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**BRAIN-INSPIRED ARTIFICIAL INTELLIGENCE
FOR ADVANCED MICROGRID PROTECTION**

**BY
JORGE ARMANDO DE LA CRUZ SAAVEDRA**

PhD Thesis 2024



AALBORG UNIVERSITY
DENMARK

BRAIN-INSPIRED ARTIFICIAL INTELLIGENCE FOR ADVANCED MICROGRID PROTECTION

PhD Thesis 2024

**BY
JORGE ARMANDO DE LA CRUZ SAAVEDRA**



AALBORG UNIVERSITY
DENMARK

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Curriculum Vitae



Jorge De La Cruz completed his bachelor's degree in electrical engineering at Universidad del Valle in Colombia in 2012. He continued to acquire a master's degree from Universidad Nacional de Colombia Sede Medellín in 2021. Later that year, he continued his PhD studies at the Center for Research on Microgrids (CROM) at Aalborg University. His PhD study, guided by Prof. Josep M. Guerrero, Assistant Prof. Najmeh Bazmohammadi, and Prof. Juan C. Vasquez, focuses on brain modeling for microgrid protection and control. Additionally, Jorge spent six months in the Division of Cognitive and Auditory Neuroscience, Institute of Neuroscience of Castilla y León (INCYL), University of Salamanca in Spain, hosted by Prof. Manuel Sanchez Malmierca. His research focuses on the use of brain-inspired artificial intelligence approaches to microgrid protection system and control, fault locations, and adaptive protections.

Curriculum vitae

Abstract

Researchers have been focusing on comprehending brain theories and taking cues from natural evolution and human intelligence. The goal is to develop devices, techniques, and methodologies to tackle societal problems. The synergy between neuroscience and artificial intelligence (AI) has enhanced our understanding of language, cognitive processing, learning strategies, sensory systems, and neural processes. Scientific, industrial, and societal improvements have all benefited from neuroscience insights.

While computational neuroscientists have developed several neural circuit models, there is still limited validation of these models outside of neuroscience, mainly in energy systems. Developing machine learning (ML) algorithms that can continuously learn in real-life scenarios and manage dynamic datasets for industrial applications remains an arduous task. Though AI-based solutions have demonstrated promise in several energy systems, current approaches face issues with biological realism, energy efficiency, high computing complexity, flexibility, and limited online learning capabilities.

Microgrids (MGs), characterized by their decentralized architecture and complex control systems, are a paradigm shift in the industrial and energy sectors. To provide autonomous and self-sufficient energy systems and facilitate optimal operation management, these intricate energy systems integrate a variety of components, such as cyber-physical control devices, smart energy storage units, and distributed energy resources (DERs). By smoothly switching between isolated and grid-connected modes, MGs can dynamically modify their operating mode, improving power supply efficiency and resilience. Their intrinsic flexibility, however, creates specific challenges that call for various monitoring and control techniques to guarantee trustworthy operation, especially in the face of variable voltages, currents, and frequencies. Furthermore, uncertainties remain regarding their bidirectional power flow, fault current limitations, and dynamic behavior.

The purpose of this PhD thesis is to investigate how neuroscience-inspired algorithms could potentially overcome these obstacles and support MGs to reach their full potential. First, it examines the fault location techniques in Smart Grids (SGs) to identify challenges, requirements, and potential

Abstract

solutions. Second, it analyzes current communication systems and AI-based methods for protecting MGs, focusing on networked microgrid protection strategies. Third, since the integration of an AC MG in a distribution system causes coordination issues in the protection system, an adaptive protection strategy is suggested to address these issues. Inspired by the remarkable automation and self-defense mechanisms in human brains, this thesis also explores different strategies to overcome the shortcomings of AI-based solutions.

This study explores the application of fundamental and theoretical amygdala brain functions as well as the predictive coding inference process to develop innovative AI strategies for MG protection that are founded in neuroscience. It evaluates the application and challenges of brain-inspired learning strategies, such as emotional learning, in the field of MGs. The Conclusion section summarizes the thesis outcome and makes recommendations for potential future research directions.

Resumé

Forskere har i de seneste år fokuseret på at forstå hjerneteorier og har taget inspiration fra naturlig evolution og menneskelig intelligens. Målet er at skabe ressourcer, strategier og metoder til at løse samfundsproblemer. Vores viden om sprog, kognitiv behandling, indlæringsstrategier, sensoriske systemer og neurale processer er blevet forbedret takket være integrationen af neurovidenskab og kunstig intelligens. Neurovidenskabelige indsigter har hjulpet videnskabelige, kommercielle og samfundsmæssige fremskridt.

Computational neuroscientists har lavet mange neurale kredsløbsmodeller, men der er kun lidt validering uden for neurovidenskab, især i energisystemer. Det er stadig en udfordrende opgave at udvikle algoritmer for maskinlæring (ML), der kan lære kontinuerligt i virkelige scenarier og håndtere dynamiske datasæt til industrielle applikationer. Biologisk realisme, energieffektivitet, høj computerkompleksitet, fleksibilitet og begrænsede online læringsmuligheder er problemer, som de nuværende tilgange står over for, selvom AI-baserede løsninger har vist sig at være lovende i flere energisystemer.

Microgrids (MG's) er et paradigmeskifte i både industri- og energisektoren på grund af deres decentraliserede arkitektur og komplekse kontrolsystemer. Disse sofistikerede energisystemer består af en række komponenter, herunder cyberfysiske kontrolenheder, smarte energilagringenheder og distribuerede energiressourcer (DER's), for at yde optimal og autonom energistyring. MG's er i stand til dynamisk at ændre deres driftstilstand ved regelmæssigt at skifte mellem nettilsluttede og isolerede tilstande. Dette forbedrer strømforsyningens effektivitet og modstandsdygtighed. Men deres naturlige fleksibilitet giver nogle problemer, der kræver en række overvågnings- og kontrolmetoder for at sikre pålidelig drift selv under variable spændinger, strømme og frekvenser. Derudover er deres tovejsstrøm, fejlstrømsbegrænsninger og dynamiske adfærd stadig usikre.

Denne ph.d.-afhandling undersøger, hvordan neurovidenskabsinspirerede algoritmer kan overvinde disse problemer og hjælpe MG's med at realisere deres fulde potentiale. Først ser den på fejllokaliseringsmetoderne i Smart Grids (SG's) for at finde problemer, mulige løsninger og fremtidige arbejder.

Resumé

For det andet fokuserer vi på kommunikationsstrategier og AI-baserede metoder til at beskytte MG's. For det tredje, efter at en AC MG er blevet integreret i et distributionssystem, foreslås en adaptiv beskyttelsestilgang til at løse de koordinationsproblemer, der opstår i beskyttelsessystemet. Denne forskning undersøger også forskellige måder at overvinde AI-baserede løsninger på grund af de bemærkelsesværdige automatiserings- og selvforsvarsmekanismer i menneskelige hjerner. Denne undersøgelse undersøger, hvordan man bruger grundlæggende og teoretiske amygdala-hjernefunktioner samt prædiktive coding-inferensprocessen for at udvikle innovative AI-strategier til MG-beskyttelse, der er baseret på neurovidenskab. Den evaluerer anvendelsen og udfordringerne ved hjerneinspirerede læringsstrategier, såsom følelsesmæssig læring, inden for MG'er. Afslutningsafsnittet opsummerer afhandlingens resultater og giver anbefalinger til mulige fremtidige forskningsretninger

Preface

Humans have always been interested in learning about and studying the brain. A superior, intelligent, and efficient machine that goes beyond what we currently understand. Humans have been motivated to create Artificial Intelligence (AI) approaches to advance our understanding of the human brain and to expand our quality of life. But to facilitate the quick advancement of AI in our world, several ethical and technological advancements must be achieved. By presenting research on some brain regions that are recognized to be experts in self-defense, automation, and inference, this thesis aims to advance AI in energy system applications.

The thesis has been submitted in fulfillment of the requirements of AAU Energy at Aalborg University for a Doctor of Philosophy in Energy Engineering. The research focuses on brain-inspired solutions for protection systems, aiming to contribute to the rapidly developing field of brain modelling in energy systems. The research articles included in this dissertation result from the author's research activities and collaborations with other researchers during their PhD studies. The conducted research activities are presented in the first section of the thesis, followed by the resulting publications in the second. The outcomes of the PhD research "Brain-inspired artificial intelligence for advanced Microgrid protection" are summarized in this thesis. For this research study, I received direction and mentoring from my Professors Josep M. Guerrero, and Juan C. Vasquez.

From November 1, 2021, to July 31, 2024, this journey has brought significant changes to my life. It began with the challenging but fulfilling decision to leave my family and country to pursue my dreams abroad, a dream that materialized much faster than I had anticipated. During this period, I achieved several milestones, publishing my first papers in prestigious journals and participating in important conferences, initiating my research on brain behavior, and studying abroad at the Cognitive and Auditory Neuroscience Laboratory (CANELab) at the Universidad de Salamanca, under the supervision of Professor Manuel Sanchez Malmierca.

With immense pleasure, I share this work in the hopes that it will stimulate additional developments and advance a more secure and safe energy

Preface

environment, benefiting academics, professionals, and industry decision-makers

Acknowledgement

Above all, I want to thank God; without you and your blessings, none of this journey would have been possible. I am extremely grateful to my wife, whose resolute support, tolerance, friendship during both happy and challenging times and faith in our common goals have served as my pillar of sustenance. You are aware that there are no words that adequately express my gratitude or communicate how much I admire and love you. My profound gratitude also extends to my parents, siblings, and other family members. Throughout my life, I have found strength and drive in their unwavering love, support, and believe in me.

I express my gratitude to Josep, and Juan, my supervisors, for giving me the wonderful chance to work with CROM. Their outstanding leadership, encouragement, and perceptive supervision were essential to finishing my study. My sincere gratitude also goes out to Professors Najmeh Bazmohammadi, Gibran David Agundis, Sanjay Chaudhary, Eduardo Gomez, John Candelo, and Eduardo Marles for their encouragement, wise counsel, unwavering availability, and feeling of responsibility—especially during trying times. Drs. Sen Tan, Amir Basati, Manuel Barrios, Babak Arbab Zavar, and Diptish Saha, are also appreciated for their thoughtful conversations and suggestions. My gratitude also goes to Professor Manuel Sanchez Malmierca for giving me the chance to work at the INCYL, located in Salamanca, Spain. My INCYL study abroad program gave me new insights and inspired me to concentrate on developing new project aspects.

My sincere gratitude goes out to the CROM Research group's friends and colleagues as well as the IT support and administrative teams at AAU. Their collaboration, excitement, and team spirit made the challenging task seem less stressful and more pleasurable. I also thank Colfuturo and the Colombian Ministerio de Ciencia y Tecnologia (MinCiencias) for their financial assistance with my PhD. I am especially thankful to the Otto Mønsted Fond, Denmark, for helping me start this incredible adventure by providing funding for conferences and possibilities for study abroad opportunities

Jorge De La Cruz
Aalborg University, September 2024.

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Thesis Details

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Ph.D. Student: Jorge Armando De La Cruz Saavedra
Main Supervisor: Prof. Josep M. Guerrero, Aalborg University
Co-supervisors: Prof. Juan C. Vasquez, Aalborg
Assistant Prof. Najmeh Bazmohammadi, Aalborg University

The following papers make up the main body of this thesis.

- [A] Jorge De La Cruz, Eduardo Gómez-Luna, Majid Ali, Juan C. Vasquez, and Josep M. Guerrero. 2023. "Fault Location for Distribution Smart Grids: Literature Overview, Challenges, Solutions, and Future Trends" *Energies* 16, no. 5: 2280, 2023 [J1].
- [B] Jorge De La Cruz, Eduardo Gómez-Luna, John Edwin Candelo Becerra, Juan C. Vasquez, and Josep M. Guerrero, "Adaptive Multi-Agent-Zonal Protection Scheme for AC Microgrids," *Conference, European Conference on Power Electronics and Applications (EPE'23 ECCE Europe)*, Aalborg, Denmark, September 2023, [C1].
- [C] Jorge De La Cruz, Ying Wu, John Edwin Candelo Becerra, Juan C. Vasquez, and Josep M. Guerrero "Review of Networked Microgrid Protection: Architectures, Challenges, Solutions, and Future Trends," *CSEE Journal of Power and Energy Systems*, vol. 10, no. 2, pp. 448-467, 2024 [J2].
- [D] Jorge De La Cruz, Sen Tan, Diptish Saha, Najmeh Bazmohammadi, Juan C. Vasquez, and Josep M. Guerrero, "Brain Modeling for Microgrid Control and Protection: State of the Art, Challenges, and Future Trends," *IEEE Industrial Electronics Magazine, Early Access*, pp 2-13, 2024 [J3].

- [E] Jorge De La Cruz, Najmeh Bazmohammadi, Juan C. Vasquez, and Josep M. Guerrero, "Brain Amygdala Modelling for Microgrid Control and Protection," *Conference*, International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia 2024), Chengdu, China, May 2024, [C2].
- [F] Jorge De La Cruz, Patricia Franco, Eduardo Gómez-Luna, Najmeh Bazmohammadi, Juan C. Vasquez, Manuel S. Malmierca, and Josep M. Guerrero, "A Brain-Inspired Framework for Advanced Microgrid Protection and Control: A Theoretical Step Toward Self-healing system" *IEEE Transaction on Smart Grid*, vol. no. XX, pp. XXXX, 2024. (Under review).

These publications have been published in addition to the main papers.

- [1] Sen Tan, Jorge De La Cruz, Juan C. Vasquez, and Josep M. Guerrero, "Sensor Faults Detection in DC Microgrids based on Unknown Input Observer," *Conference*, European conference on Power Electronics and Applications (EPE'2023 ECCE Europe), Aalborg, Denmark, pp. 1-8, 2023.
- [2] Eduardo Gómez-Luna, Jorge De La Cruz, and Juan C. Vasquez, "New Approach for Validation of a Directional Overcurrent Protection Scheme in a Ring Distribution Network with Integration of Distributed Energy Resources Using Digital Twins" *Energies* 17, no. 7: 1677, 2024

Contents

Curriculum Vitae	iii
Abstract	v
Resumé	vii
Preface	ix
Acknowledgement	xi
Thesis Details	xiii
Chapter 1 Introduction	11
1.1 Motivation.	11
1.2 Background.....	12
1.3 Protection systems in distribution grids.....	13
1.3.1 Power Failures in distribution grids	13
1.3.2 Categories of Physical Components Power Failures.....	14
1.3.3 Conventional protection schemes in distribution grids	16
1.4 Microgrids protection architectures	19
1.4.1 Microgrids Protection challenges.....	20
1.4.1.1 AC microgrids' power failures.....	20
1.4.1.2 DC Microgrids' power failures	21
1.4.1.3 Hybrid Microgrids' power failures	21
1.4.1.4 Dynamic fault condition.....	21
1.4.1.5 Islanding Faults	22
1.4.1.6 Cyberattacks.....	23
1.4.2 Microgrids protection schemes	23
1.4.3 Communication and AI-based protection schemes for MGs	25
1.5 Networked Microgrid Protection schemes.....	27
1.5.1 What is a Networked Microgrid.....	27
1.5.2 Electrical transmission challenges	29
1.5.3 Interconnection system challenges.....	30
1.5.4 Interconnection technology challenges	31
1.6 Research Questions and Hypotheses.	33
1.7 Thesis 's Outline.	35
Chapter 2: Decentralized Adaptive Protection Scheme	39
2.1. Introduction	39

Contents

2.2.	Planning and sizing of the protection scheme.....	40
2.2.1.	System description	40
2.2.2.	Operating scenarios of the Microgrid	41
2.2.3.	Protection scheme feature and adjustment criteria.....	42
2.3.	Adaptive multi-agent Scheme.....	43
2.3.1.	System´s conceptualization.....	44
2.3.2.	Agents design procedure.....	45
2.3.3.	Multi-agent interface.....	48
2.4.	Simulation test validation and analysis of the protection scheme.....	49
2.4.1.	Proposed location of protective equipment.....	49
2.4.2.	Sizing of measurement current equipment (CTs)	51
2.4.3.	Operational protection assessment – Offline analysis.....	52
2.4.3.1.	Protection selectivity and operation	53
2.4.4.	Operational protection assessment – Online analysis	55
2.5.	Conclusions	58
Chapter 3: Emotional learning modelling for Microgrid Control and Protection		61
3.1.	Introduction	61
3.2.	Emotional Control	62
3.2.1.	Emotion-inspired AI for modeling and control approaches	64
3.2.2.	Emotion-inspired modeling and control techniques for industrial applications	64
3.3.	Microgrids and brain emotional control.	66
3.3.1.	Brain Emotional Learning for Microgrids application.....	68
3.3.2.	Brain Emotional Learning for Protection.....	71
3.3.3.	Hierarchical emotional control for MGs.	72
3.3.3.1	R-Complex primary control	72
3.3.3.2	Emotional Secondary control	72
3.3.3.3	Neo Tertiary control (EMS)	73
3.3.4.	Advantages and challenges of BEL applications	74
3.4.	Conclusions	76
Chapter 4. Brain-inspired model framework for Microgrids.....		77
4.1.	Introduction	77
4.2.	Amygdala theoretical framework and physiological behavior	78
4.2.1.	Foundations of the Amygdala theoretical Framework	79

Contents

4.2.1.1.	Components of the Amygdala	79
4.2.1.2.	Key connections and projections of the Amygdala	80
4.2.2.	Physiological behavior- Phases of fear condition and extinction.....	82
4.2.2.1.	Phase 1: Conditioning phase	82
4.2.2.2.	Phase 2: Suppression of fear response	83
4.2.2.3.	Phase 3: Fear response stabilization	84
4.2.3.	Amygdala models	84
4.3.	Predictive coding and inference learning.....	87
4.4.	Brain-inspired theoretical framework for Microgrids.....	91
4.4.1.	Brain Amygdala in Microgrids – Conceptual integration.....	92
4.4.1.1.	Parallels in components and connections: Amygdala and Microgrids	92
4.4.1.2.	Physiological perspectives: Modeling Amygdala behavior in Microgrids	94
4.4.2.	Brain-inspired modeling description.....	95
4.4.2.1.	Logical rules and subsystem description	98
4.4.3.	Analysis and validation of the concept	99
4.4.3.1.	Results	103
4.5.	Conclusions	106
Chapter 5. Closing remarks.....		109
5.1.	Overall conclusion.....	109
5.2.	Contributions	110
5.3.	Future work	112
Chapter 6: Literature List		115
6.1.	References	115

