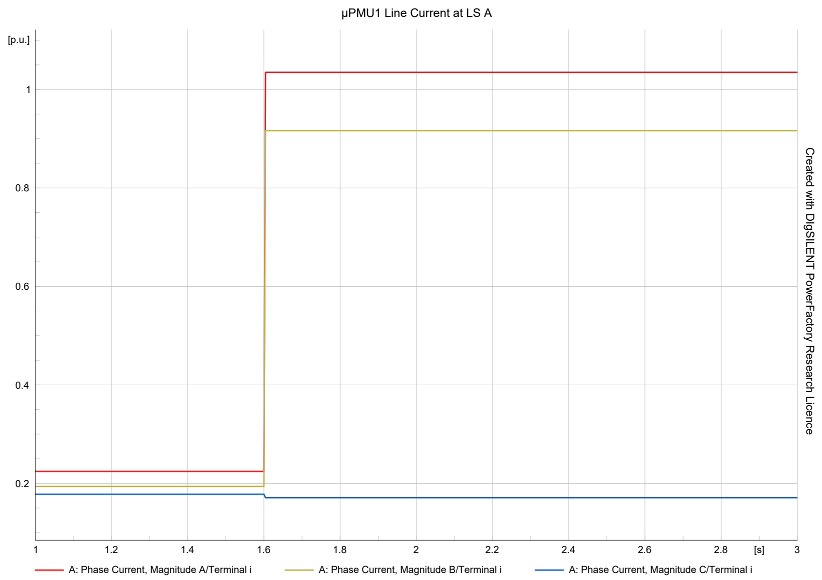


FIGURE 7.16: LL fault classification simulation results from the master μPMU.

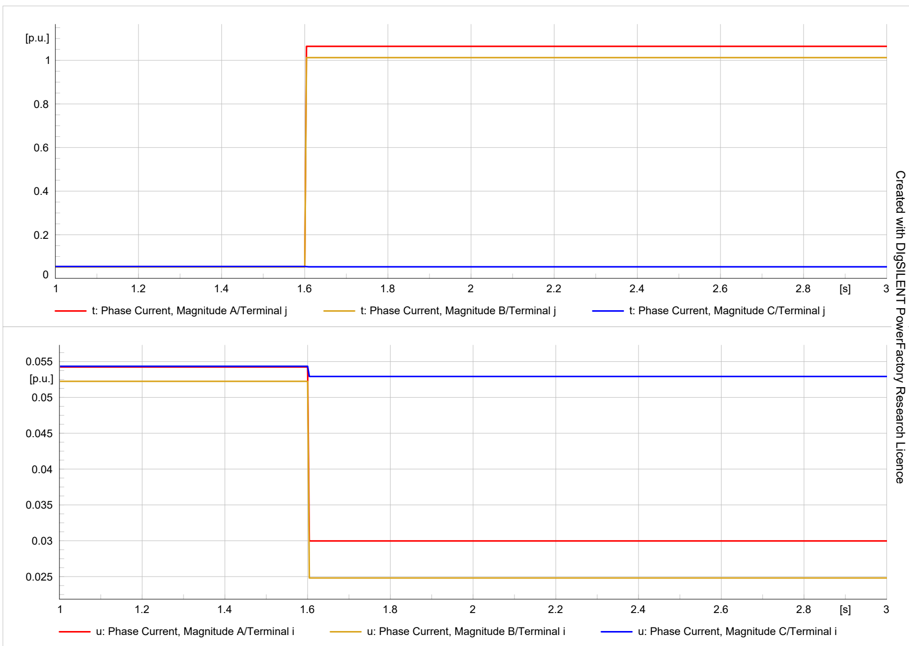


FIGURE 7.17: LL fault classification simulation results from the nearest μPMU.

7.7.2.3 LLG Fault

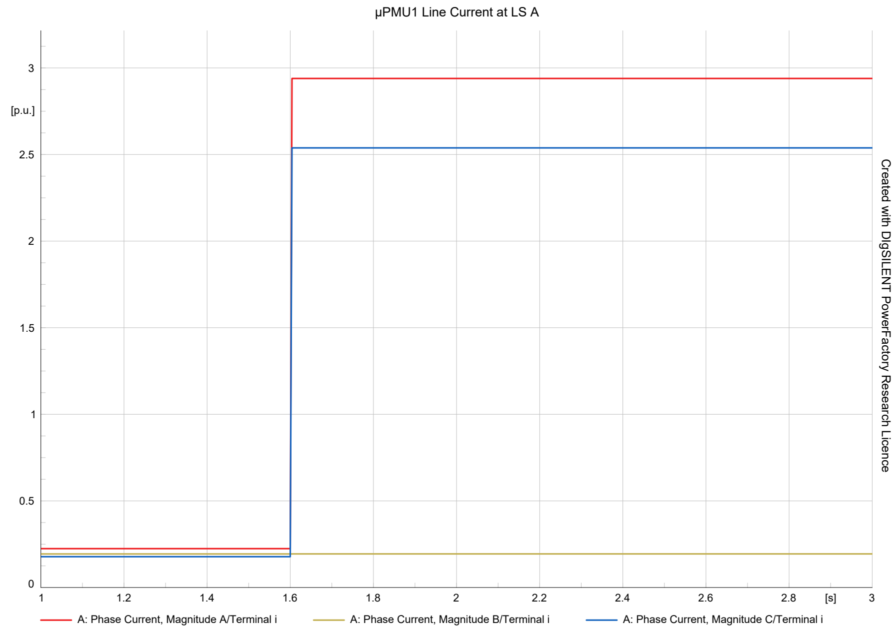


FIGURE 7.18: LLG fault classification simulation results from the master μPMU.

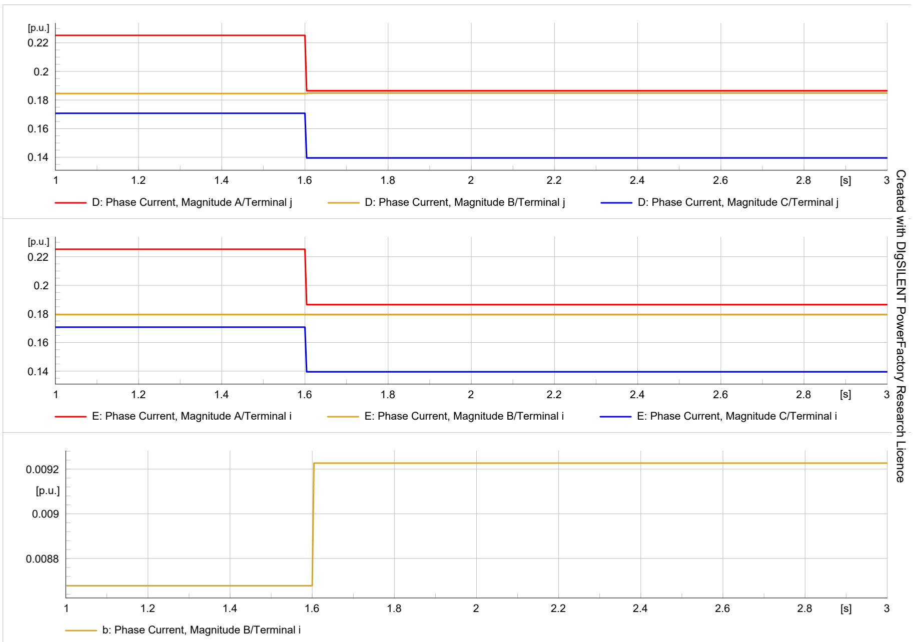


FIGURE 7.19: LLG fault classification simulation results from the nearest μPMU.

The algorithm classified the LLG fault from the line current observations of master μPMU and the μPMU nearest to the fault location is shown in Figures 7.18 and 7.19.

7.7.2.4 LLL Fault

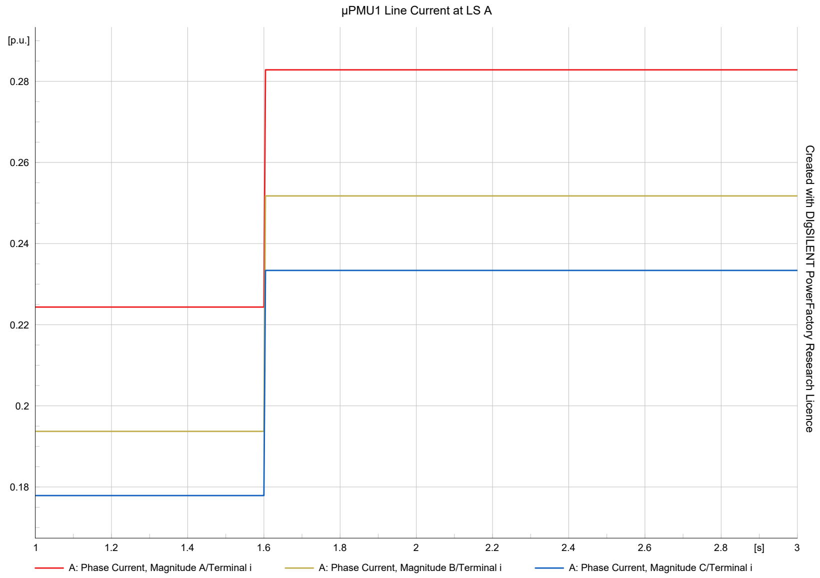


FIGURE 7.20: LLL fault classification simulation results from the master μPMU.

Figure 7.20 shows the results of the classified LLL fault observed by the master μPMU and the line current values of different phases are different from each other compared to the line currents observed by the nearest μPMU as shown in Figure 7.21.

The fault classification algorithm test was conducted for different scenarios and the

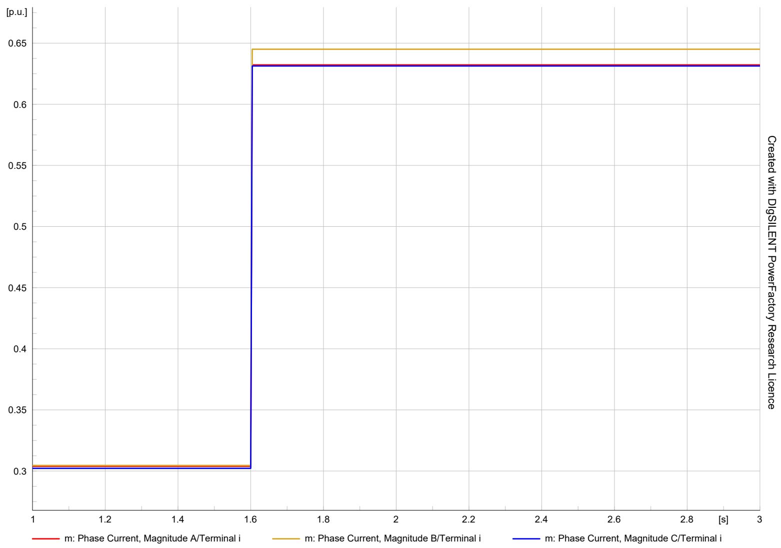


FIGURE 7.21: LLL fault classification simulation results from the nearest μPMU.

results are shown in the Table 7.3.

Table 7.3: Fault classification algorithm test results.

Events Tested	Test Location	Event Description	Fault Classified as
Fault	A	A-G at 0.001% (LS), 1 ohm	L-G Fault (A-G)
Fault	b	B-G at 50% (LS), 1 ohm	L-G Fault (B-G)
Fault	846	A-B at node 846, 20 ohm	L-L Fault (A-B)
Fault	834	C-G at node 834, 15 ohm	L-G Fault (C-G)
Fault	P	B-C at 75% (LS), 10 ohm	L-L Fault (B-C)
Fault	E	C-A at 99.99% (LS), 0.1 ohm	L-L Fault (C-A)
Fault	m	A-B-C at 99.99% (LS), 20 ohm	L-L -L Fault (A-B-C)
Fault	u	A-B-G at 30% (LS), 5 ohm	L-L -G Fault (A-B-G)
Fault	K	B-C-G at 75% (LS), 15 ohm	L-L -G Fault (B-C-G)
Fault	D	C-A-G at 50% (LS), 5 ohm	L-L -G Fault (C-A-G)

7.7.3 Fault Section Identification Test

The developed algorithm was tested with different sections of the DN. During the test, all the modes of the network connections were investigated such as nodes with one US and one DS, one US and two DS and the fault section including the US, node and DS. A couple of FSI results are listed in Table 7.4.

Table 7.4: Fault section identification algorithm test results.