Part I

Extended Summary

Extended summary

List of Figures

Figure 1.1 <i>Power failures common types in distribution grids</i>	14
Figure 1.2 <i>List of physical components' power failures in a smart distribution grid [15]</i>	15
Figure 1.3 <i>MG's schematic representation</i>	20
Figure 1.4 <i>DCMG's fault classification</i>	21
Figure 1.5 <i>MG's fault location challenges [33]</i>	22
Figure 1.6 <i>AC-NMG Parallel architecture</i>	28
Figure 1.7 <i>DC-NMG Meshed architecture</i>	28
Figure 1.8 <i>Hybrid-NMG Ring architecture</i>	29
Figure 1.9 <i>Challenges on NMGs protection in the interconnected mode</i> ...	32
Figure 2.1 <i>Microgrid Test Model</i>	41
Figure 2.2 <i>Developed Role of the MG Intelligent System (RSIMG)</i>	44
Figure 2.3 <i>Diagram of sequence</i>	46
Figure 2.4 <i>Diagram of collaboration</i>	47
Figure 2.5 <i>Architecture of the solution</i>	48
Figure 2.6 <i>Interface window of the Multi-Agent</i>	48
Figure 2.7 <i>Schematic diagram of the solution</i>	49
Figure 2.8 <i>Location of the relays</i>	50
Figure 2.9 <i>Short Circuit values in normal operating conditions</i>	51
Figure 2.10 <i>Protection scheme settings 50/51</i>	52
Figure 2.11 <i>Rmain parameter's configuration</i>	53
Figure 2.12 <i>Relay operation curve in Zone 1</i>	53
Figure 2.13 <i>Protection scheme settings 50/51 - DER connected</i>	54
Figure 2.14 <i>Relay response curves for zone 1 fault in Islanded MG</i>	54
Figure 2.15 <i>Zone 1 fault dynamics in normal operation</i>	55
Figure 2.16 <i>Zone 1 fault dynamics in MG connected</i>	56
Figure 2.17 <i>Collaboration diagram developed in JADE</i>	56
Figure 2.18 <i>Multi-Agent System message during State 1 – MG connected</i>	57
Figure 2.19 <i>Zone 1 fault dynamics with new settings</i>	58
Figure 3.1 <i>Emotional brain regions</i>	62
Figure 3.2 <i>Schematic of the AMYG-OFC computational mode [131]</i>	63
Figure 3.3 <i>BEL structure proposes by [141].</i>	65
Figure 3.4 <i>Emotion-inspired computational models applications</i>	66
Figure 3.5 <i>Analogy between hierarchical control and brain emotional control</i>	67
Figure 3.6 <i>Triune brain and key brain emotional areas</i>	68
Figure 3.7 <i>Block diagram of BELBIC for MGs</i>	69

Figure 4.1 <i>Main components of the Amygdala</i>	80
Figure 4.2 <i>Amygdala´s connections and projections</i>	81
Figure 4.3 <i>Fear response behavior of the brain – representation [172], [180]</i>	83
Figure 4.4 <i>A graphic representation of the fear inhibition behavior of the brain [172], [180]</i>	84
Figure 4.5 <i>Amygdala connections and key behaviors</i>	85
Figure 4.6 <i>Canonical microcircuits - Cortex Hierarchical model proposed by [193]</i>	88
Figure 4.7 <i>Linking concepts SI, Th, HIP</i>	93
Figure 4.8 <i>Linking concepts IL & AMYG</i>	94
Figure 4.9 <i>Amygdala model architecture [172], [180]</i>	95
Figure 4.10 <i>Sensory Information and Thalamus Blocks</i>	96
Figure 4.11 <i>Hippocampus model - blocks and projections</i>	97
Figure 4.12 <i>Brain-inspired architecture</i>	98
Figure 4.13. <i>Schematic of the proposed system for validating the TH-IL interaction</i>	100
Figure 4.14 <i>VAE architecture. Latent Space dimension (Z)=10</i>	102
Figure 4.15 <i>Thalamus block result</i>	103
Figure 4.16 <i>IL block results</i>	104
Figure 4.17 <i>Thalamus block results during second validation</i>	105
Figure 4.18 <i>IL block results during the second validation</i>	105

List of Tables

Table 1-1 <i>International standards used for protection</i>	16
Table 1-2 <i>An overvie of the advantages and drawbacks of AI applied to MG protection</i>	26
Table 1-3 <i>Summary of the interconnection system challenges</i>	30
Table 1-4 <i>Advantages and drawbacks of interconnecting technologies</i>	31
Table 2-1 <i>Topological changes</i>	42
Table 2-2 <i>RMGD Protocol</i>	45
Table 2-3 <i>Service model</i>	46
Table 2-4 <i>Sizing of Current Transformer (CTs)</i>	52
Table 3-1 <i>Applications of BEL controllers in MGs</i>	68
Table 3-2 <i>Inputs of the AMYG connectionist model</i>	70
Table 4-1 <i>Amygdala nucle´s physiological behavior, foundations, and microcircuits</i>	85

List of symbols

Decentralized multi-agent-zonal protection approach.

$CTR's$	Current transformation ratio
I_{50}	Protection Tap_{50} current
I_{51}	Protection Tap_{51} current
I_F	Instantaneous current phase
$I_{ccmax3\phi}$	Maximum 3-phase short circuit current
I_{ins}	Instantaneous pickup current
I_{nom}	Nominal current
I_p	Pickup current
ms	Milliseconds
P_{DG}	Power generation source
P_{Load}	Nominal power of the load
Tap_{50}	Tap of the instantaneous unit
Tap_{51}	Tap for the phase of the timed units
T_{ins}	Instantaneous operation time
TMS	Time Multiplier Setting
t	Protection trip time

Brain – inspired artificial intelligence framework.

\hat{y}_i	Predicted value.
Σ_o	Probability distribution variance
Σ_s	prior distribution variance
KL_i	divergence computation for each latent space dimension
R_{BA1}	First projection from BA
R_{BA2}	Second projection from BA to the CeA
R_{CeA}	Action response or output response
R_{IL}	Projection from the IL
R_{ITCd}	Projection from dorsal ITC
R_{ITCv}	Projection from ventral ITC
R_{LA}	Projection from the LA
Th^{CS}	Conditioned input sends by the Th
Th^{US}	Unconditioned input sends by the Th

\hat{x}	Reconstructed input
y_i	i-th sample's actual value.
C	Constant term
F	Free energy
MSE	Mean squared error.
$RHIP$	Projection from the HIP to the BA
n	Number of samples in the dataset.
o	New tone or observation
$p(o s)$	sensory data likelihood
$p(s)$	Prior belief
s	Size of the tone
$v(s)$	function that associates hidden states with observations
x	Original input
\mathcal{N}	Normal distribution
μ	Mean
σ	Standard deviation

Acronyms

AC	Alternate current
ACL	Agent Communication Language
ACMG	AC Microgrid
AI	Artificial Intelligence
AMYG	Amygdala
ANN	Artificial Neural Networks
AP	Agent protection
APS	Adaptive protection scheme
ASIMG	Agent of the MG intelligent system
BA	Basal amygdala
BASIC	Brain's affective system
BEL	Brain Emotional learning
BELBIC	BEL Intelligent Control
BELPR	BEL-Based prediction model
BLA	Baso lateral amygdala
CB	Circuit Breaker
CC	Computational complexity
CeA	Centro Amygdala
CeL	Central Lateral Nucleus
CeM	Central medial nucleus
CHP	Combined Heat and Power
CROM	Center for Research on Microgrids
CS	Conditioned stimulus
CTR	Current Transformation Ratio
CTs	Current transformers
DC	Direct current
DCMG	DC Microgrid
DER	Distributed Energy Resources
DG	Distributed generator
DOCR	Directional overcurrent relays
EML	Emotion-augmented machine learning
EMS	Energy Management System
EMT	Electromagnetic Transient
EPS	Electric power system
ES	Emotional signals
ESSs	Energy Storage System
EV	Electric Vehicle

Acronyms

F	Free Energy
FFNN	Feed-forward neural networks
GA	Genetic algorithm
HCA	Hierarchical control architecture
HH	Hodgkin-Huxley
HIF	High Impedance faults
HIP	Hippocampus
IC	Information capacity
IEC	International Electrotechnical Commission
IED	Intelligent Electronic Device
IL	Infralimbic Cortex
ITC	Intercalated cell cluster
ITCd	Dorsal Intercalated cell cluster
ITCv	Ventral Intercalated cell cluster
KL	Kullback-Leibler
LA	Lateral amygdala
LDS	Local distribution system
LiAENN	Limbic-based artificial emotional neural network
LIF	Leaky Integrate and Fire
LV	Low Voltage
MAS	Multi agent system
MGCC	Microgrid central controller
MGs	Microgrids
ML	Machine Learning
MMG	Multi Microgrid
MO	Model Outputs
MSE	Mean Squared Error
MV	Medium Voltage
NMGs	Networked Microgrid Protection
OCR	Overcurrent protection relay
OFC	Orbito Frontal Cortex
P	Proportional
PCC	Point of commun coupling
PE	Prediction Errors
PI	Integral proportional
PID	Integral proportional derivative
PSO	Particle Swarm Optimization
PV	photovoltaic
RIED	Role of IED
RL	Reinforcement learning

Acronyms

RMDG	Role of measurement distributed generation
RML	Role of measurement load
RMPPC	Role of measured common coupling point
RSIMG	Role of the MG intelligent system
RTSim	Real-Time Simulation
SC	Sensory cortex
SCC	Short circuit currents
SGs	Smart Grids
SI	Sensory information
SIL	Software in the loop
SVM	Support Vector Machine
Th	Thalamus
US	Unconditioned stimulus
VAE	Variational Auto Encoders
VI	Variational Inference
VPRs	Virtual Protection Relays
WT	Wavelet Transform

Chapter 1 Introduction

1.1 Motivation.

Microgrids (MGs), characterized by their innovative control systems and decentralized architecture, are a paradigm shift in the energy sector. To deliver an autonomous and self-sufficient energy system and provide optimal operation management experience, these intricate energy systems integrate a variety of components, such as cyber-physical control devices, DER, and smart energy storage units. With this all-inclusive approach, MGs may smoothly switch between grid-connected and isolated operational modes by dynamically adapting their mode of operation. Their capacity to share resources with adjacent MGs or the main grid demonstrates how their flexibility promotes reliable and effective power supply [1].

Nevertheless, the inherent flexibility of MGs presents unique challenges. A different set of monitoring and control strategies is required due to their changing topology to guarantee stable operation despite fluctuating voltages, currents, and frequencies. Furthermore, although MGs have a great deal of potential to be crucial components of smart grids (SGs) and accelerators for the energy transition, questions continue to be raised about their dynamic behavior, bidirectional power flow, and fault current limitations. To address these issues and realize MGs' full potential, sophisticated self-healing and automation solutions must be developed. MGs may operate in a variety of locations and have dynamic arrangements, which makes their protection systems more complicated. A thorough assessment of various aspects is imperative to determine the appropriate response and measurement for protective devices in these autonomous systems. These aspects include investigating diverse failure conditions, environmental elements including temperature and humidity, and the ideal location of the protection devices to minimize their impact on MG operation during transitions [2]. A recent overview of MG protection issues and potential solutions may be found in [3], [4].

In power systems, there is a noticeable transition from conventional relay-based systems to cutting-edge virtual solutions and artificial intelligence (AI)-based techniques [5], [6]. Although most MG protection strategies currently in use rely on relay operation and control, software applications and AI are beginning to attract increasing attention due to their potential advantages.

These advanced techniques are capable of dynamically controlling MG operations in the event of disruptions and failures, obviating the requirement for large-scale relay deployments or periodic adjustments. Before being used in MGs, AI-based techniques still need to address several issues, including complexity, communication challenges, data accessibility, and the biological plausibility of the AI model itself.

Furthermore, inspiration from the brain's cognitive and emotional behavior in the development of protection systems for MGs is an exciting alternative for making intelligent protection decisions. This novel fusion of AI and brain-inspired algorithms has the potential to boost energy efficiency, improve MG control systems' online learning capabilities, and transform their systems of protection [7]. Several MG control techniques currently in use make advantage of fundamental brain concepts and behaviors [7], [8], [9], [10]. However, no methods use the brain's inherent self-defense capabilities for the protection of MGs. Through the application of fundamental theories of amygdala (AMYG) brain behavior and the brain's inference process, this research will enable the development of a theoretical framework that will offer a self-protection mechanism for MGs.

1.2 Background

This thesis's research was conducted as part of a development project at the CROM that was supported by Villum. The objective of the development project is to create an AI framework inspired by the cognitive and emotional performance of the human brain to conceptualize the next generation of MGs for self-defense protection and control. The secure and reliable operation of MGs and power systems is the responsibility of protection schemes. However, it is still difficult to determine the most effective plan of action for protecting the MGs under different fault scenarios because of their dynamic operational characteristics.

To overcome these barriers, it is essential to first understand the goals of protection strategies in distribution systems, the reasons behind power outages, the various categories of failures, and how outages affect various physical elements of the power grid, including distributed generation, transformers, and power converters. Additionally, defining the best approach requires a review of conventional protection schemes and current standards that provide recommendations on the impact of protection devices on the system.

A thorough understanding of MGs, including their protection system challenges, conventional protection methods, and cutting-edge tactics like AI-based and communication approaches, was also necessary for the project. The goal of these innovative tactics is to give MGs access to more sophisticated and autonomous alternatives. To assure the effective and reliable operation of MGs, there are still issues with these sophisticated techniques such as computational complexity and cybersecurity issues, which need to be resolved. Consequently, further research into innovative techniques is needed to improve MG performance. The study also investigates the use of networked MGs to improve the system's robustness and dependability. Part of this includes examining their topologies and the extra challenges these networked systems pose to protection systems. The ensuing sections will expand on these subjects, offering an in-depth analysis of protection goals, power failure causes, conventional and advanced protection schemes, and the role of interconnected MGs.

1.3 Protection systems in distribution grids

The role of distribution grid protection systems is to reduce the amount of time that a fault remains and the number of consumers that are impacted by it. In addition, disconnecting impacted equipment such as transformers, broken lines, or other equipment, protecting consumer devices, minimizing service outages to the smallest possible portion of the system, and preventing unnecessary service disruptions are all important goals. To prevent and stop system failure, protective systems need to be rigorous.

1.3.1 Power Failures in distribution grids

A few of the many factors that can cause failures in traditional distribution grids and SGs are natural events such as winds, lightning, storms, animal contact, falling trees, and overloads [11], [12], [13]. Two criteria can be used to further categorize "*an electrical fault*", which is described as "*an abnormal electrical current in the electrical power system*" [14], namely external faults such as phase-to-ground faults and internal faults such as fuel leakage in diesel generators are possible [11].

In addition, while categorizing power outages, the length of the outage and the condition of the grid at the moment of the disruption are considered. The authors in [11] lists the following categories:

- ❖ **Incipient failures:** This failure persists for a certain amount of time. Several methods, including the Laplace and Fourier wave transforms, are used to identify failures by altering the failure’s duration and amplitude. Additionally, methods based on impedance are used, which are useful in recognizing and classifying faults with subterranean cables [11].
- ❖ **Abrupt failures:** These failures are characterized as abrupt signal changes resulting from a failed power supply within the system. Digital process transforms and relays are commonly used to categorize and detect these errors; however, they are frequency-sensitive [11].
- ❖ **Intermittent failures:** These transient failures are quick, and they might be linked to a developing fault that becomes a more serious problem. Electric power system (EPS) nodes normally use carrier signal monitoring devices and distance relays to identify this kind of failure [11].

1.3.2 Categories of Physical Components Power Failures

A distribution system may experience two primary power failure categories: open circuit faults and short circuit faults [13]. For example, the union of two phases can cause an open fault; while broken conductors that lead to broken lines can cause a short-circuit fault [11]. Figure 3 shows the common kinds of power outages in SGs. Short circuit failures fall into two distinct categories: symmetric and asymmetric faults. Symmetric faults include three-phase ground faults (ABCG) and three-phase faults (ABC). Asymmetric faults include phase-to-phase (P-P), phase-to-ground (P-G), and faults that include two phases and the ground (P-P-G).

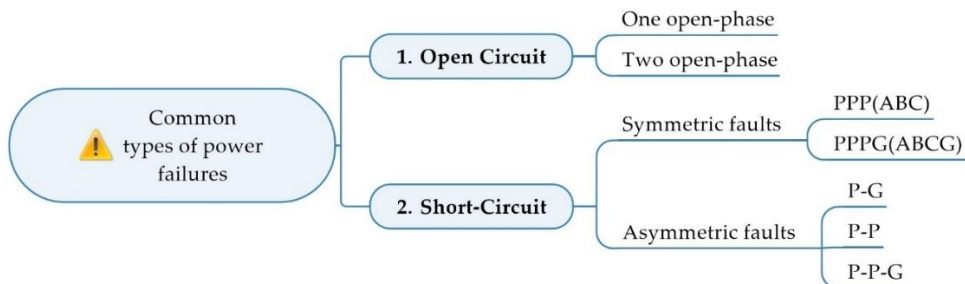


Figure 1.1 Common Power failure types in distribution grids

Synchronous machines and diesel generators may experience issues with the crankshaft, bearing, fuel leaks, stator, and rotor. Conventional power transformers are susceptible to damage and reduced dielectric capacity due to winding faults, core faults, and localized overheating. DER and power converters are not immune to the same faults that may compromise smart transformers, including open circuit and short circuit failures. Thermal runaway, ordinary wear and tear, and mechanical issues can affect subterranean cables in the distribution grid. Moreover, there are other causes of overhead line failure, such as short circuits, human errors, lightning strikes, and inadequate maintenance [15]. Lower voltage and current signals in DER resources may be the result of reduced output power from photovoltaic (PV) panel cell issues. Wind turbine problems can result in low generation efficiency, fluctuating voltage and current, and degradation [15]. Figure 1.2 lists many kinds of power outages in physical components indicated by [15].

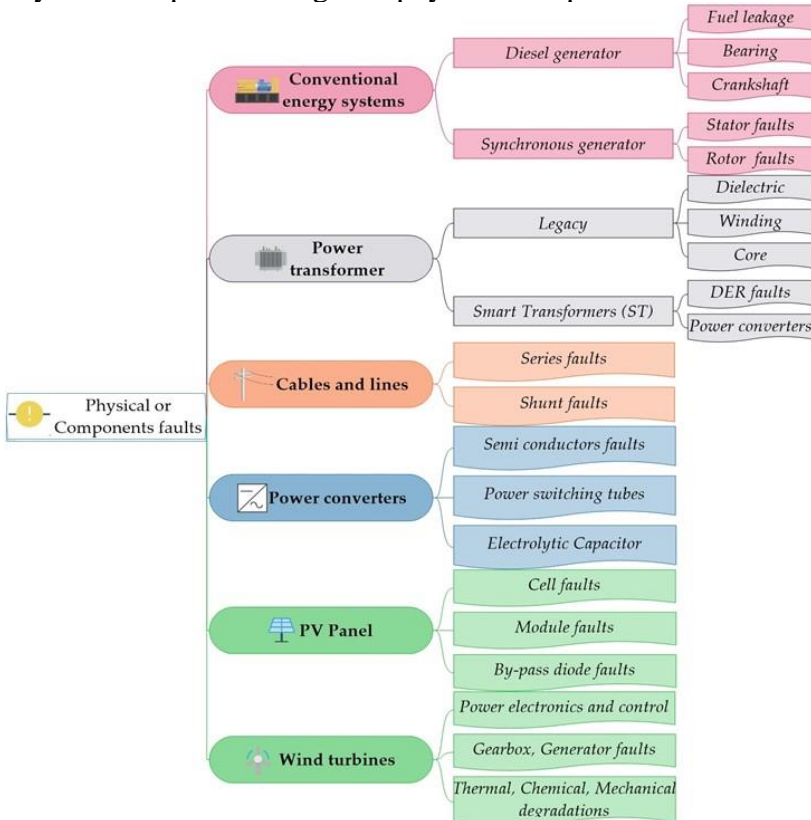


Figure 1.2 List of physical components' power failures in a smart distribution grid [15]

1.3.3 Conventional protection schemes in distribution grids

Distribution grids employ several protection strategies that protect several components, including transformers, motors, loads, feeders, and distribution lines. These traditional schemes have proven effective in mitigating frequency, voltage, and islanding amongst systems, as well as instability issues. Currently, several standards and guidelines specify the best practices to protect these components as well as the entire distribution system. The most widely used international standards for protection systems, including those for DER and MG protection, are displayed in Table 1.1. A thorough analysis of these standards can be found in [16]. Furthermore, there are diverse approaches employed by multiple nations, upon the domain specialist utilizing their expertise to protect the system.

Table 1-1 *International standards for protection*

Name	Applications	Features
IEEE C37.108 – 2002	Protection of Network Transformers	This guideline specifies how to use transformers and distributed resource protection devices in addition to applying grid protection elements.
IEEE C37.91- 2008	Protection power transformers	The guide's content is meant to assist protection engineers in using relays and other tools to protect transformers utilized in distribution and transmission systems.
IEEE C37.234-2009	Protective Relay applications to power system buses	This standard covers topics related to power bus protection and protection against manipulated relay input signals. Bus switching events, switch locations and availability, and the positions of current transformers and disconnectors are considered. There is also a detailed bus arrangement and application instructions available. It is mentioned that breaker failure protection is a part of bus protection.
IEEE C37.233-2009	Power system protection testing	This guide covers the use of protection scheme testing for the power system, system application testing, and the overall advantages of protection scheme testing. This guide also covers general system testing processes, including end-to-end testing, distributed applications inside the substation, generators, lines, line reactors,

Name	Applications	Features
		transformers, capacitors, and special protective systems.
IEEE 1547.4-2011	Design, Operation, and Integration of Distributed Resource Island System with Electric Power Systems	This is a suggested guide for microgrid design, management, control, and protection. Its goal is to give a basic understanding of distributed resources (DR) island systems and to address engineering issues with them. It also displays several planned DR island configurations in the local electric power system (EPS). It suggests that protective devices, such as fuses and single-phase reclosers, should be utilized in the protection system. To ensure that faulted conditions are cleared, this guide also suggests performing short circuit studies for the island for all foreseeable configurations and the protection devices must pass a coordination study, considering inverter-based DR's limited fault-current contribution.
IEC 62257-9-2: 2016	Renewable energy and hybrid systems for rural electrification - Part 9-2: Integrated systems - Microgrids	The general specifications for the design and deployment of MGs for decentralized rural electrification are outlined in this standard. It lays out the fundamental specifications for the development and use of MGs to guarantee both the protection of personnel and possessions and their proper operation for the intended purpose. It also covers recommendations for protecting against overcurrent and electric shocks. The standard states that the MG must have an overcurrent protection mechanism at the interface with the micropower plant This device, which might be fused switches or thermo-magnetic circuit breakers and the ratings for protective devices that should be utilized for short circuit protection at various voltage levels were also covered in this guide.
IEEE 2030.9-2019	Planning and Design of the Microgrid.	This manual presents an approach for the exterior connection and interior design of the Medium Voltage (MV) ACMG protections, together with recommended practices for their

Name	Applications	Features
		implementation. Following the recommendations and explanations in this standard, the power source, distribution transformer, and PCC on the MG side, as well as the feeder and busbar on the utility and MG sides, should all be protected. This standard does not consider the possibility of varied operational topologies, the connectivity of many MGs, or the use of hybrid or AC-DC electrical transmission.
IEC TS 62898-3-1:2020	Microgrids - Part 3-1: Technical requirements - Protection and dynamic control	The International Electrotechnical Commission (IEC) developed this standard in response to requests for protection and control issues in MGs. It provides several methods for communication-based protections (centralized protection systems), system protections (voltage protection, frequency protection), and short-circuit protections (overcurrent, directed overcurrent, distance, differential) [17].
IEEE P1547.9-2022	Interconnection of Energy Storage Distributed Energy Resources with Electric Power Systems	This standard draft discusses the use of power electronic interfaces to connect DER for energy storage to an electric power system. This guide also explains how to connect EV charging stations such that they can output either reactive or active electricity to the connected power grid. Like other DERs, this element needs to be grounded as an independent device system to be protected. A transfer switch or breaker may be used for this purpose.
IEEE 2030.12-2022	Design of Microgrid Protection Systems	On June 28, 2022, the standard draft was made accessible [18]. This standard will cover protective device design, selection, and coordination for a variety of operation modes and transitions during these modes. This standard contains additional protection schemes as well as centralized and decentralized communication-based protection measures [19].

Distribution power grid protection devices include single-action fuses, surge arresters, isolators, sectionalizers, reclosers, circuit breakers (CB),

overcurrent relays, and digital relays. Fuses can detect and interrupt problems, which is why they are commonly used in distribution lines that service residential consumers. Additionally, fuses can be used to divide up feeder segments into zones. They can be cheap, but if they are single action, they will need to be replaced, which could result in high operating costs. Surge arresters and isolators ensure full coverage across a range of fault types and operational conditions by protecting against voltage spikes and cutting off specified circuit segments for maintenance, respectively. Circuit interrupting devices, like reclosers, sectionalizers are typically found in medium voltage (MV) distribution lines but may be less costly. After a predefined number of current-interrupting operations, the sectionalizer starts and isolates the faulty section line. The number of operations performed by the backup device during a fault state is counted.

Reclosers are intelligent, automatic, high-voltage electrical switches. Depending on the current level, it detects overcurrent and interrupts the current flow. Like a CB on a residential power line, it cuts off electricity when a malfunction occurs. When a domestic CB remains off until it is manually reset, a recloser evaluates the power line automatically to determine whether the problem has been fixed. If the problem is momentary, the recloser resumes and resets itself. Reclosers automatically reclose and reenergize the line and are equipped with fault-sensing and fault-clearing capabilities. To protect feeders from overcurrent, CBs are frequently used at the substation level. Protective relays operate the CB, which is more accurate than a recloser. Both fault interruption and sensing are applications for CBs.

In MV distribution grids and industrial applications, overcurrent relays and numerical relays are often used to increase protection and reliability. Furthermore, differential relays provide security by identifying variations in current between two locations. The overcurrent unit continually measures the object's phase currents. As soon as a defect is discovered, the relay will, depending on the application and the configured relay functions, start, trip the CB, emit alarms, and record fault data.

1.4 Microgrids protection architectures

MGs are an essential part of SGs' distribution domain and are capable of working in both grid-connected and island modes. An MG is described as a *“group of interconnected loads and distributed energy resources with defined electrical boundaries that act as a single controllable entity and can operate*

in both grid-connected and islanded mode” [20] in the standard IEC 62898-3-1. A schematic representation of an MG architecture is shown in Figure 1.3.

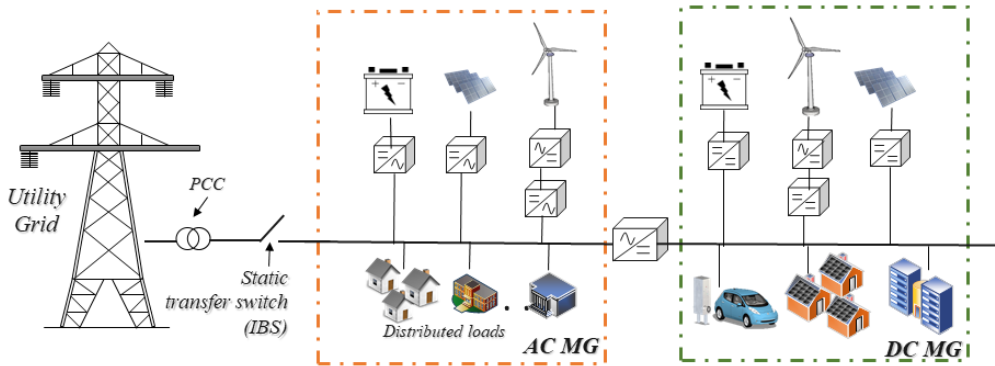


Figure 1.3 MG's schematic representation

1.4.1 Microgrids Protection challenges

Since the fault levels detected in an MG in the island mode are lower than those observed in grid-connected mode, conventional protection systems may not be able to discern between failures and network outages and may even perform worse [21]. The same types of power outages that impact standard distribution grids can also affect MGs: overloads, lightning strikes, deteriorating cables, and physical contact with animals. Furthermore, it is also possible to observe protection failures brought on by factors such as bi-directionality and current variation [11], [12]. To handle those failures, an MG system also needs to take the electrical transmission form into account. Sections 1.4.1.1 through 1.4.1.6 provide information about an MG's electrical transmission system as well as related power outages.

1.4.1.1 AC microgrids' power failures

In an AC Microgrid (ACMG), synchronization of the reactive power, active power, imbalance component, and harmonics is required. However, the appearance of harmonics may be adversely affected using power converters. Additionally, failure in AC circuits is prevented by overcurrent principles, and because MGs may operate in several modes and differ in short-circuit current, protection schemes are challenged by this characteristic [22]. Most ACMG faults are intermittent and have a short duration [23], [24].

Shunt and series faults [25]. Voltage sag faults [26], short circuit faults [27], high- and low-impedance failures [28], [29] are a few of the problems that might occur in an ACMG.

1.4.1.2 DC Microgrids' power failures

A DC microgrid (DCMG) may perform better than an AC microgrid in terms of reliability, effectiveness, management, integration of DERs, and connecting DC loads; this is because DC power is utilized by the majority of DER. Despite the many advantages of DC MGs, the peculiarities of the fault current can make it challenging to develop a reliable protection system. Because of the low line impedance in these MGs, the fault current can quickly approach excessive levels and is rather significant [30]. Two types of faults can be distinguished in DC MGs, short circuits, and arcs faults as is shown in Figure 1.4. Potential failure locations in a DC system include DC bus faults, DC feeder faults, and source faults [31].

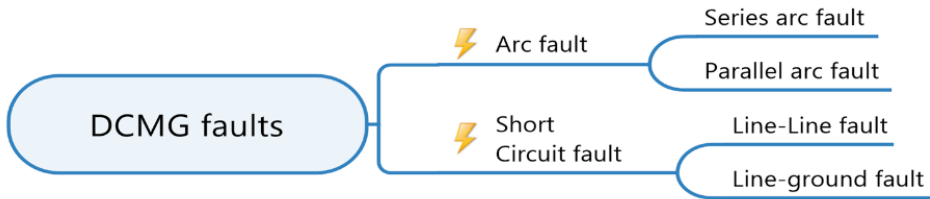


Figure 1.4 DCMG's fault classification.

1.4.1.3 Hybrid Microgrids' power failures

To increase efficiency and reliability while lowering the total conversion stages and interface converters, and power quality MGs incorporate the gains of both ACMGs and DCMGs. Similar to ACMGs or DCMGs, hybrid MGs may experience converter switch and distribution line failures due to short-circuit faults [32]. The moment the MGs start-up, they become susceptible to malfunctions in the actuators, sensors, or plants. The similar current and voltage shapes generated through the converter switching action may cause involuntary tripping.

Dynamic fault events [33], isolated faults[34], and digital attacks [35] on the communications systems present additional difficulties for the MG during regular operation

1.4.1.4 Dynamic fault condition

With the addition of more inverter generation sources, communication, and sensors, the MG requires more precise fault prediction and location algorithms [36]. The increasing number of loads (imbalanced and

fluctuating), generation sources (intermittent and unbalanced), modes of operation and topologies, failure points, and varying conductor sizes will all make fault localization an important assignment. Moreover, fast communication is essential for incorporating DCMGs, which are characterized by tiny line impedance, large fault current deviation, and rapid data acquisition rate [37]. Figure 1.5 presents a number of faults locating issues that have been covered in existing literature.

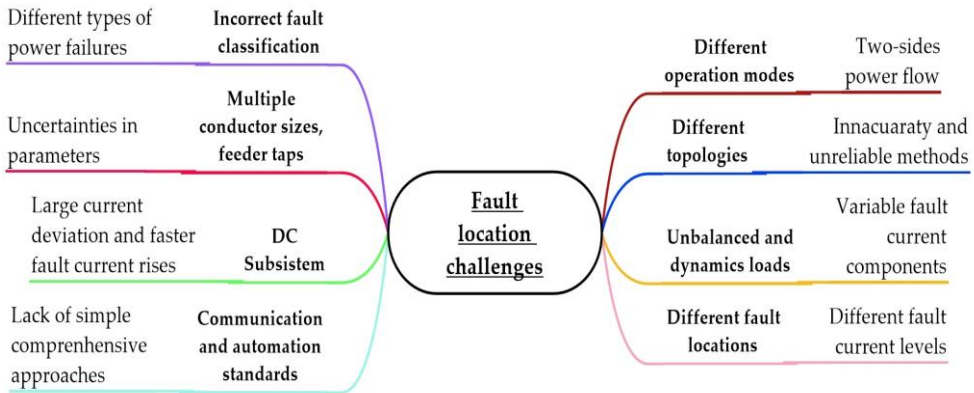


Figure 1.5 *MG's fault location challenges* [33]

1.4.1.5 Islanding Faults

An islanding fault occurs in an MG when a power system failure causes an unintentional disconnection from the MG [34]. Two types of islanding fault detection techniques exist: remote and local. MG failures usually result in a change in the operating points of the storage and generators. Eventually, problems on the power system side could cause the MG to be disconnected from the grid [34]. When the MG intentionally or accidentally disconnects from the power system, it is referred to as "islanding." The following problems are caused by the MGs' islanding issue [34]:

- ❖ Personnel risk, workers could consider the systems not in use when the generators are supplying power.
- ❖ Inappropriate frequency and voltage level
- ❖ Reconnection out of phase

Therefore, the ideal solution to address this critical issue should be to recognize the islanding fault as soon as possible and with the highest level of

accuracy. MG protection and control capabilities could eventually be either centralized or decentralized. These devices might be aware of the DER's types, location, and features, and use high-speed communication, and simultaneous measurements to coordinate fault detection and location identification to guarantee always selective islanding detection [34].

1.4.1.6 Cyberattacks

Cyberattacks on communications networks, which block the information flow between several communication devices, are another issue in the operation of MGs [38]. This is because insecure protocols and the widespread adoption of IoT devices increase the assault area. A specific instance might be an assault referred to as false data injection against an MG's synchronization system, which is essential to power systems' regular operation [39]. Typically, such synchronization frameworks use open data transfer protocols like Modbus, DNP3, or IEC 61850, which don't have built-in encryption or authentication and allow for remote governor control [35], [39].

A cybercriminal might trip a generator by sending altered control commands, which might result in instability or even a blackout. To distinguish between actual sensor or actuator problems and cyberattacks, a fault detection metric needs to be used [40]. For cyberattack detection, the most common techniques include the Kalman filter, intrusion detection and protection systems, and state estimation methods [41].

1.4.2 Microgrids protection schemes

An MG's operating plan should focus on protecting its main connection and power supply in addition to responding quickly to any failures that may arise from the outside or inside of the MG [42]. To decrease the effect on the grid when the MG operates connected, the protection strategy must be coordinated with the utility's protection system; when in island mode, it should disconnect the failing MG component with the least amount of load disturbance feasible [43].

MGs and other energy systems must operate securely and continuously, which is the responsibility of protection schemes. Currently, available conventional protection methods ensure MG operation under a variety of fault scenarios by adhering to conventional principles; Several of these strategies are listed in the following:

- ❖ **Overcurrent protection:** This protection necessitates the consideration of a maximum programmed current value, above which the protection will be active. MGs in DC, however, are unable to apply this concept. This function directly impacts the Protection scheme selectivity, which could result in a prolonged event-clearing time or unintentional protective device tripping during the error. An automatically adjusting relay, which is constructed using optimization approaches to handle the fluctuating fault current, is an option to solve the issue. It boosts the protection scheme's data transmission and reception speed [30], [44].
- ❖ **Directional overcurrent protection:** This is the most frequently used principle since DERs permit current to flow in any direction inside a system. A directional overcurrent relay operates and sends a trip signal when its input current is beyond a predetermined threshold [45]. Furthermore, the directional element identified the fault current's direction, which is reactive to the forward or backward direction [45]. Using this criterion ensures selectivity in the mesh topology scenario. If the problem is linked to a quick communication system, it may also aid in finding it more quickly [46].
- ❖ **Differential overcurrent protection:** Given that it functions fast and just monitors the current amplitude at the endpoints of the equipment that needs to be covered, it is among the best for an MG. Nevertheless, fast communication and sophisticated relays are needed to make effective use of this protection [47].
- ❖ **Distance protection:** Distance protection needs to consider the differences in behavior between DC and AC lines, such as the lack of a fundamental frequency fault and the much less effect of the conductor's inductance. To activate this protection, it is frequently necessary to measure the voltage and current at the observation node and fault distance to put this protection into operation [48].

Conventional protection strategies are well-established and may be easily applied, but their effectiveness is limited to specific fault types and topologies due to the dynamic and changing nature of MGs [49], [50]. Relays with optimization approaches are employed in various protection schemes [51], [52], [53], while superconducting current limiters and micro-phasor measuring units are employed in other solutions [54], [55]. But there is still

more to be done to provide solutions that reduce the number of settings, extensive relay deployments, and frequent adjustments. An enhanced protection scheme based on communication and AI techniques could potentially minimize these issues.

1.4.3 Communication and AI-based protection schemes for MGs

AI-based protection and communication-based methods improve MG's protection coordination by addressing challenging factors such as MG operation modes and topological changes [56], integration status of the distributed generators (DGs) [57], [58], and fault location and identification issues [59]. In addition, they can increase the overall system coordination for different grids with high accuracy, flexibility, and protective device working speed [71], [72]. The use of AI in protection schemes has the potential to enhance relay coordination by learning from real-time data and automatically modifying settings in response to changing conditions [56]; can lead to reduced testing and commissioning times for relays, more precise fault event analysis in real-world operations, and the capacity to continuously compute and draw conclusions while updating our understanding of grid status, which enables us to make decisions more quickly [60]. Some methods try to minimize communication requirements to reduce costs and enhance the speed and precision of fault location [61].