Events Tested	Test Location	Event Description	Fault Section Identified as
Fault	A	A-G at 0.001% (LS), 1 ohm	Line section 'A'
Fault	b	B-G at 50%(LS), 1 ohm	Line section 'B-C'
Fault	846	A-B at node 846, 20 ohm	node t-846-u
Fault	834	C-G at node 834, 15 ohm	Node U-834-V
Fault	P	B-C at 75% (LS), 10 ohm	Line section 'P'
Fault	E	C-A at 99.99% (LS), 5 ohm	Line section 'E-F'
Fault	m	A-B-C at 99.99% (LS), 20 ohm	Line section 'm'
Fault	u	A-B-G at 30% (LS), 5 ohm	Line section 'u-v'
Fault	K	B-C-G at 75% (LS), 15 ohm	Line section 'K-L'
Fault	D	C-A-G at 50% (LS), 5 ohm	Line section 'C-D'

7.7.4 I-FDCSI Algorithm Test

The fault detection, classification and section identification algorithms were combined with steps and tested. The results show its applicability to further develop it as a supporting stand-alone application for DCC operators. A couple of results are recorded and shown in Table 7.5.

TABLE 7.5: I-FDCSI algorithm test results.

Events Tested	Test Location	Event Description	Fault Classified as	Fault Section Identified as
Fault	A	A-G at 0.001% (LS), 1 ohm	L-G Fault (A-G)	Line section 'A'
Fault	b	B-G at 50% (LS), 1 ohm	L-G Fault (B-G)	Line section 'B-C'
Fault	846	A-B at node 846, 20 ohm	L-L Fault (A-B)	node t-846-u
Fault	834	C-G at node 834, 15 ohm	L-G Fault (C-G)	Node U-834-V
Fault	P	B-C at 75% (LS), 10 ohm	L-L Fault (B-C)	Line section 'P'
Fault	E	C-A at 99.99% (LS), 0.1 ohm	L-L Fault (C-A)	Line section 'E-F'
Fault	m	A-B-C at 99.99% (LS), 20 ohm	L-L -L Fault (A-B-C)	Line section 'm'
Fault	u	A-B-G at 30% (LS), 5 ohm	L-L -G Fault (A-B-G)	Line section 'u-v'
Fault	K	B-C-G at 75% (LS), 15 ohm	L-L -G Fault (B-C-G)	Line section 'K-L'
Fault	D	C-A-G at 50% (LS), 5 ohm	L-L -G Fault (C-A-G)	Line section 'C-D'

7.8 Conclusions

In conclusion, this chapter presents an I-FDCSI method for real distribution networks using μPMU. The proposed method is based on rules and uses current measurements from μPMU for fault detection, classification, and section identification. The performance of the I-FDCSI method was tested and validated on a real distribution network with different types of faults, and the results demonstrated that the proposed method achieved high accuracy and efficiency in fault detection, classification, and section identification. The I-FDCSI method can provide valuable information to distribution system operators for quick and accurate fault identification and restoration, which can improve the reliability and resiliency of distribution networks. The proposed method can also facilitate the integration of distributed energy resources and enable the development of smart distribution systems. Overall, the I-FDCSI method presented in this paper is a promising solution for fault management in real distribution networks using μPMU. Further research can be conducted to optimize the rule-based algorithm and to integrate other parameters such as voltage measurements for fault diagnosis in distribution systems. The authors would like to extend future studies in investigating high impedance faults detection and multiple fault location studies using μPMU.

Chapter 8

Results and Discussions

8.1 Introduction

The following section presents the results and discussions of the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method. This method was developed to address the challenges in fault management within power distribution networks, including system changes and disturbances such as the integration of distributed generation (DG) systems and network topology modifications. The performance evaluation of the I-FDCSI method is discussed, including the accuracy of fault detection, the effectiveness of fault classification, and the efficiency of section identification. The results are compared with conventional fault management methods, highlighting the advantages and improvements provided by the I-FDCSI method. The discussions explore the practical implications and potential applications of the I-FDCSI method in real-world distribution network scenarios. This section offers a comprehensive assessment of the I-FDCSI method's performance and discusses its significance in enhancing fault management in power distribution networks.

8.2 I-FDCSI Method Results

8.2.1 Evaluation of the Method

The performance of the method is evaluated using two main measures such as percentage error and percentage accuracy. Table 8.1 shows the statistical evaluation results of the 24,480 simulations carried out on the developed algorithms.

TABLE 8.1: Evalaution of results.

Algorithm	Error (%)	Accuracy (%)	Remarks
Fault Detection	1.000816993	99.91836735	upto 20 ohms fault resistance
Fault Classification	1.045751634	95.625	upto 20 ohms fault resistance
Fault Section Identification	1.053921569	94.88372093	upto 20 ohms fault resistance
IFDCSI	1.033496732	96.80902943	upto 20 ohms fault resistance

The results of the evaluation show highly accurate and reliable results to the simulations carried out up to a fault resistance of 20 ohms. This investigation and method evaluation paved the way for an important observation of high-impedance fault detection and multiple faults detection and localization that has been relevant to real-time DN. The developed algorithms are to be further fine-tuned with additional simulations on changing the fault resistance to a high value from 20 ohms and simulating the multiple-section faults. This sheds light on the future scope of this research work.

Comparative analysis of the rules-based I-FDCSI method with the existing methods in terms of key features and benefits:

Accuracy: The rules-based I-FDCSI method leverages expert knowledge and incorporates a set of rules to detect, classify, and identify faults. This knowledge-based approach enables accurate fault detection and classification, as it leverages the experience and expertise of power system experts. The rules are designed to capture diverse fault scenarios, making the method robust and reliable in different network conditions.

Real-time capability: The rules-based I-FDCSI method is designed to operate in real-time, making it suitable for time-critical applications such as service restoration. The the utilization of PMUs provides high-resolution synchronized data, enabling fast fault detection and reducing service restoration time.

Computational requirements: Compared to data-driven methods, the rules-based I-FDCSI method has lower computational requirements. The rules are based on simple decision-making processes, requiring minimal computational resources. This makes the method computationally efficient and suitable for implementation in embedded systems or devices with limited processing capabilities.

Adaptability: The rules-based I-FDCSI method is adaptable and flexible to different distribution network configurations and fault scenarios. By incorporating expert knowledge into the rules, the method can handle various fault types, fault locations, and network topologies. This adaptability enhances the method's applicability to diverse distribution network environments.

8.3 Discussion

The comparative analysis highlights the advantages of the rules-based I-FDCSI method over other methods in the literature. Its accuracy, real-time capability, lower computational requirements, and adaptability make it a promising approach for fault detection and classification, and section identification in DN. The integration of expert knowledge and the utilization of PMUs contribute to the method's effectiveness in achieving faster service restorations and enhancing the reliability of distribution networks. To ensure the compatibility of this method with high-impedance faults and multiple fault events, the algorithms need to be fine-tuned with further investigations.

8.4 Conclusions

The results and discussions of the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method demonstrate its effectiveness and superiority in fault management for power distribution networks. The evaluation showed high accuracy in fault detection, precise fault classification, and efficient section identification. Compared to conventional methods, the I-FDCSI method offers improved accuracy, faster response time, and enhanced reliability. Its practical implications were highlighted, showcasing its applicability in real-world scenarios. The I-FDCSI method provides a valuable solution for optimizing fault management, reducing downtime, and improving network resilience and efficiency. Further research can focus on refining and integrating the method into larger-scale networks for real-world applications.

Chapter 9

Conclusions and Future Research

9.1 Introduction

The chapter presents the conclusions and future research works of the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method. The I-FDCSI method was developed as an innovative approach to address the challenges in fault management for power distribution networks. This section provides a summary of the key findings and outcomes obtained from the evaluation of the I-FDCSI method's performance. The conclusions highlight the effectiveness and advantages of the I-FDCSI method in accurately detecting, classifying, and identifying faults in distribution networks. Additionally, this section explores potential avenues for future research and development to further enhance the I-FDCSI method and its applications. The identified research gaps and areas of improvement pave the way for future investigations, including the integration of advanced technologies, optimization algorithms, and the validation of the method in large-scale distribution networks. Overall, this section presents a comprehensive overview of the conclusions drawn from the I-FDCSI method's evaluation and outlines potential research directions for advancing fault management in power distribution networks.

9.2 Summary of Research Findings

The research findings on the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method demonstrate its effectiveness and advantages in fault management for power distribution networks. The evaluation of the I-FDCSI method's performance revealed accurate fault detection, precise fault classification, and efficient identification of fault sections within the distribution network. The method outperformed conventional approaches, showing higher accuracy and faster response times. The results highlighted the I-FDCSI method's potential in improving fault management processes, reducing downtime, and enhancing network reliability. Furthermore, the research findings identified areas for future research, including the integration of advanced technologies, optimization algorithms, and the validation of the method in larger-scale distribution networks. Overall, the findings underscore the significance of the I-FDCSI method in advancing fault management practices and provide a foundation for further research and development in this field.

9.3 Contribution of the Research

The following are the main contributions of this research work:

- Realistic μPMU data generation for real-time applications, such as event detection, classification and localization.

- Validation of the generated data with real data published in the literature and with the load flow variations in the network.
- Development of an integrated fault detection, classification and section identification(IFDCSI) method for an unbalanced DN which can be subsequently used as a standalone operator support application at the distribution control centres (DCC) to enhance the existing service restoration process.
- Testing and Validation of the I-FDCSI method in unbalanced distribution benchmark test feeders.

9.4 Research Contribution to Power Distribution Industry

The research contribution to the power distribution industry from the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method is significant. The developed method addresses key challenges faced by the industry in fault management, particularly in the context of system changes and disturbances such as the integration of distributed generation (DG) systems and network topology modifications. By providing accurate fault detection, precise fault classification, and efficient identification of fault sections, the I-FDCSI method enhances the overall reliability and operational efficiency of power distribution networks.

The research findings demonstrate that the I-FDCSI method offers several benefits to the power distribution industry. Firstly, it improves the accuracy of fault detection, allowing for faster identification and response to faults. This, in turn, reduces downtime and enhances the reliability of power supply to customers. Secondly, the precise fault classification provided by the I-FDCSI method enables more targeted maintenance and repair actions, optimizing resource allocation and reducing unnecessary costs. Lastly, the efficient identification of fault sections within the distribution network facilitates faster service restoration, minimizing the impact on customers and improving customer satisfaction.

By addressing the limitations of traditional approaches and machine learning-based methods, the I-FDCSI method offers a transparent and interpretable solution to fault management. This aspect is crucial in the power distribution industry, where the ability to understand and explain fault detection and classification decisions is of utmost importance for operators and engineers.

Overall, the research contribution of the I-FDCSI method to the power distribution industry lies in its ability to enhance fault management practices, improve reliability, optimize operational efficiency, and ultimately provide a more robust and resilient power supply to customers. It offers practical implications for distribution network operators, enabling them to make informed decisions and take proactive measures in maintaining and operating power systems effectively.

9.5 Practical Applications of the research works

The research works on the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method have several practical applications in the power distribution industry. Some of the key practical applications include:

Fault Management and Service Restoration: The I-FDCSI method enables more accurate and efficient fault detection, classification, and section identification in power distribution networks. This leads to faster service restoration by allowing operators to quickly identify and isolate faulty sections, minimizing downtime and improving overall network reliability.

Maintenance Planning and Resource Optimization: Precise fault classification provided by the I-FDCSI method helps in planning and optimizing maintenance activities. By accurately identifying the fault types and locations, maintenance crews can prioritize repairs, allocate resources effectively, and minimize unnecessary inspections or repairs.

Grid Resilience and Reliability Enhancement: The I-FDCSI method contributes to improving the resilience and reliability of power distribution grids. By promptly detecting and addressing faults, it helps prevent further damage to the network and minimize the impact on customers. This results in a more reliable power supply and enhanced grid resilience.

Integration of Distributed Generation (DG) Systems: As the integration of DG systems increases, the I-FDCSI method becomes particularly valuable. It can effectively handle the challenges associated with the integration of DG systems, such as changes in system behavior, fault characteristics, and fault impedance. The method ensures accurate fault detection, classification, and section identification even in the presence of DG systems, facilitating the smooth integration of renewable energy sources into the distribution network.

Decision Support for Operators and Engineers: The I-FDCSI method provides valuable decision support tools for distribution network operators and engineers. It offers transparent and interpretable fault management processes, allowing operators to understand and explain the detected faults and their classifications. This assists in making informed decisions regarding network operations, maintenance strategies, and resource allocation.

Overall, the practical applications of the research works on the I-FDCSI method extend to various aspects of power distribution, including fault management, maintenance planning, grid resilience, DG integration, and decision support. These applications contribute to improving the efficiency, reliability, and overall performance of power distribution networks, benefiting both network operators and end-users.