Furthermore, Machine learning (ML) techniques can enhance accuracy and selectivity during island operation by overcoming the limitations of conventional protection schemes [57], [58]. Reinforcement learning (RL) and deep RL algorithms can also further enhance the training process by incorporating extra information such as observations, rewards, gradients, and parameters, to achieve centralized training with decentralized execution [62], [63]. Software solutions such as Virtual Protection Relays (VPRs) offer potential benefits in automation, control, and size reduction in the protection of power systems but lack practical experience in MGs [5], [6].

Even though applying AI to protection has many benefits, there are some drawbacks as well with the actual techniques, such as requiring high computational resources [64], a limited learning process since there is insufficient historical data, and the system requires several events to happen before reacting. Also, unexpected events could cause problems. Furthermore, to guarantee optimal efficiency, MG protection systems incorporating AI may

need constant maintenance, updates, and monitoring. AI may introduce a level of technological dependency that could cause problems in the event of system failures, so maintaining the current AI algorithms with the latest developments and resolving any compatibility issues with the protection infrastructure can be time- and resource-exhaustive [65]. Limited decision-making could also be a challenge as AI-based techniques could increase dependence on processing technology within software solutions, which could cause problems if a system fails. Errors or breakdowns in AI algorithms or equipment could affect the MG's overall protection mechanism and make it susceptible to faults or disturbances [66].

The potential for cyberattacks is another drawback of using AI in MG protection. The reliability and security of the MG may be challenged because of cyberattacks against digital controllers and communication infrastructure used in AI-based protection systems [67]. To avoid illegal access and manipulation of key grid processes, the cybersecurity of AI-enabled protection systems is essential [67]. Applying neuroscience insights to the current AI-based method will help to build more accurate, efficient, and biologically plausible algorithms [68]. Table 1.2 lists the benefits and drawbacks previously discussed.

Table 1-2 *An outline of the advantages and drawbacks of AI applied to MG protection*

Advantages	Drawbacks
✓ Flexibility for several types of grids	✗ High implementation-related computational resources
✓ Suitable for a variety of conditions, including network islanding, fault detection, classification, and operating modes.	✗ Restricted learning process
✓ Enhancement of model and procedure	✗ Restricted ability to make decisions
✓ Enhancement of protection coordination	✗ Further biological plausibility is necessary.
✓ Improvement in costs	✗ Cybersecurity issues

Before AI-based approaches are implemented in practical MG systems, some challenges need to be resolved. These barriers include data availability, complexity, communication problems, and the biological plausibility of the

AI-models. Artificial Neural Networks (ANN) approaches, for example, still have limits in terms of biological realism [69], and their application in MG protection has difficulties in terms of energy efficiency, high computational complexity and flexibility, and limited online learning capabilities [70]. While there are still concerns with reproducibility and complexity, RL and deep RL algorithms may offer a way to improve training and increase energy efficiency [62], [63].

Despite these developments, more study is still required to fully address issues like figuring out the best position of measuring devices, reducing disruptions during transitions, reducing reliance on multiple settings, and ensuring a reliable communication system even in the event of a failure. These constraints prompted us to investigate alternative tactics, drawing inspiration from the remarkable self-defense systems and inference learning techniques present in the human brain.

1.5 Networked Microgrid Protection schemes

1.5.1 *What is a Networked Microgrid*

A group of nearby MGs that are physically interconnected by AC or DC lines (possibly with varied voltage levels) and have the ability to interchange energy with a distribution system are referred to as Networked Microgrids (NMGs) [71]. Among the numerous benefits offered by NMGs are increased flexibility [72], [73], [74], increased system reliability, improved power quality [75] and resilience [76], [77], extended grid availability [78], [79], and optimized resource utilization. Consequently, it is anticipated that NMGs will serve as the foundational element of next-generation smart grids (SGs) [80]. Nevertheless, the electricity network topology is altered because of these NMGs' interconnection across various nodes [79], which raises the likelihood of network failures and makes protection systems and network operation more difficult [81], [82]. Moreover, NMGs face the same difficulties currently encountered in the operation of isolated or single MGs. These consist of the bidirectionality, the SCC's fluctuation, and the integration of various DERs. The connecting of individual MGs at various voltage levels, in numerous nodes, and with a larger short circuit current in the interconnection mode must also be considered for the protection of NMGs.

The three principal NMG topologies are single feeder (parallel and serial) and NMG with many feeds [83]. Notwithstanding, these configurations can be examined according to their voltage level classification (low, medium, or

MV/LV), phase-sequence constitutional form (single or multi-phase), and constitutional electric form (AC, DC, or hybrid) [84]. Figures 1.6, 1.7, and 1.8 depict the typical structures considering voltage level categorization, constitutional electric form, and network topology.

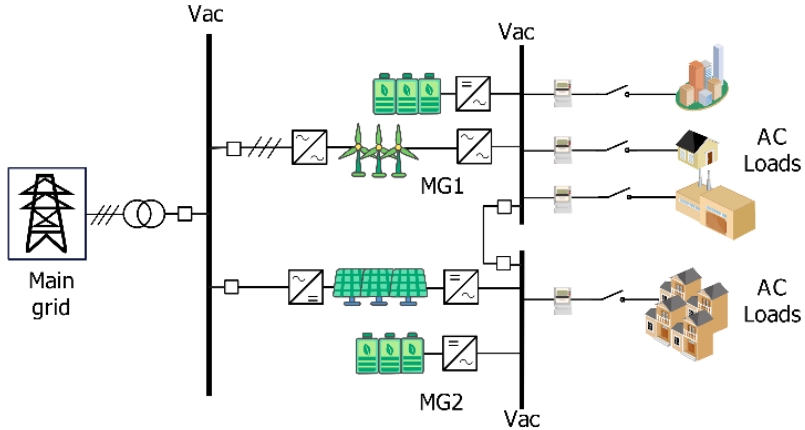


Figure 1.6 AC-NMG Parallel architecture

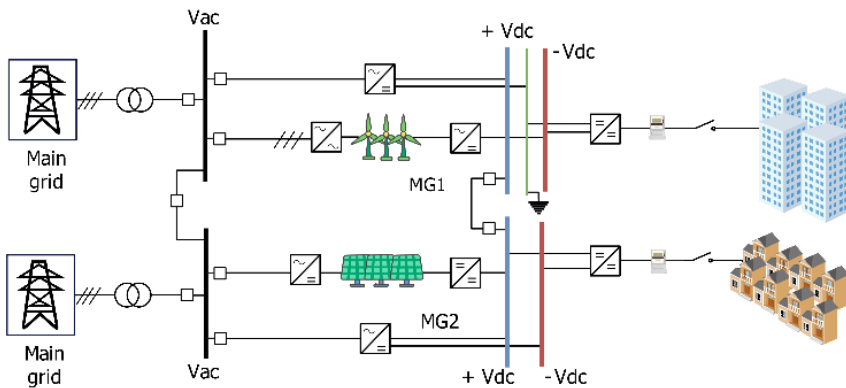


Figure 1.7 DC-NMG Meshed architecture

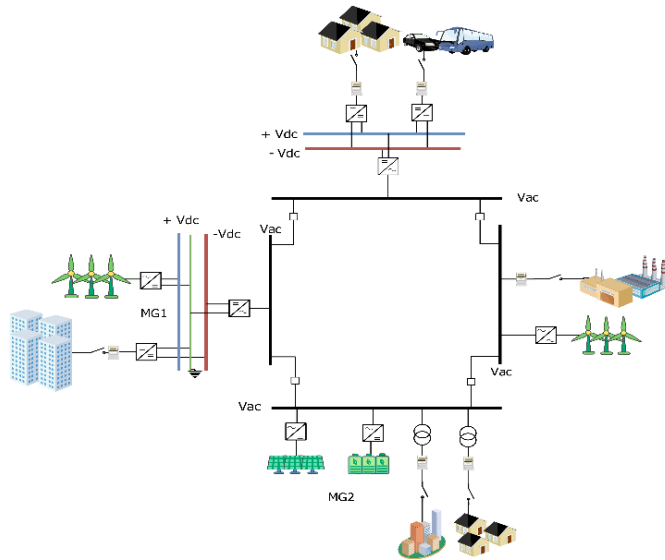


Figure 1.8 Hybrid-NMG Ring architecture

Although there are many advantages to connecting many MGs, connecting MGs at different nodes and topologies makes protection coordination more challenging and increases the chance of fault occurrence and propagation. The electrical power flow from several MGs, fluctuating generation, and changing load demand all contribute to the variation in fault current levels in NMGs [85]. Additionally, it is well known that an NMG has larger fault currents than a single MG [86]. As a result, creating protection plans that make the connection of several NMGs robust to these variations is difficult [86]. The authors in [87] provide information on the issues that NMGs face based on the electrical transmission type, interconnection system, and interconnection technology.

1.5.2 Electrical transmission challenges

Three categories of NMGs can be distinguished according to the power transmission type: hybrid (AC/DC), AC, and DC. Their operational modes (islanded, grid-connected, and interconnected) must be taken into consideration when addressing the challenges. High current levels [88], bidirectional power flows that cause unintentional protection tripping [23], main loss between the main grid and the MGs [22], and a shorter tripping range [22] are among the challenges that are present in the AC-NMG in grid-connected mode. Low current contribution [89], fault current variation, blinded protection, failure tripping, and failed reclosing [85] are all present in isolated MGs. Additionally, in contrast to one MG or single grid-connected

MG, an interconnected mode may experience higher fault current levels [90], dynamic topology changes [91], imbalanced situations, low voltage, and low inertia.

Depending on the operating mode, DCNMGs can have issues with grounding [92], current interruptions [93], a variety of fault features, and difficulties locating and identifying faults [94], [95]. In addition, according to the operation mode, hybrid NMGs may face challenges related to different fault levels, modeling for various hybrid system faults, planning and designing of protection schemes from multiple short circuit current contributions [96], [97], variable voltage levels, and power source uncertainty [98], which could impact the proper functioning of these systems.

1.5.3 Interconnection system challenges

MGs face several difficulties, including blinded protection, unauthorized resynchronization, and bidirectional power flow. A key component of the protection plan will be the NMGs' kind of interconnection. In a star or parallel NMG, for example, bidirectional power flow adds another layer of complexity to the system operation. Good selectivity is so ensured, and the protection coordination becomes simpler. Furthermore, coordination of protection is more complicated and calls for communications systems for other NMG interconnections. In ring and mesh NMGs, it is difficult to locate and remove faults, for instance, because of the multiple fault contribution channels and different short-circuit thresholds that depend on the NMG architecture. In addition, the intricacy of their connection raises the expenses associated with deployment and maintenance.

Depending on the operation modes, an NMG's interconnection networks vary [99]. Preplanning and consideration of the changes in operation modes are required [71]. Because the protection system must react correctly to faults in many kinds of topologies under a range of conditions, its design is an arduous process [100], [101]. Consequently, to enable NMGs to adapt to these changes, a communication or adaptive system is required. The key challenges in the interconnection system can be found in Table 1.3.

Table 1-3 *A description of the interconnection system challenges*

Challenges	Description
Fluctuation in the short-circuit currents (SCC)	For instance, the SCC's magnitude is too low when the operation is in island mode [49], [50].

Challenges	Description
Bidirectional power flows inside the grid	Traditional protection techniques are considered inappropriate for operation in the presence of distributed generators. The protections need to be adjusted to match the distributed generators' operating modes [51].
The need for an appropriate protective coordination system [79], [102].	Managing unexpected modifications to the network topology and variations in power flow patterns [47], [103] Addressing fault current variations in both direction and magnitude, as well as constant updates are required to maintain system reliability

1.5.4 Interconnection technology challenges

Various technologies, such as switches, power transformers, AC or DC CBs, or power converters [104], can be employed to connect MGs in an NMG system. The benefits and drawbacks of every connecting technology are presented in Table 1.4.

Table 1-4 Advantages and drawbacks of interconnecting technologies

Interconnection technology	Advantages	Drawbacks
Power transformers	Requirements for interconnection are less difficult cost-effective, utilize established technologies, and require less protection.	The fault level and the expected value of the protection devices and features of the transformers are increased by interconnected MGs [71].
	Protected by relay or fuse protection devices and may tolerate a failure for two to five seconds.	Sensitive to short circuit currents [105]
Power Converters	Effectively protected equipment	Vulnerability to overloads [105]
	Restricts each DG source's fault current contribution in an MG to no more than	Require Faster responses and more accurate protection [106], [107]

Interconnection technology	Advantages	Drawbacks
	two or three times the maximum load current.	
Switchgear such as CB, contactors, and switches	Reliable controllability and well-established technology	Requires additional components, like power converters or transformers, to isolate the MGs from other grids, and may operate slowly [82], [104].

The most common subjects discussed in the literature for the NMGs in the interconnected mode are illustrated in Figure 1.9. All these challenges highlight the need for additional studies on NMGs to deploy them and reduce operating expenses. Furthermore, the consequence of the interconnected MGs should be taken into account when protecting NMGs, and standards such as IEEE 2030.7-2017 [108], and IEEE 2030.8-2019 [19], could serve as a guide for the development and deployment of protection systems.

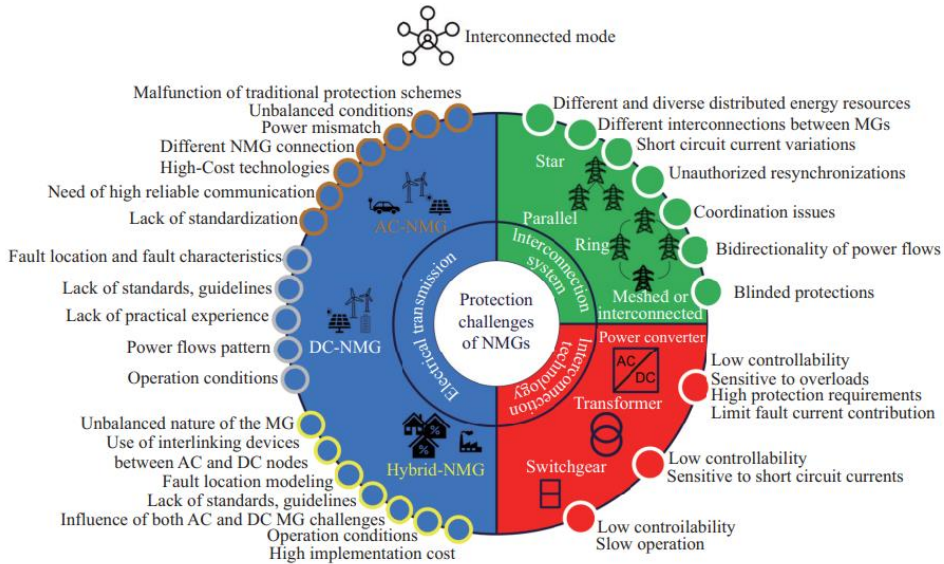


Figure 1.9 Challenges on NMGs protection in the interconnected mode

The authors in [33], [87], [109], analyze several MG protection strategies and present a review of their benefits and drawbacks. These analyses include protection based on symmetric sequence components, distance relays, differential protection schemes, overcurrent (OCR) and directional

overcurrent relays (DOCR), protection techniques, adaptive and communication-assisted protection, and some techniques for protecting NMGs. Requirements for the design of future NMGs are covered in a recent report [110]. They underline how important it is to have protection system designs that can guarantee the NMG's coordinated performance and security. A conclusion from this review is that more research on protection is required, with a focus on overcoming the limitations of current adaptive protection techniques, like communication challenges and cybersecurity concerns. An enhanced protection scheme based on communication and AI techniques could potentially address these issues.

1.6 Research Questions and Hypotheses.

Advanced protection systems are necessary to reduce the risk of outage and system collapse. These systems must be able to identify faults and protect the entire MG system in a competent, autonomous, and reliable way, with self-healing capabilities to lower the danger of outage and system collapse. Given the limitations and shortcomings of current protection strategies identified in this thesis, the research questions are formulated as follows:

- ❖ Several approaches to protecting MG systems are described in the literature. These include conventional protection strategies enhanced with advanced algorithms to optimize coordinated protection devices, centralized protection based on communication, and decentralized protection based on AI. While these solutions have been successful in protecting MGs, practical implementations remain challenging due to high costs, communication reliability issues, and the need for extensive relay deployments and settings. Therefore, additional methodologies are needed to address the current limitations, assist in selecting the best protection solution for MGs according to their operating mode and condition, as well as provide guidance for practical implementation. Therefore, the primary research question of this thesis is: ***How can advanced protection strategies for MGs be designed to overcome existing challenges and enhance MG efficiency, autonomy, and reliability?***
- ❖ AI-based protection approaches face challenges such as the lack of biological plausibility, and challenges with communication and data availability. To overcome these, AI-based approaches must be improved to offer reliable, robust, and plausible solutions as well as self-defense mechanisms that accurately predict and identify fault conditions, gain

knowledge of the system's status, and efficiently prevent outages with self-healing capabilities. Therefore, the question is: ***How can AI-based protection strategies be enhanced to accurately react during a fault condition and prompt a quick response of the protection devices?***

- ❖ Current AI-based protection methods are often very reliant on data availability, and unexpected events may lead to issues and restrict the method's ability to learn. Integrating AI algorithms into protection devices can be expensive and require specialized knowledge, new resources, and communication infrastructure. Although software solutions such as VPR can automate, control, and reduce the size of substations in distribution grids, they have not yet been used in practical MG scenarios. Therefore, the research question is: ***How can a virtual or software solution be developed for the MG control system to prevent the need for multiple relays and settings, thereby enhancing MG's protection efficiency and reducing costs?***
- ❖ In contrast to a physics-based approach to handling power failures, data-driven and learning-based techniques might be more complex and challenging to solve. To enhance the performance of current AI-based solutions, it is necessary to increase the biological plausibility. By incorporating more biologically realistic models that mimic nature and the human brain, we can better understand and use these methods in real-world situations. Thus, the research question is: ***How can the brain's fundamental self-defense mechanism be leveraged to create a self-protection scheme for strengthening the MG protection system?***

This thesis aims to provide a theoretical framework for a self-defense protection scheme inspired by the brain that might be applied to MGs control and protection. To answer the research questions, the thesis considers the following hypotheses.

- ❖ Decentralized strategies due to their local decision-making, local execution capabilities, and enhanced operational knowledge of the overall system can provide feasible and promising strategies to design advanced protection schemes to enhance the protection of MGs.
- ❖ The current AI techniques can be enhanced to develop software or virtual solutions for MGs to prevent the need for the deployment of multiple

relays and settings, respond precisely to fault conditions, and speed up the reaction time of the protection devices.

- ❖ Brain-inspired self-defense strategies are promising solutions that can be applied to strengthen MGs' protection systems. It is assumed that the brain-inspired solution will consider the AMYG's theoretical behavior and the brain's inference learning to recognize and react to malfunction conditions principles.

1.7 Thesis's Outline.

An extended synopsis of the Ph.D. student's published articles serves as the basis for the Thesis. The introduction includes the motivation behind the project, background, research questions, and hypotheses. The thesis's first chapter covered the challenges and solutions surrounding MG's protection and the benefits and drawbacks of AI-based techniques. This chapter also covered the various electrical component power system failures and the conventional methods used to protect these components. The NMGs, their topologies, and protection challenges were also discussed.

Chapter 2 analyses the advantages of designing a decentralized protection system in an MG along with the development of an approach to protecting AC MGs based on zonal multi-agent systems (MAS). A methodology to build the agents in the MG model is presented, and a coordination strategy is proposed and implemented in the Jade environment using the GAIA methodology. The forthcoming need for the implementation of this solution is investigated and studied in conjunction with the simulation results of the suggested protection method. Brain-inspired models and their industrial applications are covered in Chapter 3. The emotional system is then explored, and a connection to the hierarchical control in MGs is proposed. This approach takes the emotional system into account, which broadens our knowledge of the composition and operation of the brain.

Chapter 4 proposes a theoretical framework for brain-inspired self-protective solutions based on the behavior and functionality of the AMYG. The theoretical foundations and behavior of the AMYG and the MGs are compared to gain a better understanding of the brain-inspired solutions to be used in MGs. Furthermore, a model that reinforces the AMYG reaction by using the brain's inference process theory based on predictive coding is proposed. A final summary of the study's key findings is given in Chapter 5. A list and discussion of the thesis's contributions are also included. This chapter also

discusses potential research directions. The contents of the published articles are described as follows, and they are organized following Figure 1.10:

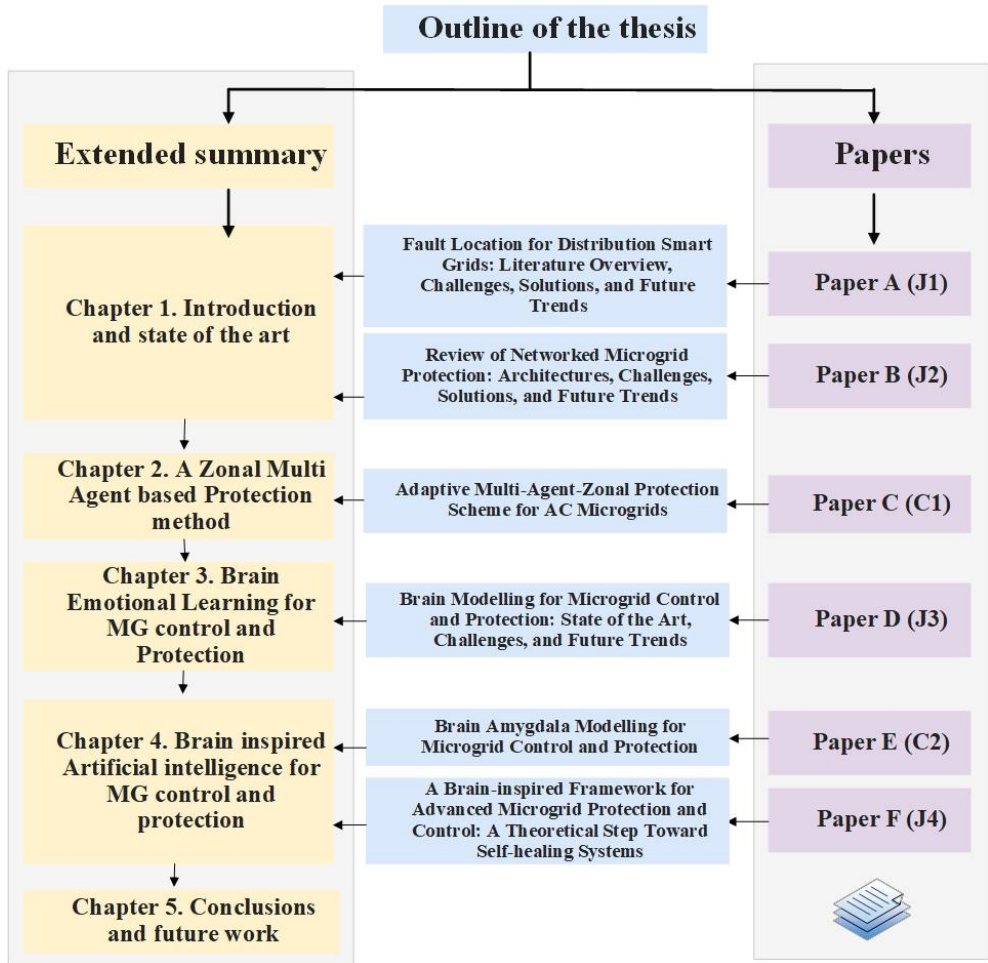


Figure 1.10 *An overview of the thesis structure and published papers*

Paper A: This research aims to explore typical power failures and challenges with fault localization that impact the majority of the physical components and communication systems in the SGs. We additionally investigate a variety of fault location strategies proposed to increase adaptability, as well as initiatives in the SG's distribution sector, to assist users in choosing a methodology for their analysis. Paper A provides the foundation for the thesis study by providing an overview of the many kinds of faults and fault location techniques that are commonly used for distribution systems and MGs.

Paper B: This study's objective is to highlight the challenges to protecting networked MGs, possible solutions, and research directions that require attention to advance this area. Although Paper A provides methods for fault location, the protection scheme should also handle other concerns such as topology identification, coordination, bidirectional power flows, low short circuit current in islanding operation, etc. Paper B discusses the protection systems that NMGs can currently use, along with the challenges they face and the alternative solutions. Finally, it addresses how MG protection strategies are now being implemented and provides some insights into that process.

Paper C: This article discusses the advantages of implementing a decentralized adaptive protection system that guarantees an MG's electrical protections react properly to topological changes. The Gaia methodology facilitates the implementation of this protection by offering autonomy through the decision-making process. It was demonstrated that adding DER to the network produces a loss of scheme selectivity and coordination and changes the nominal currents in each proposed relay and an adaptive protection is needed to update the status of the system.

Paper D: By putting into practice, a decentralized protection scheme and considering the MG protection challenges and solutions covered in Papers A and B, it became clear that more improvements in the domains of communication and AI-based protection are required to have more accurate and reliable models that more closely resemble natural or brain behavior. As a result, this article provided a summary of the emotional learning strategies used in industrial applications as well as MG control and protection, along with details on their current limitations. We also addressed the main areas of research and operational strategies, drawing comparisons between the emotional learning activity in the human brain to MG's hierarchical control architecture (HCA). Finally, some remarks on the technique's potential were offered, and possible uses of BEL for MG control and protection were explored.

Paper E: Brain-inspired models hold promise for enhancing MG operation because they mimic the cognitive and behavioral brain's functions. This is particularly relevant when considering the emotional system and the MG's capacity to defend itself and respond to a variety of stimuli, as described in Paper D. This article aimed to establish parallels between the neural processes of the AMYG, which is important for regulating emotional responses and

defensive behavior, and MGs. To do this, a conceptual framework was developed to facilitate understanding, stimulate creativity, and result in the creation of fresh strategies for the control and protection of MGs.

Paper F: MGs could benefit greatly from the application of brain-inspired algorithms for self-healing and autonomous control. However, there is still a lack of validation for these algorithms in domains outside of neuroscience, most notably energy systems. This study's novel brain-inspired framework integrates the AMYG's emotional activity during fear acquisition and extinction with the predictive coding approach, which explains the brain's ability to infer events and analyze prediction errors to improve MG's self-healing, adaptability, and reliability. To evaluate the model's ability to infer fault conditions, we used Python to create a proof of concept and assessed the model's performance using an existing fault dataset. This method guarantees a thorough assessment of the model's MG protection performance. Our integrative paradigm closes the gap between applying cutting-edge neuroscience models to MG protective mechanisms and drawing inspiration from brain function and behavior. The results are a significant advance in incorporating biologically accurate, brain-inspired algorithms into MG technology and have significant effects on MG operating systems

Chapter 2: Decentralized Adaptive Protection Scheme

This chapter's focus is to explore the advantages of developing a decentralized protection scheme in an MG. First, we introduce the MG study case and the proposed multi-agent zonal protection approach, together with its implementation methodology. Afterwards, the outcome of the real-time and offline simulations is presented and finally, the conclusions are drawn.

2.1. Introduction

Currently, establishing reliable protection and control strategies to guarantee that the system operates as intended is a current problem with the MG's implementation [111]. Conventional systems employ protection strategies that rely on radial power flows. These strategies are intended to isolate affected sections and tolerate higher fault currents [112], which helps to maintain uninterrupted network service and reduce the likelihood of system degradation. Nonetheless, the power system's process may alter as a result of the MG's dynamic operational changes, making it challenging for traditional protection systems to carry out their original roles [113].

Adaptive protection schemes (APS) monitor and control the state of the protections using sensors, digital relays, and communication protocols [114]. APS has known benefits over conventional techniques [115], [116]. Intelligent algorithms can be implemented in adaptive schemes, which can thus quickly adjust to changes in the network and update the protective settings. Unfortunately, a lot of these techniques necessitate communication protocols that lead to data latency and information uncertainty [117]. An increasingly common method for evaluating these networks' adaptive protective reaction and communication architectures prior to deployment is real-time simulation (RTSim) [118], [119].

Decentralized APS is considered an effective option for the protection of distributed networked systems. These modular and flexible solutions can handle more MGs and dynamic loads providing self-modifications of the protection devices. In order to communicate with other agents to accomplish

a common objective to enhance control and decision-making activities, they rely on communication infrastructure, or internal communications through protocols that make the data transmission efficient [120], [121]. For instance, in [122], the authors explored a decentralized adaptive method for MG protection coordination employing agents in the face of operational uncertainty and different topologies. To determine the optimal protection coordination plan in the event of many faults, a group of agents close to the fault location engaged in an online decision-making process.

Relay parameters are changed offline via simulations in [123], and faults are removed online to preserve the protective devices' selectivity. Agents were designed using an expert algorithm that emulates the cellular activity of the human immune system in order to boost protective device reliability and eliminate the need for central controllers [124]. To locate and isolate faults in MGs, the authors in [125] presented an MAS based on the size and direction of the sequence current. The authors in [126] defined Ip currents as the starting points for the MG's operating modes using the Ybus method. TCP/IP protocols allowed agents to communicate with one another. These illustrations explain how decentralized adaptive protection can be used to improve power management resilience and reliability by addressing communication problems and other difficulties in MG protection systems.

To guarantee service reliability and reduce operational costs, a MAS zonal adaptive protection method is proposed and evaluated in an RTSim environment. We incorporate DER utilizing the software in the loop (SIL) concept and use the IEEE 13-node test system to perform the simulation in real-time. Furthermore, we incorporate six IEDs into the 50/51/67 directional overcurrent function and replicated three-phase failures at various network nodes. In addition, the relay responses are evaluated in the Electromagnetic Transient (EMT) domain employing a commercial RTSim software that enhances validation and refining results. This approach facilitates quicker adaptation in practical scenarios, demonstrating the feasibility of integrating this technology into actual systems.

2.2. Planning and sizing of the protection scheme

2.2.1. System description

Figure. 2.1 shoes the MG that was used in this study. This development approach offers real-time validation and a straightforward method to evaluate various MG operating topologies and scenarios.

Chapter 2: Decentralized adaptive protection scheme

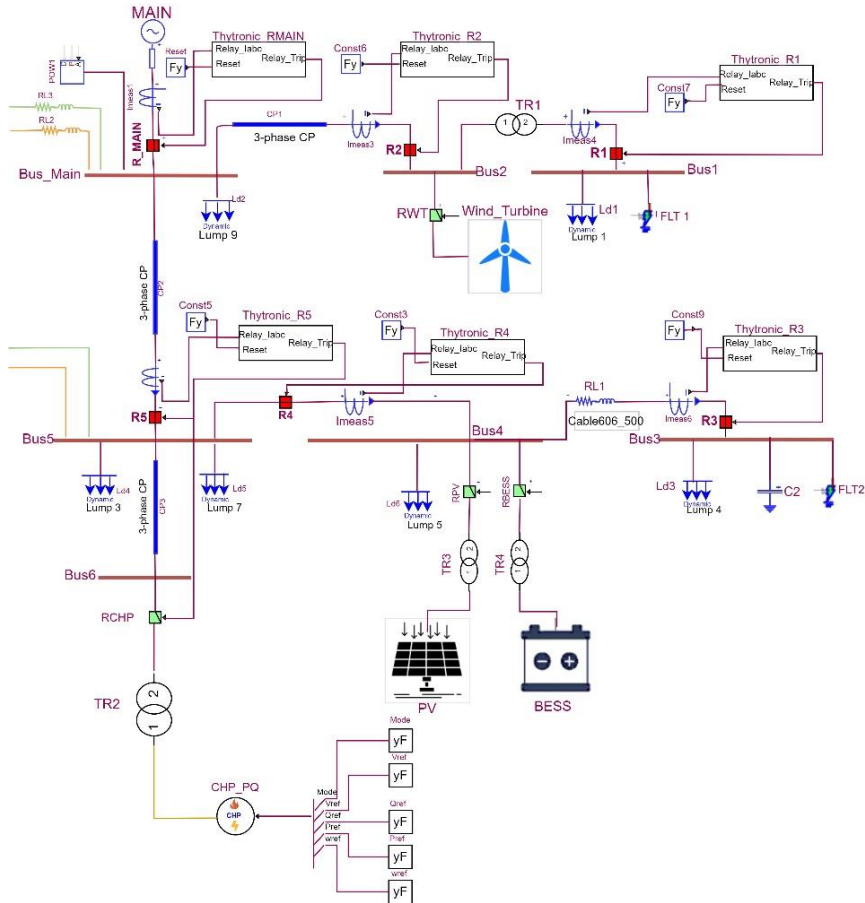


Figure 2.1 Microgrid Test Model

The components of the test model include a solar array with a capacity of 1 MW, a type 3 wind turbine rated at 1.7 MW, a lead-acid battery storage system with a 1 MW capacity, and a combined cycle plant (CHP) also rated at 1 MW [127]. The system's total load, which is split between distributed loads (200 kW) and fixed loads (3,266 kW), is roughly 3,515 kW. Six protection relays are present, and these relays are distinguished by their modular design and compatibility with a variety of communication protocols, including Modbus TCP/IP and IEC 104. To provide a PCC between the local distribution system (LDS) and the MG, between the MG and its LDS network equivalent was one of the relays (R_main).

2.2.2. Operating scenarios of the Microgrid

We've decided on two MG operational scenarios: Grid-connected and grid-isolated. Initially, all available loads are utilized without the DER, and subsequently, all available loads are utilized with the DER. We also consider five topological modifications, which are displayed in Table 2.1.

Table 2-1 *Topological changes*

Number	Topological change	Type of failure
1	Normal	3-phase failure in the system with all available loads in the absence of the DER
2	MG connected to the LDS	3-phase failure in the system with all available loads with all the DER connected
3	MG connected with solar and wind resources	3-phase failure in the system when the wind and solar generators are operating
4	MG connected with CHP and wind	3-phase failure in the system when the CHP and wind generators are operating
5	MG connected with Solar and CHP	3-phase failure in the system when the CHP and Solar generators are operating

2.2.3. Protection scheme feature and adjustment criteria

The proposed protection system makes use of DOCR, one of the most often utilized protection elements in APS [128]. Their directional capability allows them to identify shifts in power flow direction that occur when an MG is integrated. Furthermore, in terms of MG protection, the DOCR proves to be versatile, dependable, and effective. We use three non-directional relays (R_main, R1, R3) and three directional relays (R2, R4, R5) for this system.

As indicated in IEC STD 242-2001, we set the dial phase, the instantaneous phase (I_F), the delay time phase, the Tap for the phase of the timed units (Tap_{51}), the Tap of the instantaneous unit (Tap_{50}), and the Tap for the timed units (t). The following equations are used to define I_F , delay time phase, and Tap_{51} , respectively:

$$I_F = 0.5 * I_{ccmax3\phi} \quad (1)$$

For the delay time phase, a very inverse time curve is used as illustrated in equation (2)

$$t = \frac{0.14 * TMS}{\left(\frac{I}{I_p}\right)^{0.02} - 1} \quad (2)$$

Where:

t = Protection trip time.

I_p = Pickup current set at 1.5 times the maximum charging current.

T_{ins} : When the current goes above the instantaneous current pickup (I_{ins}), the instantaneous operation time is set to 50 ms.

I_{ins} : Instantaneous pickup, set to 1.05 times the maximum fault current.

This very inverse minimum time curve is used to adjust the units' phase (51) according to the nominal current as shown in (3):

$$TAP (51) = 1.2 * I_{51} * \frac{1}{CTR} \quad (3)$$

$$I_{nom} * 120 \%$$

Where:

I_{51} : Current used to determine the protection TAP.

$CTR's$: Current transformation ratio associated with protection.

In this case, the protection's TAP is calculated using current I_{51} , and the protection's current transformation ratio (CTR) is indicated. The instantaneous unit tap (50) is adjusted according to the short circuit levels. Two steps are suggested to adjust the I_{50} . Initially, studies of short-circuit current are conducted for every possible configuration of the network topology. The second phase is defining a pre-calculated adjustments matrix. There is a verification stage for the relay protection coordination based on off-line simulation, to ensure the relays' delay and adjustment timings. During this process, the highest SCC of the protection zones is adjusted by multiplying it by a factor of 1.02 to 1.05 times the Pickup instantaneous. The coordination time between the protection relays is set to 0.2 seconds [129].

2.3. Adaptive multi-agent Scheme

The GAIA methodology is used in the MAS development process. There are two steps involved in developing a MAS using this methodology. The initial step includes analyzing the power system and establishing roles and protocols. The subsequent design phase focuses on creating the agent, service, and familiarity models [130].

2.3.1. System's conceptualization

During this stage, the system is conceptualized, and typically the roles and protocols are established. The proposed system will be characterized by the roles. They consist of four parts: activities, permissions, protocols, and responsibilities. The functions of measurement load (RML), measured distributed generation (RMDG), measured common coupling point (RMPCC), IED (RIED), and MG intelligent system (RSIMG) are described below as the responsibilities that will be assigned.

Through the switches at each element's connection points, the roles RMDG, RMPCC, and RML, monitor the DG units, loads, and the MG's connection condition, respectively. The protection device, SCC, and current flow direction are all monitored by the RIED. This RIED is in charge of controlling the operation of the Intelligent Electronic Devices (IEDs) and adjusting protection settings. The RSIMG determines the MG configuration by gathering data from other roles and communicating updated settings and MG's status information. This role processes communication from measurement roles and transmits new settings to the IED role. It has permission to read all the connection states and save this information in a database. Additionally, it determines the new relay settings. Figure 2.2 shows the characteristics of the RSIMG.