9.6 Conclusions, Limitations and Future Work

9.6.1 Conclusions

The evaluation results of the I-FDCSI method demonstrate its high accuracy and reliability in fault detection, classification and section Identification simulations up to a fault resistance of 20 ohms. This investigation has provided valuable insights into high-impedance fault detection and multiple faults detection and localization, which are crucial for real-time distribution networks. To further enhance the method's capabilities, future work should focus on fine-tuning the algorithms through additional simulations involving higher fault resistances and multiple-section faults. The comparative analysis of the rules-based I-FDCSI method with existing methods reveals its distinct advantages in terms of key features and benefits:

Accuracy: The rules-based I-FDCSI method leverages expert knowledge and incorporates a set of rules that enable accurate fault detection and classification and section Identification. The method's robustness is enhanced by its ability to handle diverse fault scenarios, making it reliable in different network conditions.

Real-time capability: The rules-based I-FDCSI method is designed to operate in real time, utilizing high-resolution synchronized data from μPMUs. This capability enables fast fault detection and contributes to reducing service restoration time.

Computational requirements: Compared to data-driven methods, the rules-based I-FDCSI method has lower computational requirements. The simplicity of the decision-making processes based on rules ensures computational efficiency, making it suitable for implementation in integrated systems or devices with limited processing capabilities.

Adaptability: The rules-based I-FDCSI method demonstrates adaptability to different distribution network configurations and fault scenarios. The incorporation of expert knowledge into the rules allows the method to handle various fault types, fault locations, and network topologies, enhancing its applicability in diverse distribution network environments. The comparative analysis underscores the advantages of the rules-based I-FDCSI method over other existing methods. Its accuracy, real-time capability, lower computational requirements, and adaptability make it a promising approach for fault detection, classification, and section identification in distribution networks. The integration of expert knowledge and the utilization of μPMUs contribute to faster service restoration and improved network reliability. Future research should focus on fine-tuning the algorithms to ensure compatibility with high-impedance faults and multiple fault events, further advancing the effectiveness of the rules-based I-FDCSI method.

9.6.2 Limitations and Future Work

While the Integrated Fault Detection, Classification, and Section Identification (I-FDCSI) method offers significant benefits, it is important to acknowledge its limitations and identify areas for future work. Some limitations and potential avenues for future research include:

Scalability: The scalability of the I-FDCSI method to larger-scale distribution networks remains an area of exploration. Further research is needed to validate and optimize the method's performance in networks with a higher number of nodes and complex topologies.

Robustness to Parameter Variations: The I-FDCSI method may face challenges when confronted with variations in fault parameters, such as fault impedance or fault inception angles. Future work should focus on enhancing the method's robustness to parameter variations and investigating adaptive techniques to handle such variations effectively.

Real-Time Implementation: The real-time implementation of the I-FDCSI method is crucial for its practical application in power distribution systems. Future research should address the computational efficiency and processing speed requirements to ensure real-time performance, allowing for immediate fault detection and response.

Integration of Advanced Technologies: The incorporation of advanced technologies, such as machine learning algorithms, artificial intelligence, and data analytics, could further enhance the capabilities of the I-FDCSI method. Future research can explore the integration of these technologies to improve fault detection accuracy and optimize fault classification and section identification processes.

Validation on Field Data: While the I-FDCSI method has been evaluated using simulations and realistic measurement data, further validation on field data from real distribution networks is necessary before the field implementation. This will provide a more comprehensive assessment of its performance and validate its effectiveness in practical operational scenarios.

Standardization and Implementation Guidelines: To ensure wider adoption and practical implementation of the I-FDCSI method, future work should focus on developing standardization guidelines and implementation frameworks. This will assist distribution network operators in effectively deploying and utilizing the method in their fault management practices.

In addition, future research should capitalize on the capabilities of μPMUs, including synchronized high-resolution data, to tackle complex fault events such as high impedance fault detections, which remain problematic for utilities relying on traditional protection schemes. Another aspect of leveraging μPMUs is the identification of incipient faults, enabling utilities to anticipate, prepare for, and prevent costly outages.

In summary, future work should address the scalability, robustness to parameter variations, real-time implementation, integration of advanced technologies, validation on field data, and standardization of the I-FDCSI method. Overcoming these limitations and advancing the research in these areas will further enhance the applicability and effectiveness of the method in fault management for power distribution networks. Future research should also utilize μPMUs, leveraging synchronized high-resolution data, to address challenging events like high impedance fault detections, and to identify incipient faults, enabling utilities to anticipate and prevent costly outages.

Appendix A

Network line details, load flow results and realistic network events list

TABLE A.1: Line section representation for IEEE 34 node model in DIgSILENT Powerfactory.

Line Section	Node (i)	Node (j)
A	800	802
B	802	802′
C	802′	806
D	806	808
E	808	812
F	812	814
G	RG10	850
H	850	816
I	816	816′
J	816′	824
K	824	824′
L	824′	828
M	828	828′
N	828′	830
O	830	854
P	854	852
Q	RG11	832
R	832	832′
S	832′	858
T	858	858′
U	858′	834
V	834	834′
W	834′	860
X	860	860′
Y	860′	836
Z	836	836′
a	836′	840
b	808	808′
c	808′	810
d	816	818
e	818	818′
f	818′	820
g	820	820′
h	820′	822
i	824	824′
j	824′	826
k	854	854′
l	854′	856
m	888	890
n	858	858′
o	858′	864
p	834	842
q	842	842′
r	842′	844
s	844	844′
t	844′	846
u	846	846′
v	846′	848
w	836	862
x	862	862′
y	862′	838

TABLE A.2: Load flow results from DP model (node voltages and angles per phase).

Node	Uln, Magnitude A (p.u.)	Uln, Magnitude B (p.u.)	Uln, Magnitude C (p.u.)	Uln, Angle A (deg)	Uln, Angle B (deg)	Uln, Angle C (deg)
802	1.047	1.048	1.048	−0.05	−120.06	119.95
806	1.046	1.047	1.047	−0.09	−120.11	119.91
808	1.014	1.03	1.029	−0.75	−120.95	119.3
810		1.03			−120.95	
812	0.976	1.01	1.007	−1.58	−121.92	118.58
814	0.947	0.995	0.989	−2.27	−122.7	118.01
816	1.017	1.025	1.02	−2.28	−122.71	118
818	1.016			−2.28		
820	0.99			−2.3		
822	0.99			−2.35		
824	1.008	1.016	1.012	−2.39	−122.93	117.75
826		1.016			−122.94	
828	1.007	1.015	1.011	−2.4	−122.95	117.73
830	0.989	0.998	0.994	−2.66	−123.39	117.23
832	1.036	1.035	1.036	−3.14	−124.18	116.32
834	1.031	1.03	1.031	−3.27	−124.38	116.07
836	1.03	1.029	1.031	−3.26	−124.38	116.07
838		1.029			−124.39	
840	1.03	1.029	1.031	−3.26	−124.38	116.07
842	1.031	1.03	1.031	−3.27	−124.38	116.06
844	1.031	1.029	1.031	−3.29	−124.41	116.03
846	1.031	1.029	1.031	−3.33	−124.45	115.97
848	1.031	1.029	1.031	−3.34	−124.45	115.96
850	1.018	1.026	1.02	−2.27	−122.7	118.01
852	0.958	0.968	0.964	−3.14	−124.18	116.32
854	0.989	0.998	0.993	−2.66	−123.4	117.22
856		0.998			−123.41	
858	1.033	1.032	1.034	−3.2	−124.27	116.21
860	1.03	1.029	1.031	−3.26	−124.38	116.06
862	1.03	1.029	1.031	−3.26	−124.38	116.07
864	1.033			−3.2		
888	0.999	0.999	1	−4.67	−125.73	114.8
890	0.917	0.923	0.918	−5.15	−126.79	113.91
DG802_BB	0	0	0	0	0	0
DG840_BB	0	0	0	0	0	0
DG848_BB	0	0	0	0	0	0
DG850_BB	0	0	0	0	0	0
DG852_BB	0	0	0	0	0	0
DG862_BB	0	0	0	0	0	0
RG10	1.018	1.026	1.02	−2.27	−122.7	118.01
RG11	1.036	1.035	1.036	−3.14	−124.18	116.32
RG11	1.036	1.035	1.036	−3.1	−124.2	116.3

TABLE A.3: Load flow results from DP model (line currents and angles per phase).

Line Section	Phase Current, Magnitude A (A)	Phase Current, Magnitude B (A)	Phase Current, Magnitude C (A)	Phase Current, Angle A (deg)	Phase Current, Angle B (deg)	Phase Current, Angle C (deg)
A	51.6	44.6	40.9	−12.74	−127.67	117.32
B	51.6	44.6	40.9	−12.79	−127.73	117.26
C	51.6	42.5	39.2	−12.81	−126.78	118.48
D	51.6	42.5	39.2	−12.83	−126.8	118.46
E	51.8	41.3	39.3	−13.46	−127.07	117.71
F	52	41.3	39.3	−14.18	−127.97	116.85
G	48.5	40	38.2	−14.73	−128.67	116.18
H	48.5	40	38.2	−14.73	−128.67	116.18
I	35.8	40	38.2	−10.43	−128.67	116.17
J	35.9	39.8	38	−10.57	−128.87	116.31
K	35.9	36.9	38	−10.7	−127.36	116.19
L	35.9	36.9	37.8	−10.72	−127.37	116.38
M	35.9	36.9	37.8	−10.73	−127.38	116.37
N	35.4	36.9	37.8	−10.79	−127.64	116.14
O	34.2	36.2	36.5	−9.98	−127.44	116.21
P	34.2	35.9	36.5	−9.99	−127.69	116.2
Q	31.8	33.6	34	−11.01	−128.63	115.35
R	21.3	23.4	24.3	0.44	−116.87	128.32
S	20.9	23.1	24	0.95	−116.27	128.54
T	20.7	23.1	24	0.98	−116.37	128.45
U	20.3	22.4	23.2	2.3	−115.92	130.14
V	11.2	9.1	10.6	−43.07	−154.82	99.32
W	5.9	7.7	5.3	−33.49	−156.41	86.22
X	4.2	6	3.6	−30.2	−154.63	90.23
Y	1.5	4.4	1.7	−18.98	−150.47	68.5
Z	1.5	2.3	1.7	−20.02	−151.97	67.98
a	0.8	0.8	0.8	−40.72	−161.81	78.55
b		1.2			−144.6	
c		0			−30.95	
d	13			−26.66		
e	13			−26.74		
f	10.5			−27.6		
g	10.6			−28.96		
h	0.1			87.67		
i		3.1			−148.91	
j		0			−32.94	
k		0.3			−98.38	
l		0.1			−33.41	
m	69.9	70	69.5	−32.3	−152.74	87.37
n	0.1			−22.8		
o	0			86.8		
p	14.7	16.3	15.1	34.63	−95.6	151.02
q	14.7	16.3	15.1	34.62	−95.61	151.01
r	14.5	16.3	15.1	37.11	−95.64	150.97
s	9.8	9.4	9.4	78.83	−63.85	−170.68
t	9.8	9.4	9.8	78.8	−52.49	−161.91
u	9.8	9.4	9.8	78.76	−52.53	−161.94
v	9.8	9.8	9.8	78.75	−42.46	−161.95
w	0	2.1	0	90.43	−149.37	−150.76
x		2.1			−149.49	
y		0			−34.39	

TABLE A.4: List of realistic real-time events generated using DP in the test feeder

Sl. No	Event Execution Time(s) on 21 August 2022 11:00 AM	Event Description *	Event Location	Event Category
1	40.05	Unbalanced Voltage complaint from SL 890	SL 890	Unbalanced voltage
2	52.05	Rectification of Unbalanced Voltage from SL 890	SL 890	Unbalanced voltage rectification
3	54	XF10 DE-ENERGIZED for Maintenance	XF10	Transformer outage
4	74	VR2 Tap Lowered (13-11-12 to 12-10-11)	VR2	Tap changer event
5	94	VR2 Tap Lowered (12-10-11 to 11-09-10)	VR2	Tap changer event
6	114	VR2 Tap Lowered (11-09-10 to 10-08-09)	VR2	Tap changer event
7	134	VR2 Tap Lowered (10-08-09 to 09-07-08)	VR2	Tap changer event
8	154	VR2 Tap Lowered (09-07-08 to 08-06-07)	VR2	Tap changer event
9	174	Cap844 Switch Off	S Capacitor 1	Capacitor bank event
10	194	DG848 Switch On	DG848	DG-switching event
11	214	C-G Fault 20ohm Temporary Fault at A	A	Temporary fault event
12	214.04	Main Feeder Circuit Breaker Tripped on C-G Fault	Main Feeder Circuit Breaker	CB trip event
13	214.135	C-G Temporary Fault Cleared	A	Fault clearing

Table A.5: List of realistic real-time events generated using DP in the test feeder Cont.

Sl. No	Event Execution Time(s) on 21 August 2022 11:00 AM	Event Description *	Event Location	Event Category
14	234.185	Main Feeder Circuit Breaker Reclosed	A	CB-switching event
15	254.185	Heavy Load 844 (3PH) Switch Off	SL 844	Load trip event
16	274.185	B-N Jumper Parted OpenCircuit Flt808-810	808-810 B-N Jumper	Open circuit fault event
17	294.185	XF10 ENERGIZED After Maintenance	XF10	Transformer energization
18	314.185	DG848 Switch Off	DG848	DG-switching event
19	334.185	3Phase Short-Circuit Fault 10 ohms at G	G	Short circuit fault event
20	334.225	Main Feeder Circuit Breaker Tripped on ABC SC Fault	Main Feeder Circuit Breaker	CB trip event
21	354.225	Fault Rectified and Cable Kept in Service	G	Fault Clearing
22	374.225	Main Feeder Circuit Breaker Closed_1	Main Feeder Circuit Breaker	CB-switching event
23	394.225	DG840 Switch On	DG840	DG-switching event
24	414.225	ABC Short-Circuit Fault 10 ohm at G DG840	G	Short circuit fault event
25	414.265	Main Feeder Circuit Breaker Tripped on ABC SC wDG840	Main Feeder Circuit Breaker	CB trip event
26	434.265	Fault Rectified and Cable Kept in Srvc	G	Fault clearing
27	454.265	Main Feeder Circuit Breaker Closed_2	Main Feeder Circuit Breaker	CB-switching event
28	474.265	VR1 Tap Lowered (12-05-05 to 13-06-06)	VR1	Tap changer event
29	494.265	DG840 Switch Off	DG840	DG-switching event
30	514.265	A-B Fault 10ohms at O	O	Short circuit fault event
31	514.305	Main Feeder Circuit Breaker Tripped on A-B Fault	Main Feeder Circuit Breaker	CB trip event
32	534.048	Fault Rectified and Cable Kept in SRVC	O	Fault clearing
33	554.048	Main Feeder Circuit Breaker Closed_3	Main Feeder Circuit Breaker	CB-switching event
34	574.048	Customer requested outage at SL848	SL 848	Load-switching event
35	594.048	Cap 848 Switch Off	S Capacitor 2	Capacitor bank Event
36	614.048	OHL section D De-energized 4 Jumper Connection	D	Line De-energization
37	634.048	OHL section E De-energized 4 Jumper Connection	E	Line energization
38	654.048	B-N Jumper 808-810 Connected	808-810 B-N Jumper	OHL jumper connection
39	674.048	OHL section E Connected for engzn	E	Line energization
40	694.048	OHL section D Connected and Svc restd2al	D	Line energization
41	714.048	DG852 Switched On	DG852	DG-switching event
42	734.048	A_G Fault at A	A	Short circuit fault event
43	734.088	DG852 Tripped on A-G Fault	CB	DG trip event
44	734.128	Main Feeder Circuit Breaker Tripped on A-G Fault	Main Feeder Circuit Breaker	CB trip event
45	754.128	Fault Rectified and Cable Kept in SVC	A	Fault clearing
46	774.128	Main Feeder Circuit Breaker Closed_4	A	CB-switching event
47	794.128	B-C Jumper OP between 834-842	p	OHL jumper opening
48	814.128	B_C Fault at p	p	Short circuit fault event
49	814.168	Main Feeder Circuit Breaker Tripped on BC SC Fault	Main Feeder Circuit Breaker	CB trip event
50	834.168	SC Fault Cleared	p	Fault Clearing
51	854.168	Jumper Closed 834 to 842	Jumper	OHL jumper connection
52	874.168	Main Feeder Circuit Breaker Closed_5	Main Feeder Circuit Breaker	CB-switching event

Table A.6: List of realistic real-time events generated using DP in the test feeder Cont.

Sl. No	Event Execution Time(s) on 21 August 2022 11:00 AM	Event Description *	Event Location	Event Category
53	894.168	DG 850 Switched On	DG850	DG-switching event
54	914.168	BCN Load Trip Event	DL 802-806	Load trip event
55	934.168	A-B-G Fault at F	F	Short circuit fault event
56	934.208	DG850 Tripped	DG850	DG trip event
57	934.248	Main Feeder Circuit Breaker tripped on A-B-G Fault	Main Feeder Circuit Breaker	CB trip event
58	954.248	A-B-G Fault Cleared	F	Fault clearing
59	974.248	Main Feeder Circuit Breaker Closed_6	Main Feeder Circuit Breaker	CB-switching event
60	994.248	C-phase of DL 834-860 Tripped	DL 834-860	Load trip event
61	1014.248	MCB of C-phase Closed for DL 834-860	DL 834-860	Load-switching event
62	1034.248	DG802 Switched On	DG802	DG-switching event
63	1054.248	DG840 Switched On Generation Increased	DG840	DG-switching event
64	1074.248	ABCN-G Fault at L	L	Short circuit fault event
65	1074.288	DG840 Tripped	DG840	DG trip event
66	1074.328	DG802 Tripped	DG802	DG trip event
67	1074.368	Main Feeder Circuit Breaker Tripped on ABCG Fault	Main Feeder Circuit Breaker	CB trip event
68	1094.368	ABCG Fault Cleared	L	Fault Clearing
69	1114.368	Main feeder Circuit Breaker Closed07	Main Feeder Circuit Breaker	CB-switching event
70	1134.368	2 PH YN load Switched On (DL 802-806)	DL 802-806	Load-switching event
71	1154.368	2 PH YN load Switched Off (DL 844-846)byC	DL 844-846	Load-switching event
72	1174.368	2 PH YN load Switched On (DL 844-846)by C	DL 844-846	Load-switching event
73	1194.368	B-G Fault 10 ohms at m	m	Short circuit fault event
74	1194.408	XF10 Tripped	XF10	Transformer trip event
75	1214.408	B-C-G Fault 10 ohms at q	q	Short circuit fault event
76	1214.448	Main Feeder Circuit Breaker Tripped on B-C-G Fault	Main Feeder Circuit Breaker	CB trip event
77	1234.448	B-C-G Fault Cleared	q	Fault Clearing
78	1254.448	Main Feeder Circuit Breaker Closed_8	Main Feeder Circuit Breaker	CB-switching event
79	1274.448	A-N load Switch Off (DL 820-822)	DL 820-822	Load-switching event
80	1294.448	C-A Fault 10 ohms at B	B	Short circuit fault event
81	1294.488	Main Feeder Circuit Breaker Tripped on C-A Fault	Main Feeder Circuit Breaker	CB trip event
82	1314.488	C-A Fault Cleared	B	Fault clearing
83	1334.488	Main Feeder Circuit Breaker Closed_9	Main Feeder Circuit Breaker	CB-switching event
84	1354.488	B-G Fault Cleared at m	m	Fault clearing
85	1374.488	XF10 Switched On	XF10	Transformer energization
86	1394.488	DG852 Switch On	DG852	DG-switching event
87	1414.488	VR2 Tap Raised (08-06-07 to 09-07-08)	VR2	Tap changer event
88	1434.488	VR2 Tap Raised (09-07-08 to 10-08-09)	VR2	Tap changer event
89	1454.488	VR2 Tap Raised (10-08-09 to 11-09-10)	VR2	Tap changer event
90	1474.488	VR2 Tap Raised (11-09-10 TO 12-10-11)	VR2	Tap changer event
91	1494.488	VR2 Tap Raised (12-10-11 to 13-11-12)	VR2	Tap changer event
92	1514.488	DG852 Switch Off	DG852	DG-switching event
93	1534.488	C-A-G Fault 10 ohms at A	A	Short circuit fault event
94	1534.528	Main Feeder Circuit Breaker Tripped on C-A-G Fault	Main Feeder Circuit Breaker	CB trip event
95	1554.528	C-A-G Fault Cleared at A	A	Fault clearing
96	1574.528	Main Feeder Circuit Breaker Closed	Main Feeder Circuit Breaker	CB-switching event

TABLE A.7: List of realistic real-time events generated using DP in the test feeder Cont.

Sl. No	Event Execution Time(s) on 21 August 2022 11:00 AM	Event Description *	Event Location	Event Category
97	1594.528	A-N load Switch On (DL 820-822)	DL 820-822	Load-switching event
98	1614.528	C-G Fault 10 ohms at A	A	Short circuit fault event
99	1614.568	Main Feeder Circuit Breaker Tripped onC-G Fault	Main Feeder Circuit Breaker	CB trip event
100	1634.568	C-G Fault cleared at A	A	Fault clearing
101	1654.568	Main Feeder Circuit Breaker Closed	Main Feeder Circuit Breaker	CB-switching event
102	1674.568	Low Voltage Complaint from SL 890	SL 890	LV complaint
103	1694.568	VR1 Tap Raised (13-06-06 to 14-07-07)	VR1	Tap changer event
104	1714.568	VR1 Tap Raised (14-07-07 to 15-08-08)	VR1	Tap changer event
105	1734.568	SL 890 Energized after V regulation	SL 890	Load-switching event
106	1740.568	Cap844 Switch On	S Capacitor 1	Capacitor bank event
107	1746.025	SL 844 Switch On	SL 844	Load-switching event
108	1777.123	SL 848 Switch On	SL 848	Load-switching event
109	1799.001	Cap848 Switch On	S Capacitor 2	Capacitor bank event

* A, B, C, N, and G are Phases A, B, C, Neutral, and Ground respectively.

Appendix B

Load flow settings and data generation settings

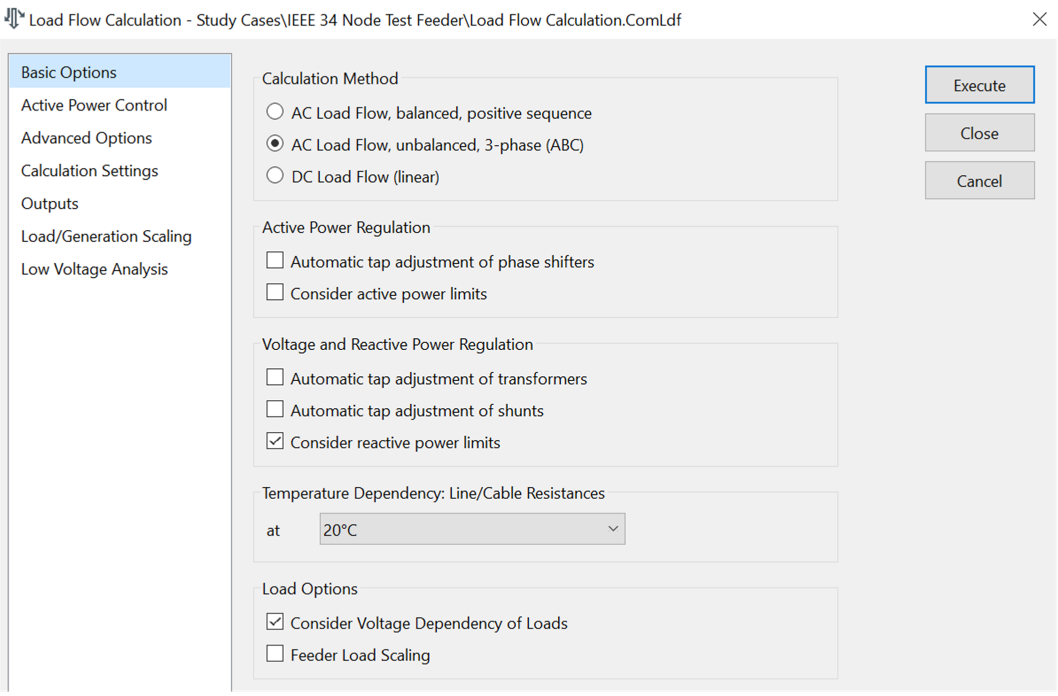


FIGURE B.1: Load flow basic settings.

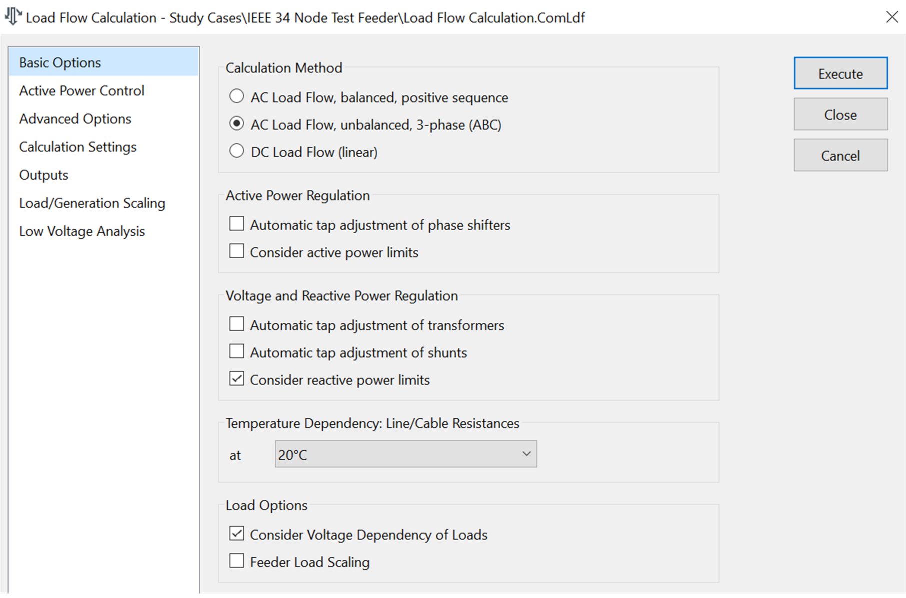


Figure B.2: Load flow iteration control settings.