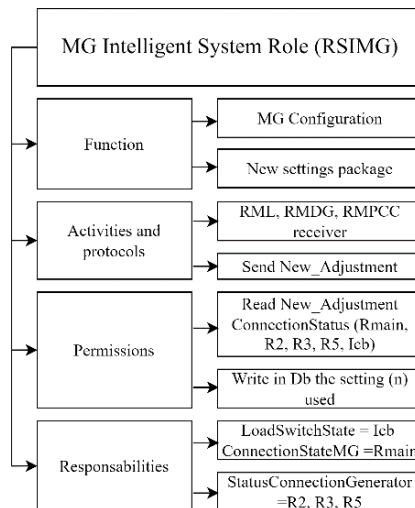


Figure 2.2 Developed Role of the MG Intelligent System (RSIMG)

A role is defined by a number or quantity of protocols. The manner of interaction between the roles is defined by protocols. For instance, the RSIMG receives a message (sender role) from the RMDG, which tracks the system generators' state and takes necessary action to update the MG status. The RSIMG then analyzes the connection status of the generators. Table 2.2 shows an example of the protocol purpose for the RMDG.

Table 2-2 RMDG Protocol

Protocol Goal: Notify the generation source's on or off status	
Role of sender	RMDG
Role of receiver	RSIMG
Inputs	P_{DG}
	On_{DG}
	Off_{DG}
Outputs	$P_{Load} = n$
	$On_{DG} > 0 \rightarrow true$
Processing	Check if the generation is on or off
Responsibilities	Indicated if P is more than zero; indicated if P is less than zero.

Where P_{DG} is the power of the generation source that is available, on and off is the generation source connection status, P_{Load} is the nominal power of the load.

2.3.2. Agents design procedure

During this phase, each agent's models, and related service models are created. Furthermore, a familiarity model is developed that includes a sequence diagram to establish an operation logic between the agents, a collaboration diagram to comprehend how the agents interact, and the architecture used to solve the problem. The GAIA methodology's goal is to identify the responsibilities that require the creation of groups, and it is recommended that each role be given to an agent to maximize efficiency.

The agent's function is called a service, and it describes the inputs and outputs of the agent along with whether it needs to transmit a message or state after it has finished its task or present a precondition. For example, the service comprises voltage and current measurements; the agents' input may be the state of the switch connections, and the output would be the node's source or

load's connection status. Prerequisites include the main PCC relay being unconnected, the voltage level being at zero, and the generator being in the on or off position. Furthermore, the agent must update the data with postcondition messages, such as those indicating generation or connected load. Table 2.3 describes the service model.

Table 2-3 *Service model*

Service	Input	Output	Preconditions	Postconditions
Measurements Voltage and current	State of the switch	Connection status of source or load on the node.	StateConnectionPCC = 0; V = 208 V GeneratorState = 0	On or off message.
Send Adjustment	New Adjustment (n)	Interface file	Send='N'	Send='Y'
Confirmations	id_Setting	Approval or rejection of setting	State='01'	State='02'

The familiarity model, which describes how agents cooperate with the design architecture, must also be designed using this methodology. Figure 2.3 shows the sequence diagram, Figure 2.4 shows the agents' collaboration, and Figure 2.5 shows the architecture of the design, all of which are detailed by the familiarity model.

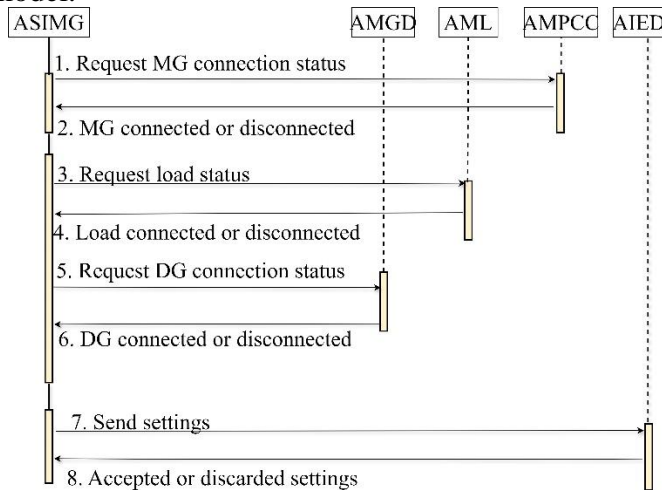


Figure 2.3 *Diagram of sequence*

In Figure 2.3, the MG intelligent system agent (ASIMG) is continuously requesting data from the various measurement agents. It will first inquire whether the MG is connected and will communicate with the common coupling point measuring agent (AMPCC) requesting information about the MG's connection status and receiving a confirmation from this agent. Next, it will inquire about the connection status of the various current generation sources, and lastly, it will obtain information regarding the load status. It then defines the programmed scenario's setting using the information that has been processed and then forwards it to the protection agent. This agent replies if they can accept and change their setting or if it is not possible to do so.

The collaboration diagram displays the exchange of information between each agent as well as the confirmations needed to update the MG topology and the LDS connection's status as required by the ASIMG. The settings supplied by the ASIMG are approved or refused using Agent Protection (AP). As seen in Figure 2.4, the graphical interface of the cooperation diagram between the measurement agents and the ASIMG is represented by the measurement agent interface or COM.

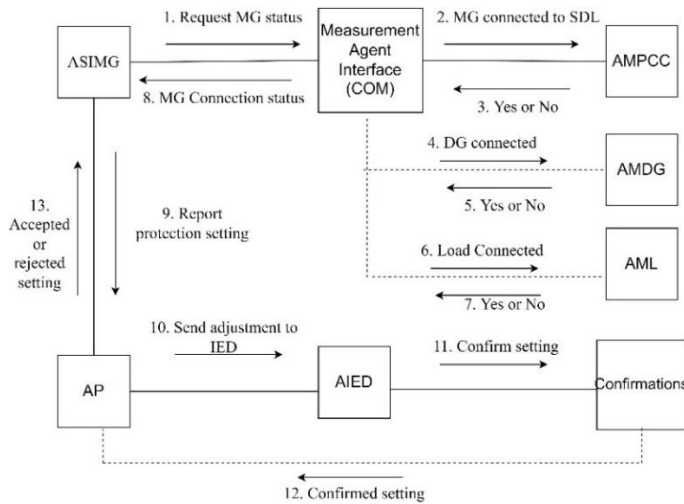


Figure 2.4 *Diagram of collaboration*

The solution's architecture and the channels of communication used by the agents and the test network created by the real-time software are shown in Figure 2.5. Information about the load in the system, PCC, and the status of the generator switches is received by the measurement agents (AMGD, AMPAC, and AML), who then transmit it to the ASIMG via internal

messages. After receiving this data, the ASIMG creates a graphical interface on the workstation and shows a status message along with the new parameters that the IED agent needs to follow. Similarly, a database containing this data will be used to review the various statuses that were acquired.

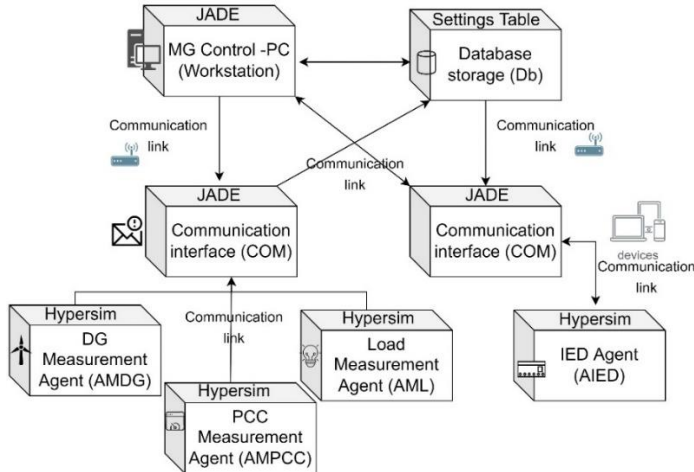


Figure 2.5 Architecture of the solution

2.3.3. Multi-agent interface

Every agent is built following the design procedure, and they are all tasked with using the JADE software on the FIPA agent platform to monitor and act on network activity. Figure 2.6 illustrates a multi-agent interface. Moreover, JADE and the real-time software communicate with each other via the TCP/IP-based IEC 104 communication protocol. Using the IEC 104 library, it is discovered that the control switch that controls the DG and the PCC is found to be in a connected state that regulates the PCC and the DGs are in a connected condition. These connection states are read by the MAS algorithm as zero (0) for unconnected and one (1) for connected, determining which setting is suitable for each of the relays that are evaluated.

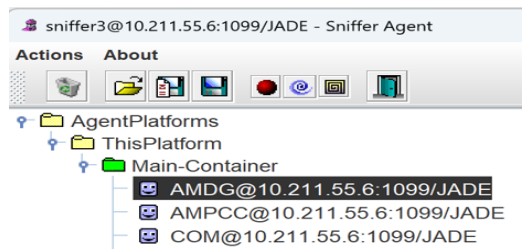


Figure 2.6 Interface of the Multi-Agent JADE software

An example of the architecture is provided in Figure 2.7, which shows the association between a workstation, real-time technology, the IEEE 13-node model created by the software, and the MAS created using JADE.

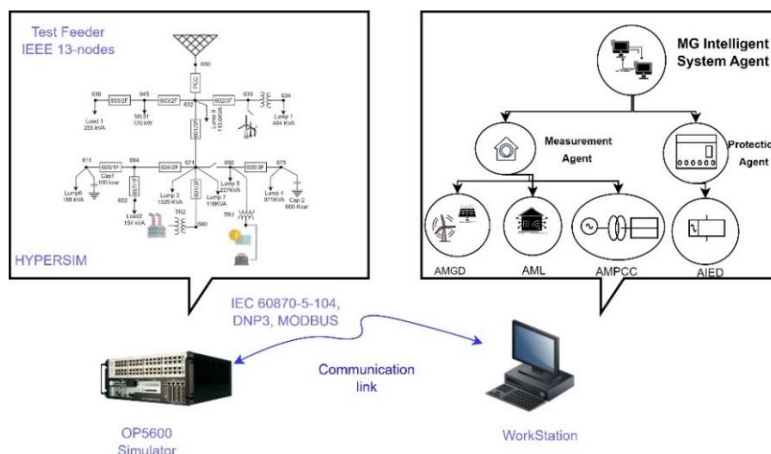


Figure 2.7 Schematic diagram of the solution

2.4. Simulation test validation and analysis of the protection scheme

This section provides an explanation of the validation of the simulation test and the analysis of the suggested protection scheme are explained in this section. The relays' location and their default mode settings are defined first. Second, the selectivity and functionality of the relays in the system are shown using three-phase faults. Finally, the integration of the multi-agent algorithm and real-time software is demonstrated.

2.4.1. Proposed location of protective equipment

To protect every node and ensure selectivity in the case of a failure across the MG six overcurrent relays (50/51) are incorporated and two protection zones are developed as Figure 2.8 illustrates.

Chapter 2: Decentralized adaptive protection scheme

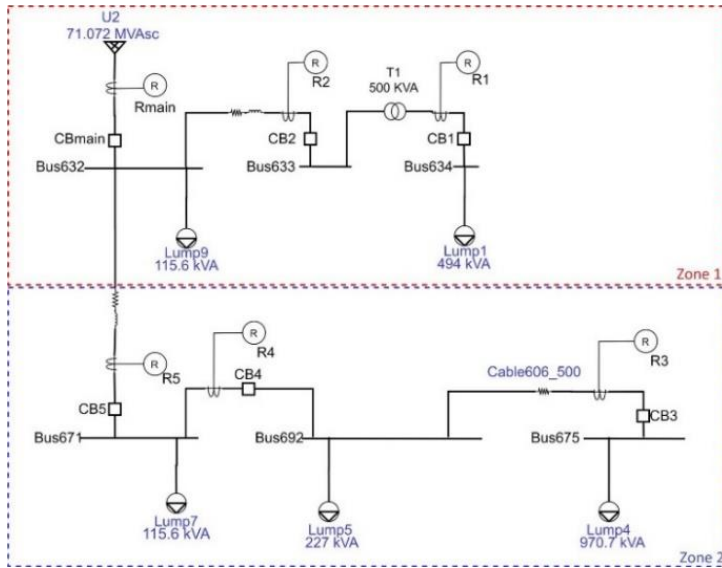


Figure 2.8 Location of the relays

Load flows and short-circuited tests are performed to determine the necessary measuring devices and the protection settings in the MG. Under normal operating conditions, the short circuit results are displayed in Figure 2.9.

Chapter 2: Decentralized adaptive protection scheme

Contribution		3-Phase Fault		Line-To-Ground Fault				Positive & Zero Sequence Impedances Looking into "From Bus"				
From Bus ID	To Bus ID	% V From Bus	kA Symm	% Voltage at From Bus			kA Symm rms		% Impedance on 100 MVA base			
				Va	Vb	Vc	Ia	3I0	R1	X1	R0	X0
Bus632	Total	0.00	12.362	0.00	123.99	131.43	9.008	9.008	3.91E+001	1.17E+002	1.12E+002	2.37E+002
Bus671	Bus632	19.97	2.025	22.80	120.03	124.85	1.395	1.237	1.34E+002	7.42E+002	4.19E+002	1.86E+003
Bus633	Bus632	1.50	0.394	2.56	123.10	130.37	0.390	0.598	1.56E+003	3.55E+003	1.58E+003	3.62E+003
U2	Bus632	110.00	9.864	110.00	110.00	110.00	7.143	7.055	5.30E+001	1.45E+002	1.58E+002	2.95E+002
Lump9	Bus632	110.00	0.106	110.00	110.00	110.00	0.106	0.164	2.14E+003	1.43E+004	2.14E+003	1.43E+004
Bus680	Bus671	19.97	0.000	22.80	120.03	124.85	0.000	0.000				
Lump3	Bus671	110.00	0.998	110.00	110.00	110.00	0.485	0.000	1.86E+002	1.24E+003		
Lump7	Bus671	110.00	0.087	110.00	110.00	110.00	0.084	0.126	2.14E+003	1.43E+004	2.14E+003	1.43E+004
Bus675	Bus692	21.67	0.769	25.00	120.91	123.14	0.743	1.111	2.64E+002	1.61E+003	3.16E+002	1.61E+003
Lump5	Bus692	110.00	0.171	110.00	110.00	110.00	0.083	0.000	1.09E+003	7.26E+003		
Bus634	Bus633	14.25	0.394	15.20	121.55	127.61	0.390	0.598	1.52E+003	3.50E+003	1.52E+003	3.50E+003
Lump4	Bus675	110.00	0.769	110.00	110.00	110.00	0.743	1.111	2.37E+002	1.58E+003	2.37E+002	1.58E+003
Lump1	Bus634	110.00	3.416	110.00	110.00	110.00	3.382	5.186	1.31E+003	3.11E+003	1.31E+003	3.11E+003
Bus692	Bus671	19.97	0.940	22.80	120.03	124.85	0.826	1.111				
			3-Phase	L-G	L-L	L-L-G						
Initial Symmetrical Current (kA, rms)		:	12.362	9.008	10.706	11.598						
Peak Current (kA), Method C		:	24.319	17.722	21.061	22.814						
Breaking Current (kA, rms, symm)		:	9.008	9.008	10.706	11.598						
Steady State Current (kA, rms)		:	9.864	9.008	10.706	11.598						
# Indicates a fault current contribution from a three-winding transformer. * Indicates a zero sequence fault current contribution (3I0) from a grounded Delta-Y transformer.												

Figure 2.9 Short Circuit values in normal operating conditions

2.4.2. Sizing of measurement current equipment (CTs)

The IEC 61869-2-2012 standard is followed to set restrictions in the primary current to prevent saturation due to a fault current. Hence, the nominal precision limit, which is the primary current multiplied by a factor (m), must be bigger than the largest short-circuit current. The nominal current values are used to determine the current meter measurements of every relay as shown in Table 2.4.

Table 2-4 Sizing of Current Transformer (CTs)

Relay	Nominal current (In)	Maximum short circuit current per relay (A) Icc3	Icc3/20	CT
Rmain	517	9864	493,2	600:1
R2	68,3	8564	428,2	500:1
R1	591,8	20134	1006,7	1200:1
R3	118.2	6051	302.55	400:1
R4	140.2	6679	333.95	300:1
R5	371	5373	268.65	300:1

2.4.3. Operational protection assessment – Offline analysis

Following the CT selection process, the protections are coordinated. The dial current and Pickup values for the timed protection (51) and the delay time and Pickup values for the instantaneous protection (50) are shown in Figure 2.10. Furthermore, Figure 2.11 displays how the Rmain software's parameters are configured.

Relay	Bus	CT	ANSI/IEEE	Instantaneous protection setting (50)		Timed protection setting (51)	
				Pickup	Delay	Ipickup	dial
Rmain	632	600:1	VI	4932	0.03	1.077	3.72
R1	633	1200:1	VI	10067	0.03	0.493	1.87
R2	634	500:1	VI	4282	0.03	0.171	1.04
R3	671	400:1	VI	2686	0.03	1.159	1.16
R4	675	300:1	VI	3025	0.03	0.49	0.45
R5	675	300:1	VI	3025	0.03	0.49	0.45

Figure 2.10 Protection scheme settings 50/51

Chapter 2: Decentralized adaptive protection scheme

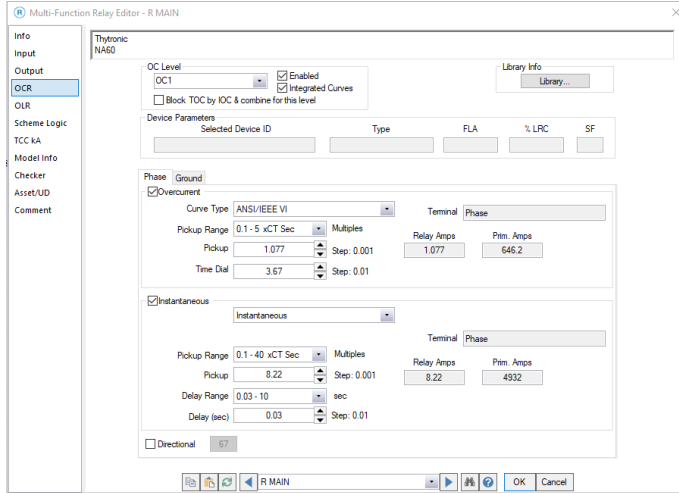


Figure 2.11 Rmain parameter's configuration

2.4.3.1. Protection selectivity and operation

To evaluate the integrated relays' selectivity and performance, a three-phase failure is simulated in the tail of Zone 1. It has come to our attention that the recommended protection plan is exclusive to the tested network. The results show that, as shown in Figure 2.12, protective coordination is ensured in the fault zone by the Rmain operating at 2220 ms, R2 at 237 ms, and R1 at 30 ms.