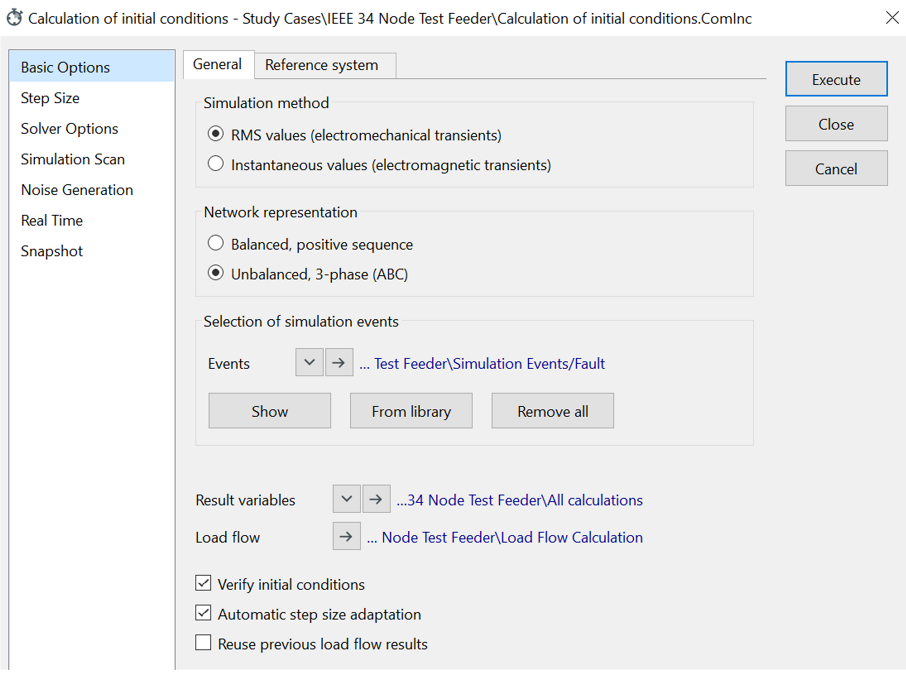


Figure B.3: RMS Simulation basic settings.

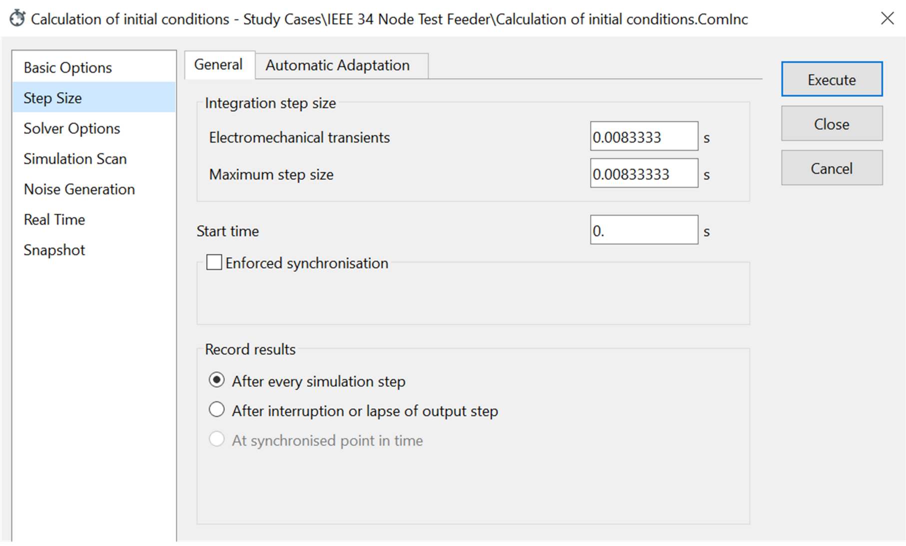


FIGURE B.4: Data generation step size settings1.

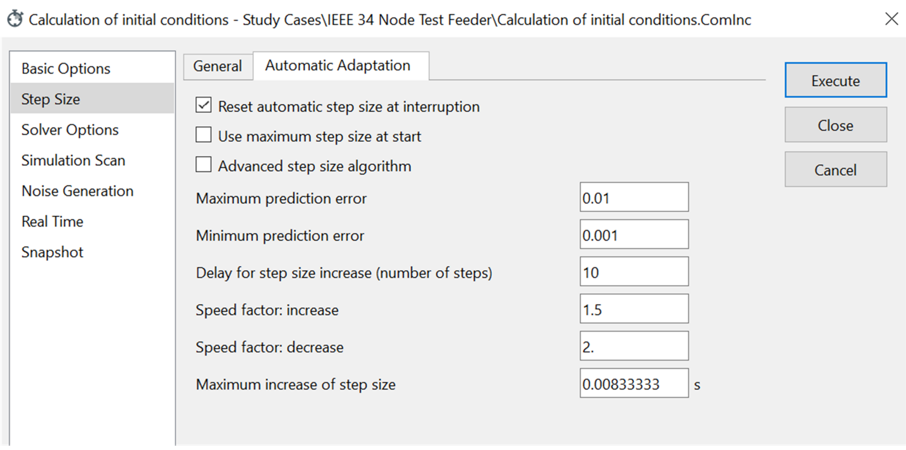


FIGURE B.5: Data generation step size settings2.

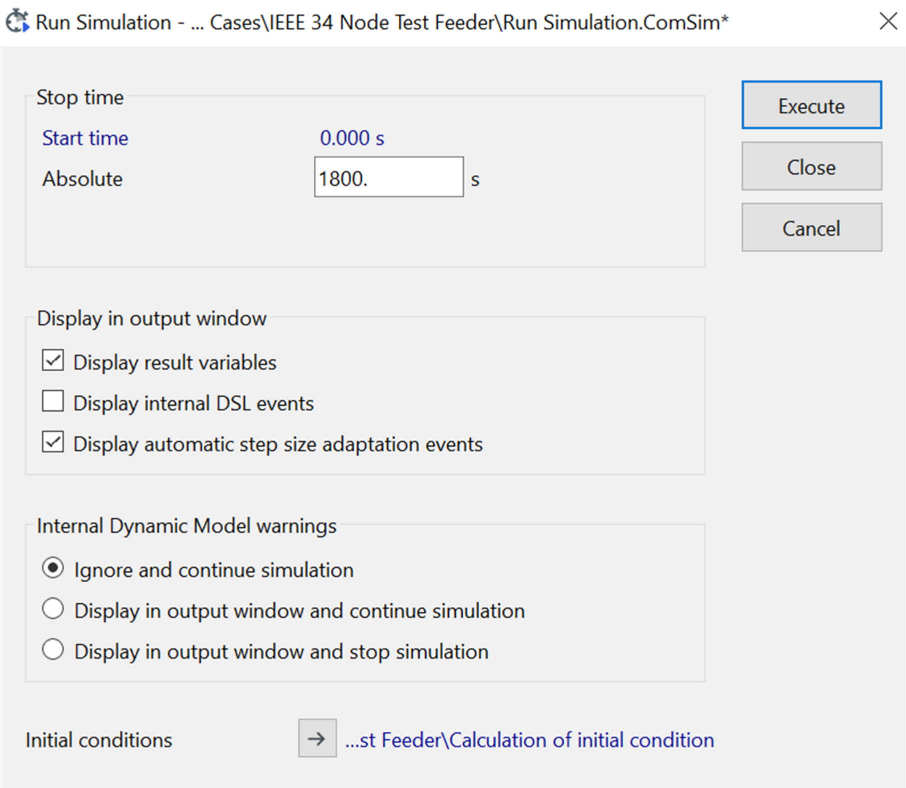


Figure B.6: Run Simulation Settings.

Bibliography

[1] Chiang, Leo H., Evan L. Russell, and Richard D. Braatz. *Fault detection and diagnosis in industrial systems*. Springer Science & Business Media, 2000.

[2] Patnaik, Bhaskar, Manohar Mishra, Ramesh C. Bansal, and Ranjan Kumar Jena. "AC microgrid protection–A review: Current and future prospective." *Applied Energy* 271 (2020): 115210.

[3] Freire Pérez, Santiago. "Application of micro PMUs on Low Voltage networks." (2020).

[4] Usman, Muhammad Usama, Juan Ospina, and Md Omar Faruque. "Fault classification and location identification in a smart distribution network using ANN." *In 2018 IEEE power & energy society general meeting (PESGM)*, pp. 1-6. IEEE, 2018.

[5] Nsaif, Younis M., MS Hossain Lipu, Afida Ayob, Yushaizad Yusof, and Aini Hussain. "Fault detection and protection schemes for distributed generation integrated to distribution network: Challenges and suggestions." *IEEE Access* 9 (2021): 142693-142717.

[6] Ahmad, Fiaz, Akhtar Rasool, Emre Ozsoy, Raja Sekar, Asif Sabanovic, and Meltem Elitaş. "Distribution system state estimation-A step towards smart grid." *Renewable and Sustainable Energy Reviews* 81 (2018): 2659-2671.

[7] Lopes, JA Pecas, Nikos Hatziargyriou, Joseph Mutale, Predrag Djapic, and N. Jenkins. "Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities." *Electric power systems research* 77, no. 9 (2007): 1189-1203.

[8] Chowdhury, S. P., S. Chowdhury, and P. A. Crossley. "Islanding protection of active distribution networks with renewable distributed generators: A comprehensive survey." *Electric power systems research* 79, no. 6 (2009): 984-992.

[9] Walling, R. A., Robert Saint, Roger C. Dugan, Jim Burke, and Ljubomir A. Kojovic. "Summary of distributed resources impact on power delivery systems." *IEEE Transactions on power delivery* 23, no. 3 (2008): 1636-1644.

[10] Capitanescu, Florin, Luis F. Ochoa, Harag Margossian, and Nikos D. Hatziargyriou. "Assessing the potential of network reconfiguration to improve distributed generation hosting capacity in active distribution systems." *IEEE Transactions on Power Systems* 30, no. 1 (2014): 346-356.

[11] Gururajapathy, Sophi Shilpa, Hazlie Mokhlis, and Hazlee Azil Illias. "Fault location and detection techniques in power distribution systems with distributed generation: A review." *Renewable and sustainable energy reviews* 74 (2017): 949-958.

[12] Mora-Florez, J., Joaquim Meléndez, and Gilberto Carrillo-Caicedo. "Comparison of impedance based fault location methods for power distribution systems." *Electric power systems research* 78, no. 4 (2008): 657-666.

[13] Zimmerman, Karl, and David Costello. "Impedance-based fault location experience."In 2006 *IEEE Rural Electric Power Conference*, pp. 1-16. IEEE, 2006.

[14] Ramar, K., and E. E. Ngu. "A new impedance-based fault location method for radial distribution systems." In *IEEE PES General Meeting*, pp. 1-9. IEEE, 2010.

[15] Krishnathevar, Ramar, and Eng Eng Ngu. "Generalized impedance-based fault location for distribution systems." *IEEE Transactions on power delivery* 27, no. 1 (2011): 449-451.

[16] El-Fouly, T. H. M., and C. Abbey. "On the compatibility of fault location approaches and distributed generation." In 2009 *CIGRE/IEEE PES Joint Symposium Integration of Wide-Scale Renewable Resources Into the Power Delivery System*, pp. 1-5. IEEE, 2009.

[17] Rajeev, Aneesh, T. S. Angel, and Faraz Zafar Khan. "Fault location in distribution feeders with optimally placed PMU's." In 2015 *International Conference on Technological Advancements in Power and Energy (TAP Energy)*, pp. 438-442. IEEE, 2015.

[18] Patynowski, Daniel, Jorge Cardenas, David Menendez, Zhiying Zhang, Jose Manuel Roca, Jean Gardy Germain, Angel Yunta Huete et al. "Fault Locator approach for high-impedance grounded or ungrounded distribution systems using synchrophasors." In 2015 *68th Annual Conference for Protective Relay Engineers*, pp. 302-310. IEEE, 2015.

[19] Girgis, Adly A., Christopher M. Fallon, and David L. Lubkeman. "A fault location technique for rural distribution feeders." *IEEE Transactions on Industry Applications* 29, no. 6 (1993): 1170-1175.

[20] Saha, M. M., F. Provoost, and E. Rosolowski. "Fault location method for MV cable network." (2001): 323-326.

[21] Short, T. A., D. D. Sabin, and M. F. McGranaghan. "Using PQ monitoring and substation relays for fault location on distribution systems." In 2007 *IEEE Rural Electric Power Conference*, pp. B3-B3. IEEE, 2007.

[22] Liao, Yuan. "Generalized fault-location methods for overhead electric distribution systems." *IEEE Transactions on power delivery* 26, no. 1 (2010): 53-64.

[23] Salim, Rodrigo Hartstein, Mariana Resener, André Darós Filomena, Karen Rezende Caino De Oliveira, and Arturo Suman Bretas. "Extended fault-location formulation for power distribution systems." *IEEE Transactions on power delivery* 24, no. 2 (2009): 508-516.

[24] Ferreira, Gustavo D., Daniel S. Gazzana, Arturo S. Bretas, and Afonso S. Netto. "A unified impedance-based fault location method for generalized distribution systems." In 2012 *IEEE Power and Energy Society General Meeting*, pp. 1-8. IEEE, 2012.

[25] Das, Swagata, Surya Santoso, and Arindam Maitra. "Effects of distributed generators on impedance-based fault location algorithms." In 2014 *IEEE PES General Meeting| Conference & Exposition*, pp. 1-5. IEEE, 2014.

[26] Robson, Stephen, Abderrahmane Haddad, and Huw Griffiths. "Fault location on branched networks using a multiended approach." *IEEE Transactions on power delivery* 29, no. 4 (2014): 1955-1963.

[27] Borghetti, Alberto, Sandro Corsi, Carlo Alberto Nucci, Mario Paolone, Lorenzo Peretto, and Roberto Tinarelli. "On the use of continuous-wavelet transform for fault location in distribution power systems." *International Journal of Electrical Power & Energy Systems* 28, no. 9 (2006): 608-617.

[28] Borghetti, Alberto, Mauro Bosetti, Mauro Di Silvestro, Carlo Alberto Nucci, and Mario Paolone. "Continuous-wavelet transform for fault location in distribution power networks: Definition of mother wavelets inferred from fault originated transients." *IEEE Transactions on Power Systems* 23, no. 2 (2008): 380-388.

[29] Borghetti, Alberto, Mauro Bosetti, Carlo Alberto Nucci, Mario Paolone, and A. Abur. "Integrated use of time-frequency wavelet decompositions for fault location in distribution networks: Theory and experimental validation." *IEEE Transactions on power delivery* 25, no. 4 (2010): 3139-3146.

[30] Javadian, S. A. M., A. M. Nasrabadi, M-R. Haghifam, and J. Rezvantalab. "Determining fault's type and accurate location in distribution systems with DG using MLP neural networks." In 2009 *International conference on clean electrical power*, pp. 284-289. IEEE, 2009.

[31] Thukaram, D., H. P. Khincha, and H. P. Vijaynarasimha. "Artificial neural network and support vector machine approach for locating faults in radial distribution systems." *IEEE Transactions on power delivery* 20, no. 2 (2005): 710-721.

[32] Chunju, Fan, K. K. Li, Wai Lok Chan, Yu Weiyong, and Zhang Zhaoning. "Application of wavelet fuzzy neural network in locating single line to ground fault (SLG) in distribution lines." *International Journal of Electrical Power & Energy Systems* 29, no. 6 (2007): 497-503.

[33] Rafinia, Ali, and Jamal Moshtagh. "A new approach to fault location in three-phase underground distribution system using combination of wavelet analysis with ANN and FLS." *International Journal of Electrical Power & Energy Systems* 55 (2014): 261-274.

[34] Pourahmadi-Nakhli, Meisam, and Ali Akbar Safavi. "Path characteristic frequency-based fault locating in radial distribution systems using wavelets and neural networks." *IEEE Transactions on power delivery* 26, no. 2 (2010): 772-781.

[35] Mora, J. J., G. Carrillo, and L. Perez. "Fault location in power distribution systems using ANFIS nets and current patterns." In 2006 *IEEE/PES Transmission & Distribution Conference and Exposition: Latin America*, pp. 1-6. IEEE, 2006.

[36] Robson, Stephen, Abderrahmane Haddad, and Huw Griffiths. "Fault location on branched networks using a multi-ended approach." *IEEE Transactions on power delivery* 29, no. 4 (2014): 1955-1963.

[37] Goudarzi, M., B. Vahidi, R. A. Naghizadeh, and S. H. Hosseinian. "Improved fault location algorithm for radial distribution systems with discrete and continuous wavelet analysis." *International Journal of Electrical Power & Energy Systems* 67 (2015): 423-430.

[38] Thukaram, D., H. P. Khincha, and H. P. Vijaynarasimha. "Artificial neural network and support vector machine approach for locating faults in radial distribution systems." *IEEE Transactions on power delivery* 20, no. 2 (2005): 710-721.

[39] Mora, J. J., G. Carrillo, and L. Perez. "Fault location in power distribution systems using ANFIS nets and current patterns." In 2006 *IEEE/PES Transmission & Distribution Conference and Exposition: Latin America*, pp. 1-6. IEEE, 2006.

[40] Javadian, S. A. M., A. M. Nasrabadi, M-R. Haghifam, and J. Rezvantalab. "Determining fault's type and accurate location in distribution systems with

DG using MLP neural networks." In 2009 *International conference on clean electrical power*, pp. 284-289. IEEE, 2009.

[41] Mora-Florez, J., V. Barrera-Nunez, and G. Carrillo-Caicedo. "Fault location in power distribution systems using a learning algorithm for multivariable data analysis." *IEEE Transactions on power delivery* 22, no. 3 (2007): 1715-1721.

[42] Salim, Rodrigo Hartstein, Karen Rezende Caino de Oliveira, André Darós Filomena, Mariana Resener, and Arturo Suman Bretas. "Hybrid fault diagnosis scheme implementation for power distribution systems automation." *IEEE Transactions on power delivery* 23, no. 4 (2008): 1846-1856.

[43] Gazzana, D. S., G. D. Ferreira, A. S. Bretas, A. L. Bettiol, A. Carniato, L. F. N. Passos, A. H. Ferreira, and J. E. M. Silva. "An integrated technique for fault location and section identification in distribution systems." *Electric power systems research* 115 (2014): 65-73.

[44] Magnago, Fernando H., and Ali Abur. "A new fault location technique for radial distribution systems based on high frequency signals." In 1999 *IEEE Power Engineering Society Summer Meeting.* In *Conference Proceedings (Cat. No. 99CH36364)*, vol. 1, pp. 426-431. IEEE, 1999.

[45] R. Dashti, J. Sadeh, " Fault section estimation in power distribution network using impedance-based fault distance calculation and frequency spectrum analysis" , *IET Gener. Transm. Distrib.*, Vol.8 pp. 1406–1417, 2014

[46] Dashti, Rahman, and Javad Sadeh. "Fault section estimation in power distribution network using impedance-based fault distance calculation and frequency spectrum analysis." *IET Generation, Transmission & Distribution* 8, no. 8 (2014): 1406-1417.

[47] Alwash, Shamam Fadhil, Vigna K. Ramachandaramurthy, and Nadarajah Mithulananthan. "Fault-location scheme for power distribution system with distributed generation." *IEEE Transactions on power delivery* 30, no. 3 (2014): 1187-1195.

[48] Arghandeh, Reza, Alexandra Von Meier, Laura Mehrmanesh, and Lamine Mili. "On the definition of cyber-physical resilience in power systems." *Renewable and sustainable energy reviews* 58 (2016): 1060-1069.

[49] Hojabri, Mojgan, Ulrich Dersch, Antonios Papaemmanouil, and Peter Bosshart. "A comprehensive survey on phasor measurement unit applications in distribution systems." *Energies* 12, no. 23 (2019): 4552.

[50] Dua, Gagandeep Singh, Barjeev Tyagi, and Vishal Kumar. "Deploying micro-PMUs with channel limit in reconfigurable distribution systems." *IEEE Systems Journal* 16, no. 1 (2021): 832-843.

[51] Elbana, Mohamed Salah, Nabil Abbasy, Ashraf Meghed, and Nahil Shaker. "µPMU-based smart adaptive protection scheme for microgrids." *Journal of Modern Power Systems and Clean Energy* 7, no. 4 (2019): 887-898.

[52] Shahsavari, Alireza, Mohammad Farajollahi, Emma M. Stewart, Ed Cortez, and Hamed Mohsenian-Rad. "Situational awareness in distribution grid using micro-PMU data: A machine learning approach." *IEEE Transactions on Smart Grid*10, no. 6 (2019): 6167-6177.

[53] Zhou, Yuxun, Reza Arghandeh, Ioannis Konstantakopoulos, Shayaan Abdullah, Alexandra von Meier, and Costas J. Spanos. "Abnormal event detection with high resolution micro-PMU data." In *2016 Power Systems Computation Conference (PSCC)*, pp. 1-7. IEEE, 2016.

[54] Jamei, Mahdi, Anna Scaglione, Ciaran Roberts, Emma Stewart, Sean Peisert, Chuck McParland, and Alex McEachern. "Anomaly Detection Using Optimally Placed μPMU Sensors in Distribution Grids." *IEEE Transactions on Power Systems* 33, no. 4 (2017): 3611-3623.

[55] Niazazari, Iman, and Hanif Livani. "Disruptive event classification using PMU data in distribution networks." In 2017 *IEEE Power & Energy Society General Meeting*, pp. 1-5. IEEE, 2017.

[56] Shahsavari, Alireza, Mohammad Farajollahi, Emma Stewart, Ciaran Roberts, Fady Megala, Lilliana Alvarez, Ed Cortez, and Hamed Mohsenian-Rad. "Autopsy on active distribution networks: A data-driven fault analysis using micro-PMU data." In 2017 *North American Power Symposium (NAPS)*, pp. 1-7. IEEE, 2017.

[57] Sanitha, G., and J. S. Savier. "Faulty phase and fault location identification using micro-PMU data." In 2019 *International Conference on Power Electronics Applications and Technology in Present Energy Scenario (PETPES)*, pp. 1-6. IEEE, 2019.

[58] Oliveira, Angelo Rocha, Paulo Augusto Nepomuceno Garcia, Leonardo Willer Oliveira, Edimar Jose Oliveira, and Helio Antonio Silva. "Fault classification in distribution systems bsaed on fault current angles." *IEEE Latin America Transactions* 14, no. 1 (2016): 199-205.

[59] Usman, Muhammad Usama, Juan Ospina, and Md Omar Faruque. "Fault classification and location identification in a smart distribution network using ANN." *In 2018 IEEE power & energy society general meeting (PESGM)*, pp. 1-6. IEEE, 2018.

[60] Grando, Flávio Lori, André Eugenio Lazzaretti, Miguel Moreto, and Heitor Silvério Lopes. "Fault classification in power distribution systems using PMU data and machine learning." *In 2019 20th International Conference on Intelligent System Application to Power Systems (ISAP)*, pp. 1-6. IEEE, 2019.

[61] Dashtdar, Majid, and Masoud Dashtdar. "Fault location in distribution network based on phasor measurement units (PMU)." *The Scientific Bulletin of Electrical Engineering Faculty* 19, no. 2 (2019): 38-43.

[62] Pignati, Marco, Lorenzo Zanni, Paolo Romano, Rachid Cherkaoui, and Mario Paolone. "Fault detection and faulted line identification in active distribution networks using synchrophasors-based real-time state estimation." *IEEE Transactions on power delivery* 32, no. 1 (2016): 381-392.

[63] Zhang, Mengsheng, Yi Wang, Zhiguo Zhou, and Zufu Li. "Research on fault location based on PMU for multi-source distribution network." In 2016 *IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 1877-1882. IEEE, 2016.

[64] Usman, Muhammad Usama, and Md Omar Faruque. "Validation of a PMU-based fault location identification method for smart distribution network with photovoltaics using real-time data." *IET Generation, Transmission & Distribution* 12, no. 21 (2018): 5824-5833.

[65] Ren, J., S. S. Venkata, and E. Sortomme. "An accurate synchrophasor based fault location method for emerging distribution systems." *IEEE Transactions on power delivery* 29, no. 1 (2013): 297-298.

[66] Dashtdar, Masoud, Arif Hussain, Hassan Z. Al Garni, Abdullahi Abubakar Mas' ud, Waseem Haider, Kareem M. AboRas, and Hossam Kotb. "Fault location in distribution network by solving the optimization problem based on

power system status estimation using the PMU." *Machines* 11, no. 1 (2023): 109.

[67] Sheta, Ahmed N., Gabr M. Abdulsalam, and Abdelfattah A. Eladl. "Online tracking of fault location in distribution systems based on PMUs data and iterative support detection." *International Journal of Electrical Power & Energy Systems* 128 (2021): 106793.