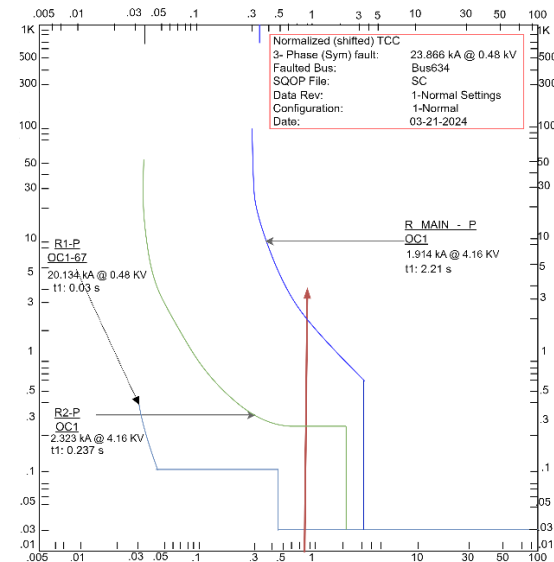


Figure 2.12 Relay operation curve in Zone 1

In Zone 2, we similarly produce a three-phase failure of the same type. The relay R3 runs at 30 ms, according to the results; relays R4 and R5, which operated at 240 ms and 456 ms, accordingly come next. It ensures that protections in the appropriate fault zone are properly coordinated. We perform the same simulations with the DER, but with the same protection procedure and settings. We observe that the relays' adjustment times vary, which has an impact on their coordination. This means that the relay settings, as indicated in Figure 2.13, have to be changed. The new setting for the relays is configured again following the same configuration displayed in Figure 2.11.

Relay	Node	CT	ANSI /IEE E	Instantaneous protection setting (50)		Timed protection setting (51)		Directional (67)
				Pickup	Delay	Ipickup	dial	
Rmain	632	600/1	VI	4932	0.03	0.24	6.8	-----
R1	633	1200/1	VI	10291	0.03	0.49	0.78	-----
R2	634	500/1	VI	4443	0.03	0.31	2.38	Back
R3	671	400/1	VI	3398	0.03	0.37	0.02	-----
R4	675	300/1	VI	3771	0.03	0.23	2.71	Back
R5	675	300/1	VI	2737	0.03	0.52	4.86	Forward

Figure 2.13 Protection scheme settings 50/51 - DER connected

We perform the same simulations with DER included, nonetheless, we isolated the MG. Using the same adjustments as in Figure 2.13, we carry on protection's selectivity against fault in Zones 1 and 2's circuit tails. The R4 protection, situated in Zone 2, comes into action before a fault occurs in Zone 1, as demonstrated in the Fig. 2.14 panel. The interconnected DER sources in Zones 1 and 2 are contributing to the fault current that is causing this unwanted tripping.

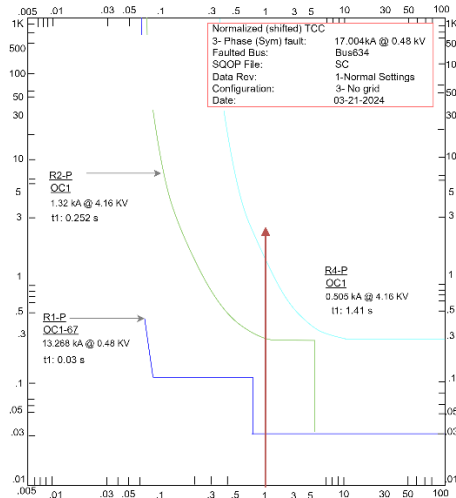


Figure 2.14 Relay response curves for zone 1 fault in Islanded MG

In summary, a fault in Zone 1 or Zone 2 induced protections R4 and R2 to trip unexpectedly during the integration of DER. When the MG is working alone, the process is followed. When the MG disconnects from the LDS, a drop in short-circuit levels has been noticed. The kind of generation source that is operative in the system also affects these short-circuit values and it is necessary to adjust the MG operation protection periods based on the DG type.

2.4.4. Operational protection assessment – Online analysis

The MG chosen for testing is then created in the real-time software, as seen in Fig. 2.1. We model the DORC (50/51/67) and use the SIL configuration of the real-time simulation to verify the protection scheme operation during a short circuit fault (see Fig. 2.15).

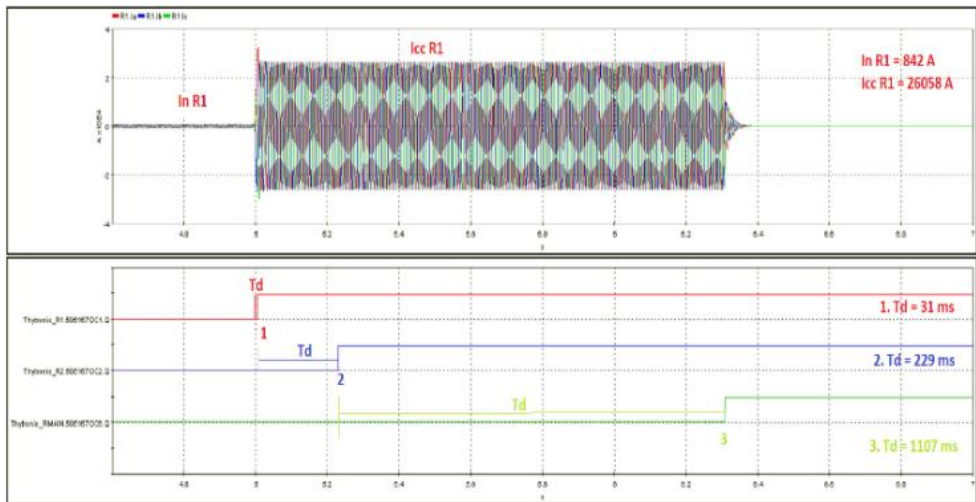


Figure 2.15 Zone 1 fault dynamics in normal operation

The coordination and selection of relay operations are shown in Figure 2.15. At 31 ms, the protection nearest to the failure (R1) opens, R2 at 229 ms, followed by Rmain at 1107 ms. An analogous fault in Zone 1 with DER connected displays R2 activating prior to the fault because of an overload, with Rmain and R1 functioning at roughly 1770 ms and 450 ms, respectively (Figure 2.16). This suggests that the addition of renewable energy sources may change the relay’s nominal currents, leading to a decrease in selectivity and coordination.

The TCP/IP-based IEC 104 communication protocol is utilized to establish communication between JADE and the real-time software. The information to be processed by the multi-agent algorithm is extracted from the simulator using a library that is modified from IEC 104. The IEC 104 library is used to find the connection statuses of the DGs and PCC by reading the state of the switch that controls each of them. The MAS algorithm then reads these states as 0 for unconnected and 1 for connected, determining the correct setting for each relay under review. Figure 2.18 shows the graphical user interface of the produced software. It shows that the application delivers configuration data, the dial time, and the pick-up current of each relay to the user along with an alert message stating that the timed adjustment needs to be adjusted when the MG is connected.



Figure 2.18 Multi-Agent System message during State 1 – MG connected

Selectivity and coordination are not possible with the normal network settings when the MG is connected, as was previously demonstrated. Fig. 2.19 displays the results that were acquired after the relays' modified settings from the adaptive approach were implemented.

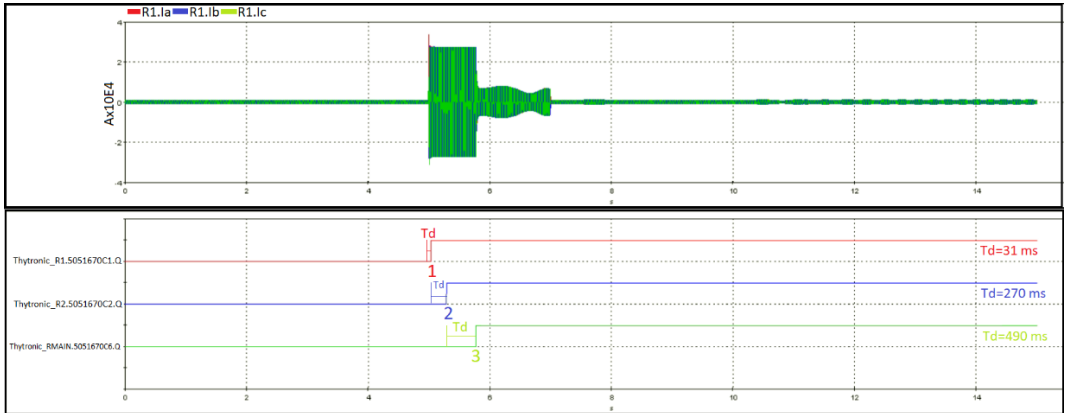


Figure 2.19 Zone 1 fault dynamics with new settings

There are two instances in the graph. Initially, it demonstrates that the relays operate according to the new settings R1. Second, it shows that selectivity and coordination are ensured by R2's operation following the failure. Lastly, the MAS detects the DG's connection status and sends a message with the relay settings when the MG is switched off from the SDL (MG0). However, depending on the kind of linked resources, decreases in the SCC levels are noted. This suggests that to ensure that the relays function appropriately, a matrix of modifications must be made for every kind of setup.

2.5. Conclusions

This chapter presented the design of a MAS for adaptive protection that consists of five agents to assess the network topology and outline the new changes needed for the protection devices, and six directional overcurrent protections in different MG zones. Additionally, we used off-line simulations to verify the operation for the chosen MG protection and demonstrate how the protection parameters need to be modified when integrating the MG in a typical operation scenario—that is, without integrating distributed resources. Moreover, we proved that the protections cannot continue to operate selectively with the same modifications in the event of a topological change or MG isolation. Furthermore, we saw a timing mismatch because of the inclusion of DG while using the real-time simulation, which did not happen with the off-line simulation because of its evaluation in the time domain. Likewise, we showed how the MAS sets the new system relay settings, ensuring the MG's selective protection.

In conclusion, improved active protection will come from the progress of the decentralized systems. There are still issues with the reliability of

communication during an online connection, difficulties with relay interoperability, and manipulation of commercial relay settings that require further testing and comparison with more sophisticated algorithms. Therefore, to achieve the effective functioning of these protections, more AI and software-based protection techniques are required to enable proper decision-making, operational autonomy, scalability, and proper monitoring and fault diagnostics. To prove the reliability of these systems, further real-time simulation tests—including those involving the used communication technologies—are thus required.

Chapter 3: Emotional learning modelling for Microgrid Control and Protection

MGs are the fundamental components of smart power systems, which emerge from the integration of energy storage devices, power-consuming equipment, and local power generation resources. Although MGs have several advantages, including greater flexibility and resilience, more efficient control and protection strategies are still required to guarantee the high performance of MGs and self-healing capabilities in the presence of dynamic operating conditions and failure events. Getting inspired by the emotional response of human brains to external stimuli researchers have recently investigated model-free emotional-learning adaptive techniques that apply to MGs' control. These model-free control procedures have many advantages over conventional methods and are capable of handling the MG's intrinsic complexity, nonlinear behavior, and variability.

This chapter investigated how emotional learning might be used in energy systems, as well as their limitations and prospects. Additionally, the research explores how MGs can use emotional learning to strengthen their protection and control systems and draws comparisons between the human brain's emotional processing and MGs' HCA. In conclusion, a final set of observations regarding the possible applications of this method are presented, along with a discussion of future directions promoting the use of brain emotional learning (BEL) to protect and control MGs.

3.1. Introduction

The previous chapter concluded that the use of AI-based and virtual protection solutions could improve decision-making, autonomy, and accurate fault identification in MGs. However, there are still issues with data dependability, high complexity, and communication requirements that need to be resolved before using these techniques in MG applications. Therefore, the research question at hand is how to improve AI-based protection strategies that can precisely react during a fault condition and trigger a prompt response from the protection devices. Furthermore, VPR arrived as a valuable instrument for power system protection, control, and digitalization, which could improve the protection schemes in digital substations. However, MG

energy systems lacked applications for VPR, so the question arose as to how to develop a virtual or software solution that could be used in the MG control system to avoid the deployment of multiple relays and settings. These inquiries forced us to investigate the brain and the cognitive process to gain new perspectives on methods and ideas that may be applied to improve or better comprehend real AI methods.

More realistic AI models that draw inspiration from neuroscience advances, in our opinion, may be beneficial for improved processing, decision-making, learning—all functions that the human brain performs daily. Keeping that in mind, we began investigating the brain, the functional roles of its many parts, and the connections between them. We then investigated the brain’s functionalities theories—triume, fear, and adaptation—to understand the differences and functions of different brain regions. This makes it possible for us to do additional research on thinking, emotions, memory, and problem-solving. Emotions are quick reaction patterns that enable us to react rapidly to a threat or challenge. They are an integrated brain response to a particular situation. We are motivated to examine the applicability of emotions in energy systems by this emotion’s quick reaction.

3.2. Emotional Control

Emotion is one of the elements that constitute the intricate process of learning [131]. In humans, certain sensory inputs cause the AMYG to react according to the stimulus [132]. The Orbito frontal cortex (OFC), which aids in determining the emotional significance of a situation, receives signals from the AMYG through which it assesses information about potential rewards or risks. Figure 3.1 illustrates the primary emotional brain regions in humans.

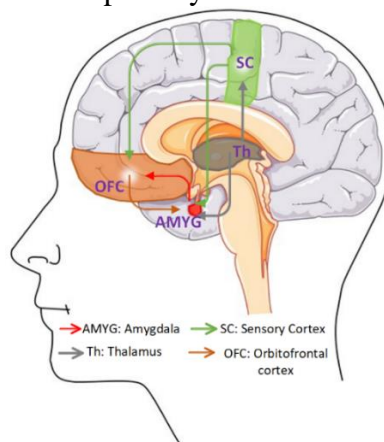


Figure 3.1 Emotional brain regions

To enhance knowledge of the relationship between the AMYG and OFC during learning, a computational model of this relationship is proposed by the authors in [131] (refer to Figure. 3.2). Thalamus (Th), sensory cortex (SC), AMYG, and OFC are the model's components. The first two are considered in a simplified way, while the latter two are modeled comprehensively.

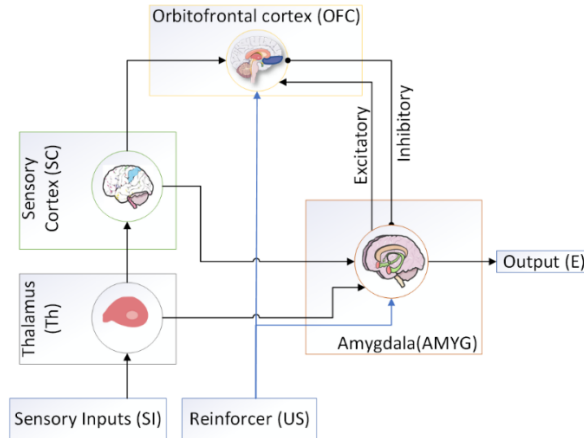


Figure 3.2 Schematic of the AMYG-OFC computational mode [131]

The model proposed in [131] suggests that signals are sent to the SC through the Th. The Th also provides the AMYG with a main signal. The SC's job is to give the AMYG and OFC a more complete and precise representation of the stimuli. Once the OFC has addressed the stimuli, this representation aids in the AMYG's early learning process and makes it easier for the emotional reaction to extinction. Three senses are received by the AMYG: 1) Inputs from the Th and SC; 2) A reinforced signal that provides information regarding the emotional value of stimuli whose origin is still unknown; and 3) An inhibitory input from the OFC that suppresses emotions that are not appropriate.

Figure 3.2 illustrates how excitatory learning and inhibitory signals are necessary for AMYG to operate properly. A learning input and sensory nodes are components of excitatory learning. As part of a negative feedback loop, the learning input turns off the learning signal when the reinforced signal and the AMYG output signal match. The emotional reaction is guaranteed to be proportionate to the learning signal by this process. The inhibitory signal from the OFC modulates the AMYG's output signal. The OFC receives input signals from the SC in addition to the actual and anticipated reinforcing data from the AMYG. The OFC initiates learning if, upon comparing these two signals, the predicted reward is not obtained. As a result of this learning, the

inhibitory signal that is sent to the AMYG and triggers the emotional response to extinction can be modulated by the current stimuli.

3.2.1. Emotion-inspired AI for modeling and control approaches

Several recent research has emphasized the significance of emotion in ML [133] and AI [134]. An overview of emotion-augmented machine learning (EML) techniques is provided by the authors in [134]. They analyze the psychological and neuroscientific implications of applying emotion theory to ML algorithms. Emotion theory has also been applied by AI to optimization tasks, such as emotional backpropagation learning and multilayer perception [133]. The authors of [133] give an outline of the significance of emotion in the development of artificial cognitive processing and real-world instances of emotion-augmented AI. They also go over important obstacles and relevant studies for the development of emotion-AI.

Brain Emotional Learning (BEL), BEL Intelligent Control (BELBIC) [135], BEL- based prediction model (BELPR) [136], and Limbic-based artificial emotional neural network (LiAENN) [137] form a category of EML methods. Founded in the anatomical model of the emotional brain, each model employs neural network models to replicate midbrain connectivity and behavior. BEL has been used to handle the challenges posed by model complexity and classification problems in control applications [138], decision-making [139], model predictions [136], nonlinearities [140], [141], multi-objective capabilities [142], disturbances and parameters variations [143]. These models are useful for control system applications where they improve performance through less computational time and complexity, facilitating swift learning, rapid reaction, increased precision, robustness, and generalization [144].

3.2.2. Emotion-inspired modeling and control techniques for industrial applications

A bio-inspired intelligent controller is suggested in [141] to improve a nonlinear system's efficiency. The mammalian brain's emotional intelligence and the brain's affective system (BASIC) served as inspiration for the control architecture as seen in Figure 3.3. The SC is specifically incorporated into the mathematical concept and architecture in this model. This system reacts more effectively to environmental and dynamic changes in the plant than traditional P, PI, and PID controllers, which might result in system failures or

disruptions. Furthermore, compared to AI-based controllers, the suggested controller permits more input variables [141].

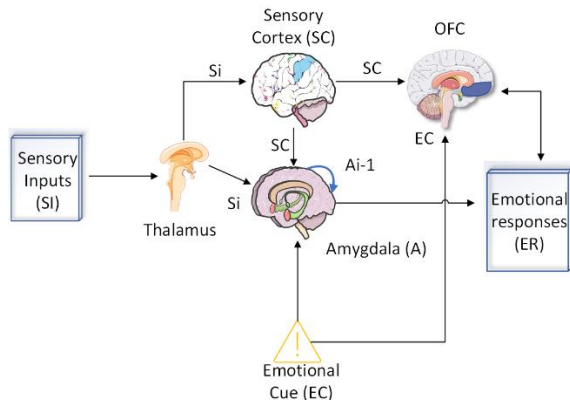


Figure 3.3 BEL structure proposes by [141].

The BELBIC model has been applied to improve decision-making [135], computational time [145], power control [146], and power ripple reduction [147]. It is suggested in [135] for decision-making and control engineering, and it consists of six elements: control reaction, sensory inputs, emotional signals (ES), AMYG, OFC, and Th. By eliminating the need for prior knowledge of process dynamics, BELBIC's usage in control systems is made simpler when it is integrated into a MATLAB-Simulink toolbox [145]. Compared to neuro-fuzzy adaptive algorithms, it is easier to develop and has a lower computing overhead. A BELBIC technique based on SIMULINK is validated for industrial control applications [146]. To provide better transient responsiveness and less power ripples in a Doubly Fed Induction Generator system, BELBIC is recommended in [147]. Some applications of emotion-inspired computational models are shown in Figure 3.4.