[68] Yao, Weiqiang, Xiaoqing Gao, Shu Liu, Yongjie Zhang, and Xiaojun Wang. "A CNN-Based Fault Section Location Method in Distribution Network Using Distribution-Level PMU Data." *In Proceedings of PURPLE MOUNTAIN FORUM 2019-International Forum on Smart Grid Protection and Control: Volume II*, pp. 623-633. Springer Singapore, 2020.

[69] Mirshekali, Hamid, Rahman Dashti, Ahmad Keshavarz, and Hamid Reza Shaker. "Machine learning-based fault location for smart distribution networks equipped with micro-PMU." *Sensors* 22, no. 3 (2022): 945.

[70] Mar, Adriana, Pedro Pereira, and João F. Martins. "A survey on power grid faults and their origins: A contribution to improving power grid resilience." *Energies* 12, no. 24 (2019): 4667.

[71] Northcote-Green, James, and Robert G. Wilson. *Control and automation of electrical power distribution systems*. CRC press, 2017.

[72] Chowdhury, Ali, and Don Koval. *Power distribution system reliability: practical methods and applications*. John Wiley & Sons, 2011.

[73] Schuerger, Robert, Robert Arno, and Neal Dowling. "Why existing utility metrics do not work for industrial reliability analysis." *IEEE Transactions on Industry Applications* 52, no. 4 (2016): 2801-2806.

[74] Okorie, P. U., U. O. Aliyu, B. Jimoh, and S. M. Sani. "Reliability indices of electric distribution network system assessment." *Journal of Electronics and Communication Engineering Research* 3, no. 1 (2015): 01-06.

[75] LaCommare, Kristina Hamachi, Joseph H. Eto, Laurel N. Dunn, and Michael D. Sohn. "Improving the estimated cost of sustained power interruptions to electricity customers." *Energy* 153 (2018): 1038-1047.

[76] Poudineh, Rahmatallah, and Tooraj Jamasb. "Electricity supply interruptions: sectoral interdependencies and the cost of energy not served for the Scottish economy." *The Energy Journal* 38, no. 1 (2017): 51-76.

[77] Sinsel, Simon R., Rhea L. Riemke, and Volker H. Hoffmann. "Challenges and solution technologies for the integration of variable renewable energy sources—a review." *Renewable energy* 145 (2020): 2271-2285.

[78] Clavijo-Blanco, José Antonio, and José Antonio Rosendo-Macías. "Failure rates in distribution networks: Estimation methodology and application." *Electric power systems research* 185 (2020): 106398.

[79] Campbell, Richard J., and Sean Lowry. "Weather-related power outages and electric system resiliency." *Washington, DC: Congressional Research Service, Library of Congress*, 2012.

[80] Bou-Harb, Elias, Claude Fachkha, Makan Pourzandi, Mourad Debbabi, and Chadi Assi. "Communication security for smart grid distribution networks." *IEEE Communications Magazine* 51, no. 1 (2013): 42-49.

[81] Etherden, Nicholas, and Math HJ Bollen. "Overload and overvoltage in low-voltage and medium-voltage networks due to renewable energy–some illustrative case studies." *Electric power systems research* 114 (2014): 39-48.

[82] Fang, Xi, Satyajayant Misra, Guoliang Xue, and Dejun Yang. "Smart grid—The new and improved power grid: A survey." *IEEE communications surveys & tutorials* 14, no. 4 (2011): 944-980.

[83] Davidson, Innocent E. "Utility asset management in the electrical power distribution sector." In 2005 *IEEE power engineering society inaugural conference and exposition in Africa*, pp. 338-343. IEEE, 2005.

[84] Al-Rubaye, Saba, Ekhlas Kadhum, Qiang Ni, and Alagan Anpalagan. "Industrial internet of things driven by SDN platform for smart grid resiliency." *IEEE Internet of Things Journal* 6, no. 1 (2017): 267-277.

[85] Daily, Jim, and Jeff Peterson. "Predictive maintenance: How big data analysis can improve maintenance." *Supply chain integration challenges in commercial aerospace: a comprehensive perspective on the aviation value chain* (2017): 267-278.

[86] Li, Weilin, Antonello Monti, and Ferdinanda Ponci. "Fault detection and classification in medium voltage DC shipboard power systems with wavelets and artificial neural networks." *IEEE Transactions on Instrumentation and Measurement* 63, no. 11 (2014): 2651-2665.

[87] Du Toit, Willem. "DistriBution automation and how it directly contributes to the smart grid concept." *Water and Energy International* 66, no. 4 (2009): 65-69.

[88] Adefarati, Temitope, and Ramesh C. Bansal. "Integration of renewable distributed generators into the distribution system: a review." *IET Renewable Power Generation* 10, no. 7 (2016): 873-884.

[89] Younesi, Abdollah, Hossein Shayeghi, Zongjie Wang, Pierluigi Siano, Ali Mehrizi-Sani, and Amin Safari. "Trends in modern power systems resilience: State-of-the-art review." *Renewable and sustainable energy reviews* 162 (2022): 112397.

[90] Ravi, Kumar, and Nand Lal Shah. "A Review on Power Quality Issues and Reactive Power Compensation System." *Research Journal of Engineering Technology and Medical Sciences* (ISSN: 2582-6212) 5, no. 03 (2022).

[91] Wu, Yingjun, Zhiwei Lin, Chengjun Liu, Tao Huang, Yuyang Chen, Yingtao Ru, and Jinjuzheng Chen. "Resilience enhancement for urban distribution network via risk-based emergency response plan amendment for ice disasters." *International Journal of Electrical Power & Energy Systems* 141 (2022): 108183.

[92] Kayal, Partha. "Resiliency improvement in power distribution infrastructure employing distributed generation and switches-a review summary." *Energy, Ecology and Environment* 8, no. 3 (2023): 195-210.

[93] Huang, Zhao, Pengbo Ma, Mengmeng Wang, Baling Fang, and Ming Zhang. "A Hierarchical Strategy for Multi-Objective Optimization of Distribution Network Considering DGs and V2G-Enabled EVs Integration." *Frontiers in Energy Research* 10 (2022): 869844.

[94] Kaushik, Ekata, Vivek Prakash, Om Prakash Mahela, Baseem Khan, Adel El-Shahat, and Almoataz Y. Abdelaziz. "Comprehensive overview of power system flexibility during the scenario of high penetration of renewable energy in utility grid." *Energies* 15, no. 2 (2022): 516.

[95] Kabeyi, Moses Jeremiah Barasa, and Oludolapo Akanni Olanrewaju. "Sustainable energy transition for renewable and low carbon grid electricity generation and supply." *Frontiers in Energy research* 9 (2022).

[96] Hasan, Mohammad Kamrul, AKM Ahasan Habib, Zarina Shukur, Fazil Ibrahim, Shayla Islam, and Md Abdur Razzaque. "Review on cyber-physical and cyber-security system in smart grid: Standards, protocols, constraints, and recommendations." *Journal of Network and Computer Applications* 209 (2023): 103540.

[97] Mortensen, Lasse Kappel, Hamid Reza Shaker, and Christian T. Veje. "Relative fault vulnerability prediction for energy distribution networks." *Applied Energy* 322 (2022): 119449.

[98] Shi, Qingxin, Wenxia Liu, Bo Zeng, Hongxun Hui, and Fangxing Li. "Enhancing distribution system resilience against extreme weather events: Concept review, algorithm summary, and future vision." *International Journal of Electrical Power & Energy Systems* 138 (2022): 107860.

[99] Shafik, M. B., Zakaria MS Elbarbary, Bu Siqi, Ahmed M. Azmy, and Mohamed G. Hussien. "Distribution networks reliability assessment considering distributed automation system with penetration of DG units and SOP devices." *Energy Reports* 9 (2023): 6199-6210.

[100] Watitwa, Jeff Kimasere. "State Estimation in Active Distribution Systems: Comparison Between Weighted Least Squares and Extended Kalman Filter Algorithms." (2022).

[101] Liang, Xiaodong, Md Abu Saaklayen, Mosayeb Afshari Igder, Shah Mohammad Rezwanul Haque Shawon, Sherif O. Faried, and Mehrnoosh Janbakhsh. "Planning and service restoration through microgrid formation and soft open points for distribution network modernization: A review." *IEEE Transactions on Industry Applications* 58, no. 2 (2022): 1843-1857.

[102] Suhaimy, Nurshazlina, Nurul Asyikin Mohamed Radzi, Wan Siti Halimatul Munirah Wan Ahmad, Kaiyisah Hanis Mohd Azmi, and M. A. Hannan. "Current and future communication solutions for smart grids: A review." *IEEE Access* 10 (2022): 43639-43668.

[103] De La Cruz, Jorge, Eduardo Gómez-Luna, Majid Ali, Juan C. Vasquez, and Josep M. Guerrero. "Fault location for distribution smart grids: Literature overview, challenges, solutions, and future trends." *Energies* 16, no. 5 (2023): 2280.

[104] Prenc, Rene, Michele Rojnić, Dubravko Franković, and Saša Vlahinić. "On the development of overcurrent relay optimization problem for active distribution networks." *Energies* 15, no. 18 (2022): 6528.

[105] Peter, Geno, Albert Alexander Stonier, Punit Gupta, Daniel Gavilanes, Manuel Masias Vergara, and Jong Lung sin. "Smart fault monitoring and normalizing of a power distribution system using IoT." *Energies* 15, no. 21 (2022): 8206.

[106] Stefanidou-Voziki, P., Nikolaos Sapountzoglou, Bertrand Raison, and José Luis Dominguez-Garcia. "A review of fault location and classification methods in distribution grids." *Electric power systems research* 209 (2022): 108031.

[107] Baba, Maveeya, Nursyarizal Nor, Aman Sheikh, Grzegorz Nowakowski, Faisal Masood, Masood Rehman, Muhammad Irfan, Ahmed Amirul Arefin, Rahul Kumar, and Baba Momin. "A review of the importance of synchrophasor technology, smart grid, and applications." *Bulletin of the Polish Academy of Sciences Technical Sciences* (2022): e143826-e143826.

[108] Vahidi, Saghar, Mohsen Ghafouri, Minh Au, Marthe Kassouf, Arash Mohammadi, and Mourad Debbabi. "Security of wide-area monitoring, protection,

and control (WAMPAC) systems of the smart grid: A survey on challenges and opportunities." *IEEE Communications Surveys & Tutorials* (2023).

[109] Muthiah, Geethanjali, Meenakshi Devi Manivannan, Hemavathi Ramadoss, and Sharmeela Chenniappan. "Distribution Phasor Measurement Units (PMUs) in Smart Power Systems." *Artificial Intelligence-based Smart Power Systems* (2023): 311-325.

[110] Bu, Siqi, Lasantha Gunaruwan Meegahapola, Darshana Prasad Wadduwage, and Aoife M. Foley. "Stability and dynamics of active distribution networks (ADNs) with D-PMU technology: A review." *IEEE Transactions on Power Systems* 38, no. 3 (2022): 2791-2804.

[111] Gargoom, Ameen, Mohammed Elmusrati, and Ahmed Gaouda. "Enhancing the operation of smart inverters with PMU and data concentrators." *International Journal of Electrical Power & Energy Systems* 140 (2022): 108077.

[112] Kersting, William H. "Radial distribution test feeders." In 2001 *IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No. 01CH37194)*, vol. 2, pp. 908-912. IEEE, 2001.

[113] Radial Distribution Test Feeders. Available online: http://ewh.ieee.org/soc/pes/dsacom/testfeeders.html (accessed on 13 November 2022).

[114] Digsilent Powerfactory 2022 Technical References. Available online: https://www.digsilent.de/en/powerfactory-download (accessed on 13 November 2022).

[115] IEEE Tutorial Course on Distribution Automation; 88 EH0280-8 PWR; IEEE Power Engineering Society: Piscataway, NJ, USA, 1988.

[116] IEEE Tutorial Course on Power Distribution Planning; 92 EHO 381-6 PWR; IEEE Power Engineering Society: Piscataway, NJ, USA, 1992.

[117] Birt, Kenneth A., James J. Graffy, John D. McDonald, and A. H. El-Abiad. "Three phase load flow program." *IEEE transactions on power apparatus and systems* 95, no. 1 (1976): 59-65.

[118] Chen, T-H., M-S. Chen, K-J. Hwang, Paul Kotas, and Elie A. Chebli. "Distribution system power flow analysis-a rigid approach." *IEEE Transactions on power delivery* 6, no. 3 (1991): 1146-1152.

[119] Chen, T-H., M-S. Chen, Toshio Inoue, Paul Kotas, and Elie A. Chebli. "Three-phase cogenerator and transformer models for distribution system analysis." *IEEE Transactions on power delivery* 6, no. 4 (1991): 1671-1681.

[120] Lin, Whei-Min, and Jen-Hao Teng. "Three-phase distribution network fast-decoupled power flow solutions." *International Journal of Electrical Power & Energy Systems* 22, no. 5 (2000): 375-380.

[121] Teng, Jen-Hao, and Chuo-Yean Chang. "A novel and fast three-phase load flow for unbalanced radial distribution systems." *IEEE Transactions on Power Systems* 17, no. 4 (2002): 1238-1244.

[122] Kotha, Sravan Kumar, Bhooshan Rajpathak, Bhuvanagiri Ramesh, and M. K. Khedkar. "Optimal Placement Of Micro-PMUs for Real-time Monitoring of Inter-Connected Smart Distribution Networks." In 2022 2nd *Asian Conference on Innovation in Technology (ASIANCON)*, pp. 1-5. IEEE, 2022.

[123] Tahabilder, Anik, Pronob K. Ghosh, Soumesh Chatterjee, and Noorjahan Rahman. "Distribution system monitoring by using micro-PMU in graph-theoretic

way." In 2017 *4th International Conference on Advances in Electrical Engineering (ICAEE)*, pp. 159-163. IEEE, 2017.

[124] Chen, Xuebing, Tengpeng Chen, King Jet Tseng, Yuhao Sun, and Gehan Amaratunga. "Hybrid approach based on global search algorithm for optimal placement of μPMU in distribution networks." In 2016 *IEEE innovative smart grid technologies-Asia (ISGT-Asia)*, pp. 559-563. IEEE, 2016.

[125] Jamil, Emad, Mohd Rihan, and M. A. Anees. "Towards optimal placement of phasor measurement units for smart distribution systems." In 2014 *6th IEEE Power India International Conference (PIICON)*, pp. 1-6. IEEE, 2014.

[126] Silva, James A., Hamed B. Funmilayo, and Karen L. Bulter-Purry. "Impact of distributed generation on the IEEE 34 node radial test feeder with overcurrent protection." In 2007 39th *North American Power Symposium*, pp. 49-57. IEEE, 2007.

[127] Shahsavari, Alireza, Mohammad Farajollahi, Emma Stewart, Alexandra von Meier, Lilliana Alvarez, Ed Cortez, and Hamed Mohsenian-Rad. "A data-driven analysis of capacitor bank operation at a distribution feeder using micro-PMU data." In 2017 *IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1-5. IEEE, 2017.

[128] Short, T.A. *Electric Power Distribution Handbook*, 2nd ed.; CRC Press: Boca Raton, FL, USA, 2014.

[129] Shahsavari, Alireza. *Data-Driven Analysis of Power Distribution Synchrophasors with Applications to Situational Awareness, Load Modeling, and Reliability* , University of California, Riverside, 2019.

[130] Hasan, Mohammad Kamrul, AKM Ahasan Habib, Shayla Islam, Mohammed Balfaqih, Khaled M. Alfawaz, and Dalbir Singh. "Smart grid communication networks for electric vehicles empowering distributed energy generation: Constraints, challenges, and recommendations." *Energies* 16, no. 3 (2023): 1140.

[131] Real-Time Application of Synchrophasors for ImprovingReliability. Available online: https://www.naspi.org/sites/default/files/reference_documents/rapir_final_20101017.pdf (accessed on 13 November 2022).

[132] Izadi, Milad, and Hamed Mohsenian-Rad. "A synchronized lissajous-based method to detect and classify events in synchro-waveform measurements in power distribution networks." *IEEE Transactions on Smart Grid* 13, no. 3 (2022): 2170-2184.

[133] Vosughi, Amirkhosro, Sanjeev Pannala, and Anurag K. Srivastava. "Event Detection, Classification and Localization in an Active Distribution Grid using Data-Driven System Identification, Weighted Voting and Graph." *IEEE Transactions on Smart Grid* (2022).

[134] Medattil Ibrahim, Abdul Haleem, Madhu Sharma, and Vetrivel Subramaniam Rajkumar. 2023. "Realistic μPMU Data Generation for Different Real-Time Events in an Unbalanced Distribution Network" *Energies* 16, no. 9: 3842

[135] Charles, A.A. Investigation of Methodologies for Fault Detection and Diagnosis in Electric Power System Protection (Thesis). Available online: https://etd.cput.ac.za/handle/20.500.11838/1273 (accessed on 1 December 2022).

[136] X. Huang, Z. Xie and X. Huang, "Fault Location of Distribution Network Base on Improved Cuckoo Search Algorithm," in *IEEE Access*, vol. 8, pp. 2272-2283, 2020

[137] T. -X. Ma, X. Duan, Y. Xu, R. -L. Wang and X. -Y. Li, "Research on Fault Location in DC Distribution Network Based on Adaptive Artificial Bee Colony Slime Mould Algorithm," in *IEEE Access*, vol. 11, pp. 62630-62638, 2023

[138] Z. Tong, S. Lanxiang, L. Jianchang, et al., “Fault diagnosis and location method for active distribution network based on artificial neural network,” *Electr. Power. Components Syst.*, vol. 46, pp. 985–996, 2018.

[139] I. Kiaei and S. Lotfifard, "Fault Section Identification in Smart Distribution Systems Using Multi-Source Data Based on Fuzzy Petri Nets," in *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 74-83, Jan. 2020

[140] Chen, T. "Fault location of distribution network with distributed power based on simulated annealing particle swarm optimization." *Electrical Technology* 20, no. 08 (2019): 59-63.

[141] Li, Guanbin, Qing Chen, and Jianlei Zhang. "Novel faulted section location method for distribution network based on status information of fault indicating equipment." *Applied Sciences* 10, no. 17 (2020): 5910.

[142] Pang, Qingle, Lin Ye, Houlei Gao, Xinian Li, Yangjie Wang, and Tong Cao. "Multi-timescale-based fault section location in distribution networks." *IEEE Access* 9 (2021): 148698-148709.

[143] Huang, Xiaoli, Zhenyu Xie, and Xinyi Huang. "Fault location of distribution network based on improved cuckoo search algorithm." *IEEE Access* 8 (2019): 2272-2283.

[144] Wang, Xuhai, Xiangyang Yu, Yuan Xue, Yong Zhu, and Jianing Fu. "Application of improved quantum genetic algorithm in fault location of distribution

network." In 2018 *IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, pp. 2524-2529. IEEE, 2018.

[145] Zhou, Ke, Qingrun Jin, Zhiyue Mo, Wei Tao, Jiekang Wu, and Zhen Lei. "An identification method for disturbance signal basing on support vector machine with optimized multi-universe algorithm." In 2023 3rd *International Conference on Intelligent Power and Systems (ICIPS)*, pp. 321-325. IEEE, 2023.

[146] Sun, Ye, Qing Chen, Dan Xie, Ning Shao, Wei Ding, and Yuzhan Dong. "Novel faulted-section location method for active distribution networks of new-type power systems." *Applied Sciences* 13, no. 14 (2023): 8521.

[147] Kersting, William H. "Distribution system modeling and analysis." In *Electric power generation, transmission, and distribution*, pp. 26-1. CRC press, 2018.

Curriculum Vitae

Abdul Haleem Medattil Ibrahim

(Senior Power System Consultant)

EXPERTISE- Power System (Research & Development): Power System Monitoring, Operation, Automation & Control |Real-Time Contingency Analysis | Smart, Micro & Future Grids| Intelligent Substations |Package Substations | Commissioning |Case Studies| Network Reliability Studies and Solutions | Fault Identification & Service Restoration |Power Failure Emergency | Strategic Planning | Outage Management | Operations Management |Conference & Workshop Coordination and Management | System Voltage Control |Power System Modelling| Real-Time Simulation | Research Writing |Mentoring.

EDUCATIONAL CREDENTIALS

- **Bachelor of Technology** in **Electrical & Electronics Engineering** from Calicut University, India (2008)
- **Master of Technology (Power System)** in Electrical Engineering from Singhania University, India (2013)
- **Pursuing Ph.D. (Power System)** in Electrical Engineering from the University of Petroleum & Energy Studies, India (2015-2024)

RESEARCH PUBLICATIONS

Journals/Conferences:

- 3 Scopus indexed Journal Articles
- 4 Scopus indexed IEEE Conference Articles

PATENTS FILED

Indian Patent:

- 4 Indian patents (filed)

PROFESSIONAL CONTOUR

Senior R&D Engineer -SGI, R&D CENTRE, Dubai Electricity & Water Authority (DEWA), UAE (2021 - Present)

Guest Researcher-Intelligent Electrical Power Grids Group Lab, T U Delft, Netherlands (Remote) (2022- 2024)

PhD Candidate, EEE Department, University of Petroleum & Energy Studies, India (2015 - 2024)

Shift In charge -Distribution Power-GO, Dubai Electricity & Water Authority, (DEWA), UAE (2010 - 2021)

Electrical - Design Engineer/Asst. Design Manager, ETA ASCON, Dubai, UAE (2009 - 2010)

Junior Electrical Design Engineer, SWAPNA ENTERPRISES, Hyderabad, INDIA (2008 - 2009)

PROFESSIONAL MEMBERSHIPS

- **IEEE Power and Energy Society** Member
- **IEEE Smart Grid Community** Member
- **IEEE UAE Chapter** Member
- **IEEE Industry Application Society** Member
- **International Society of Research and Development (ISRD)** Life Member
- **International Association of Engineers (IAENG)** Member
- **DEWA Certified Grid Operations Engineer**

SOFTWARE KNOWLEDGE

Power System Research /lab tools:	DIgSILENT PowerFactory, SCADA (ABB &Siemens), ETAP, RSCAD/RTDS, OPAL-RT, EDWIN XP, PLC, MATLAB, Electrical CAD
Lighting Design Software:	Dialux, Relux
Operating Systems:	Windows
Programming Languages:	C, C++
Applications:	MS Office

List of Publications

Articles Published in Scopus Indexed Journals

1. **Abdul Haleem M I**, Madhu Sharma, and Vetrivel Subramaniam Rajkumar. "Realistic μPMU Data Generation for Different Real-Time Events in an Unbalanced Distribution Network." *Energies* 16, no. 9 (2023): 3842. (Impact factor: 3.252, Scopus, SCIE (Web of Science)) **(Status: Published)**.

2. **Abdul Haleem M I**, Madhu Sharma, and Vetrivel Subramaniam Rajkumar. "Integrated Fault Detection, Classification and Section Identification (I-FDCSI) Method for Real Distribution Networks Using μPMUs." *Energies* 16, no. 11 (2023): 4262., (Impact factor: 3.252, Scopus, SCIE (Web of Science)) **(Status: Published)**.

3. **Abdul Haleem M I**, Sajan, K. S, Tareg Ghaoud, Subramaniam Rajkumar, V, & Madhu Sharma, "Incipient Fault Detection in Power Distribution Networks: Review, Analysis, Challenges and Future Directions", *IEEE Access* (2024), (Impact factor: 3.4, Scopus)**(Status: Published)**.

Articles Published in IEEE Conferences

1. **Abdul Haleem M I**, Madhu Sharma, K S Sajan and K N Dinesh Babu, "A Comparative Review of Fault Location/Identification Methods in Distribution

Networks", In *Proceedings of IEEE Advanced Research in Engineering Science Conference*, Dubai, 15th June 2018, pp. 1-6. (Scopus,SCIE (Web of Science)) **(Status: Published)**.

Plagiarism Certificate and Similarity Index Report

UPES
UNIVERSITY OF TOMORROW

PLAGIARISM CERTIFICATE

1. I Dr. Madhu Sharma (Internal Guide), - (Co Guide/ External Guide) Certify that the Thesis titled Fault Classification and Section Identification in Distribution Network for Faster Service Restoration

   Submitted by scholar Mr/ ~~Ms~~ Abdul Haleem M I having SAP ID 500043732 has been run through a Plagiarism Check Software and the Plagiarism Percentage is reported to be 8 %.

2. Plagiarism Report generated by the Plagiarism Software is attached.

Madhu Sharma

Signature of the Internal Guide

-

Signature of External Guide/ Co Guide

Haleem M I

Signature of the Scholar

ah

ORIGINALITY REPORT

8%	5%	6%	1%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	creativecommons.org Internet Source	1%
2	doaj.org Internet Source	1%
3	repository.tudelft.nl Internet Source	1%
4	www.naspi.org Internet Source	<1%
5	Md Shafiullah, Mohammad Ali Abido. "A Review on Distribution Grid Fault Location Techniques", Electric Power Components and Systems, 2017 Publication	<1%
6	www.researchgate.net Internet Source	<1%
7	Submitted to Grand Canyon University Student Paper	<1%
8	Jen-Hao Teng, Chuo-Yean Chang. "A novel and fast three-phase load flow for unbalanced	<1%