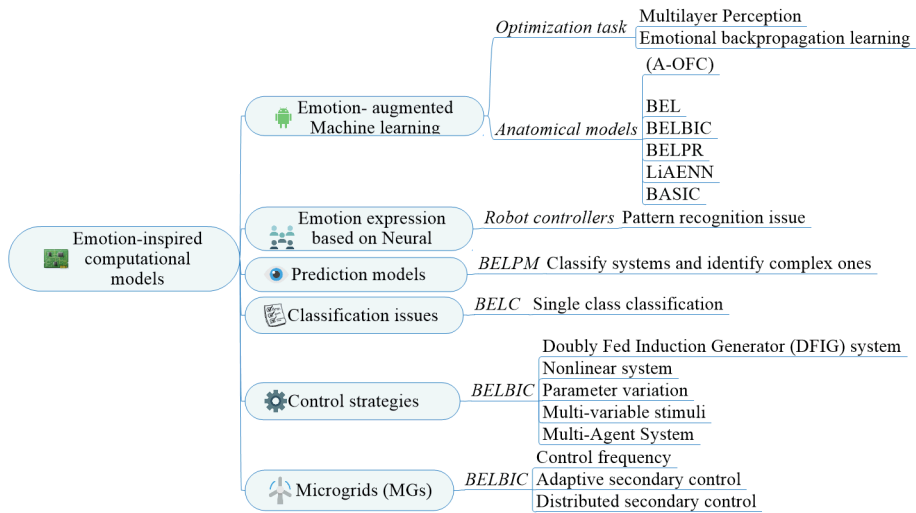


Figure 3.4 *Emotion-inspired computational models applications*

3.3. Microgrids and brain emotional control.

MGs may operate connected to the grid, but if there is a fault or problem in the main grid, they may switch to island mode. When the MG enters an islanded mode, it modifies its operating parameters as well as the way different technologies, including ESSs, generating sources, and power converters, synchronize. HCA in MGs enhanced its operability during this transition and improved its reliability by using three control levels. The ability to incorporate effective features was made possible by the differences between each level in terms of capacity, response time, operating duration, and communication requirements. It has proven advantageous by increasing the MG's intelligence, speed, and adaptability since the controls aren't overburdened by attempting to perform several tasks at once [148].

The primary control, which is the most reactive controller in this hierarchy of control, oversees power sharing and fault protection in addition to maintaining voltage and frequency stability during MG operation. However, when the primary controllers are operating, there may be variations in voltage and frequency, which could lead to problems with power quality. The secondary control monitors and corrects problems with voltage and frequency deviation, power flow and control, fault management, and operation [149]. The secondary control then sends control references to the primary control. The tertiary level ensures that the MG's long-term objectives and operational

conditions are satisfied. This includes optimum power flow, resource optimization, and economical operation [149]. The control references for the secondary level control are produced by the tertiary level control, which functions at the slowest time scale of the three control levels. Further information about the HCA is available in [150].

The left side of Figure 3.4 illustrates the HCA of MGs and the control level features. The raising adoption of information and communication technology has made MGs more sophisticated, but it has also created new cybersecurity risks, necessitating the improvement of MG's cyber resilience. As a result, attacks on MG can be lessened or even eliminated by brain-inspired methods that mimic human intellect and can carry out tasks for which it is not always trained or developed. In addition to offering online learning capabilities, applying BEL for MG control may be advantageous in resolving the operational deviations, changes in voltage and frequency during disturbance and equipment failure, and complexity of the MG's operation.

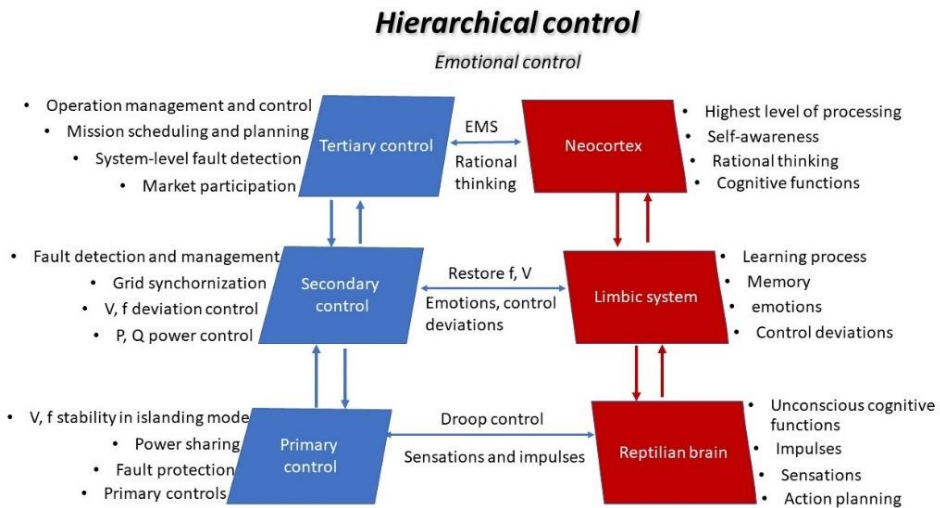


Figure 3.5 Analogy between hierarchical control and brain emotional control

According to the 1990 triune brain model [151], the limbic system includes numerous important brain regions involved in emotional responses that make up the BEL system. The limbic system, the neocortex, and the reptile brain, or R-Complex, are the three components of the triune brain theory. Along with complex cognitive, verbal, motor, sensory, and social capacities, the neocortex is the location of rational thought [152]. Primary in human emotions, the limbic brain serves as a bridge between the neocortex and the

ancient reptilian brain. The Triune brain and key brain emotional areas are represented in Figure 3.6.

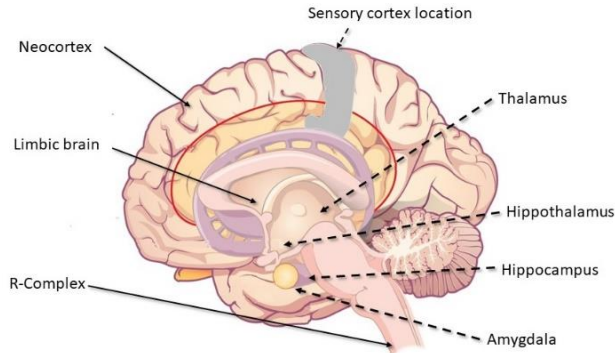


Figure 3.6 Triune brain and key brain emotional areas

3.3.1. Brain Emotional Learning for Microgrids application.

Several MG control techniques are inspired by BEL. Table 3.1 shows its applications and advantages and the proposed block diagram of the BEL for MGs by [153] is displayed in Figure 3.7.

Table 3-1 Applications of BEL controllers in MGs

Application	Use	Advantages	References
secondary-level control	Stabilize frequency and voltage in case of disturbance	Quicker reaction time, more robustness, model free Reduce overshoot, shorter time to settle Handle sudden system changes and compensation of parameters with less error	[7]
Distributed secondary control strategy	Restore frequency deviations	Real-time implementation of the BEL strategy	[9]
EMS improvement	Wind/photovoltaic (PV) isolated MG under different disturbances	Stabilize the MG with varying load and frequency with high accuracy	[10]

Application	Use	Advantages	References
Online tuning	Enhance the performance of the converter against uncertainties and dynamically varying operating conditions with optimal weighting factor design and control robustness.	Lower complexity, faster dynamic response, and higher frequency bandwidth	[153], [154]
Isolated MGs	Frequency control, Online learning capabilities, and real-time updates	Frequency deviation for a shorter period, lower steady-state error, and lower overshoot than decentralized PID or fractional-order (FO) PID controllers	[7], [154]
Secondary control strategy	Regulate frequency deviations	lower control effort, less overshoot, less frequency deviation, and faster frequency recovery.	[155]

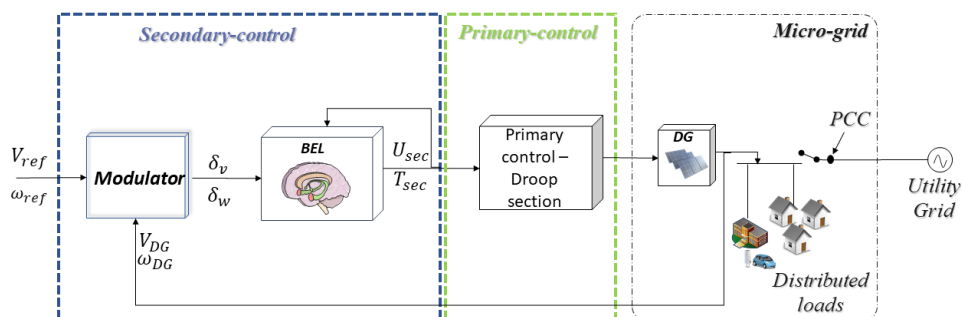


Figure 3.7 Block diagram of BELBIC for MGs

The Amygdala-Orbitofrontal Cortex (AMYG-OFC) model, which has been developed by [131], is the foundation for the connectionist approach used in the BEL model block of the system described by [153] and illustrated in Figure 3.7. The connectionist method in AI uses neural network designs to mimic the composition and functions of the human brain. The AMYG and the OFC are the two main parts of the BEL model, and these components all perform distinctive functions in emotional learning and control.

- ❖ **Amygdala (AMYG):** The emotional learning process is guided by the AMYG. It processes both SIs and ES. The Sis represents the actual status of the system, including errors, references, and measured outputs, while ES often represents the objectives such as reflecting the reference tracking performance or other objectives like reducing overshoot or minimizing energy expense. Table 3.2 displays the system’s inputs.

Table 3-2 *Inputs of the AMYG connectionist model*

Inputs	Type	Description
Sensory Inputs	System errors	Errors in voltage and frequency (δ_v, δ_w)
	System inputs	References values in voltage and frequency (V_{ref}, ω_{ref})
	Measured outputs	Measured system frequency and voltage (V_{DG}, ω_{DG})
Emotional Signals (ES)	System objectives	Reference tracking performance, reducing overshoot

Each AMYG node’s output ($AMYG_i$), is obtained as follows

$$AMYG_i = V_i \times SI_i \quad (1)$$

The subsequent rule is used to update the weights (V_i), where (V_i) is the weight corresponding with the i-th sensory input.

$$\Delta V_i = K_v \times SI_i \times \max(0, ES - \sum_i AMYG_i) \quad (2)$$

Where K_v is the learning rate.

In addition, the AMYG receives a signal straight from the Th ($AMYG_{th}$)

$$AMYG_{th} = V_{th} \times \max(SI_i) \quad (3)$$

Where V_{th} is the weight, updated using the same rule as (V_i)

- ❖ **The orbitofrontal cortex (OFC):** Ensures that only appropriate emotional reactions are enhanced by blocking improper learning in the AMYG. It receives the same Sis as the AMYG.

The output of each node is OFC_i is calculated as:

$$OFC_i = W_i \times SI_i \quad (4)$$

The next rule is used to update the weights (W_i), and the weight connected to the i -th sensory input is denoted by (W_i)

$$\Delta W_i = K_w \times SI_i \times (MO - ES) \quad (5)$$

Here, K_w is the rate of learning and the model output is MO.

By this approach, the ES is the reference tracking error, which will cause the system to feel unfulfilling, and the adaptive intelligent control will reduce this emotion, resulting in the system performing properly.

- ❖ **Model Outputs (MO):** It is the control Reaction
The difference between the ($AMYG_i$) and (OFC_i) outputs determines the BEK model outputs (MO):

$$MO = \sum_i [AMYG_i - OFC_i] \quad (6)$$

To maximize the model's performance in several applications, different techniques are used to adjust its parameters [156], [157], [158]. These parameters include the learning rates (K_v and K_w) and the weights (V_i and W_i). [7], [157].

3.3.2. Brain Emotional Learning for Protection

Although BEL strategies for controlling MGs were discussed in the preceding section [7], [8], [9], [10], existing approaches are yet to utilize the advantage of the brain's inherent self-defense structures to protect MGs. Nowadays, MG protection methods mostly depend on relay control and management [4]. AI techniques and software programs such as VPR are being used more and more in modern innovations because of their potential to enhance MG protection by reducing physical size, improving automation and control infrastructure, and increasing reliability at low cost [5]. Relays may be able to coordinate by autonomously adjusting their operational parameters in response to changing conditions and learning from real-time system status data if brain-inspired algorithms, like BEL, are incorporated with MG protection systems [159].

Furthermore, to reduce the effect on MGs' performance during transitions, the best location for protective devices needs to be determined. To achieve centralized training with decentralized execution, RL algorithms can further improve the training process by incorporating additional data from neighboring agents such as their gradients, rewards, observations, and parameters [80]. Nevertheless, the application of these models in MGs necessitates a multidisciplinary strategy that makes it possible to create biological models that are more accurate.

3.3.3. Hierarchical emotional control for MGs.

The triune brain model and the HCA in MGs have architectural characteristics, as illustrated in Figure 3.4, even though recent research indicates that the brain is more complex than a triune brain model [160]. In this thesis, we suggest "hierarchical emotional control for MGs," which uses the triune brain model as a broad analogy for HCA in MGs.

3.3.3.1 R-Complex primary control

The reptilian brain or R-Complex is at the base of the complex hierarchical organization that is the human brain. This area, which is external to each Th, regulates instincts, body language, feelings, and natural responses. The reptilian brain finds it difficult to learn from errors and tends to repeat instinctual behaviors in response to stimuli and during unconscious cognitive processes like language grammar and syntax understanding. It releases hormones that cause impulsive actions, for instance, fighting, freezing, or running away from danger [159], and controls essential survival functions such as breathing, heart rate, and balance [152].

Like this, primary controls in an MG system handle critical operational and spontaneous changes using droop control, load sharing between converters, island mode voltage, current, and frequency stabilization, fault management, and control over the MG's protection activities for autonomous operation [150]. To facilitate grid functioning, the injected power is additionally controlled at the primary level at the PCC in conjunction with the grid voltage [161]. The principal controllers of MGs can prevent instabilities and reply quickly to instabilities or changes in the dynamic, just as the brain of a reptile controls basic human actions and activities.

3.3.3.2 Emotional Secondary control

The limbic system, which also has a significant impact on human emotion, cognition, conscious behavior, experiences, and other domains, is thought to generate emotional experiences [162]. It connects the more modern neocortex to the evolutionary reptilian brain. It lies next to the lateral ventricles on the inner cerebral hemispheres. The limbic system carries out processes such as positive reinforcement and negative punishment, producing rewards or punishments in accordance [152].

The secondary control of MGs corrects voltage, frequency, and amplitude deviations and maintains the nominal operation of the system during load fluctuations, much like the limbic system, which oversees controlling and regulating emotions [7]. To regulate the variations, this control might also be associated with rewards or penalties, either positive or negative. For NMG, the authors in [163] propose a MAS and RL-based distributed optimal secondary control. The suggested approach combines global coordination amongst the agents with coordinated frequency recovery and control of voltage using a local reward system. It has been shown that the technique improves distributed control's flexibility and reliability. To enhance primary frequency response in NMG system operation, the authors in [164] suggest an RL-based controller. The suggested approach reduces the frequency fluctuations in low inertia MGs during transient events by altering the set points of the regulation device on a diesel machine using a deep-network dynamic model. The ongoing adaptation to shifting conditions is improved by the RL approach.

3.3.3.3 *Neo Tertiary control (EMS)*

The neocortex, the part of the brain responsible for logical thought, serves as the brain's task manager and is crucial for higher-order functions such as our verbal, motor, sensory, cognitive, and social abilities [152]. The six-layered neocortex is imaginative and adaptable enough to adjust to a changing environment and can predict thanks to its inference process. The EMS in the tertiary control of an MG system can similarly autonomously adjust to various system variations and dynamic behaviors, including load fluctuation, power deviation, market engagement, and NMG topological changes carried on by faults and disasters. A model-free RL-based online optimal (RL-OPT) control technique is employed in [152] to integrate hybrid ESSs in hybrid AC-DC MGs, enhance charging and discharging profiles, and reduce disturbances. Compared to conventional PI controllers, the control approach can adapt to the system's dynamics more easily.

3.3.4. *Advantages and challenges of BEL applications*

Several advantages of BEL controllers have been documented in the literature:

- ❖ Model-free structure [154] and does not require a thorough understanding of the dynamics of the system [153].
- ❖ Fast thinking and learning [138].
- ❖ The potential for online learning and real-time changes [7], [154].
- ❖ May handle multiple tasks and has low computing complexity [7], [154].
- ❖ Better performance when compared to fuzzy logic controllers and PI [9], [10].
- ❖ A straightforward control structure appropriate for real-time applications [9].

Nevertheless, despite these benefits, several challenges still need to be solved to make it easier to integrate BEL into real-world MG applications as:

- ❖ Computational complexity [9], [156], [165]
- ❖ Real-Time Implementation [9], [156], [165]
- ❖ Convergence and stability control issues [153]
- ❖ Parameters tuning [69], [158], [166]

BEL methods keep computational complexity at an $O(n)$ level, which is in line with the basic neurocircuits of emotional brains and allows for fast learning, accuracy, simplicity, and reduced computational load [156], [165]. However, a low information capacity (IC) could be the result of the limited quantity of BEL weights, or $O(n)$. The traditional method of boosting IC frequently requires the addition of hidden neurons, which has a significant computational cost. Consequently, [156] formulates a competitive property structure that can raise the model's IC without raising the computational complexity. Additionally, the enduring and continuously developing nature of emotional learning within the AMYG is a crucial component. Studies have demonstrated that adjusting neural network weights can improve the precision of BEL algorithms for fast classification by substantially increasing classification accuracy without negatively impacting computing complexity.

For instance, a Genetic Algorithm (GA)-BEL is developed and tested for two facial recognition tasks in [157], utilizing the global optimum solution of GA and the quick learning and low computing cost of BEL. To improve the predicting effectiveness of the BEL, a neo-fuzzy network is introduced into

the orbitofrontal brain region [167]. Similarly, a BELPR based on Neo-Fuzzy is created for classification tasks that preserves the properties of both networks and simultaneously enhances BEL performance [168].

It is difficult to ensure that BEL models will converge and remain stable during the learning process because of their dependence on multiple elements, including the training data quality, architectural design, and the requirement to adjust several parameters. It is still challenging to provide a convergence guarantee. However, there are several steps that BEL-based models have made to improve convergence. These include lowering computational complexity, using suitable weight initialization approaches, and continuously adjusting model weights to reduce tracking errors in the system. A Lyapunov analysis is employed by the authors in [153] to evaluate the system's stability during learning and control convergence. The findings indicate that the model's weights in the learning-based method asymptotically converge to the intended goals. The study examines the convergence of the model during two distinct periods: the non-adapting and adaptation phases. For BELBIC, the asymptotic stability of the weight estimate errors, and the model generation state were also established by the authors through a closed-loop stability analysis.

The BEL controller's settings have been adapted using different approaches. These techniques include trial-and-error techniques to lower computational complexity [135] as well as heuristic approaches [153]. Further metaheuristic techniques that have been used to improve parameter tuning performance include PSO [7], [9], GA [69], and the CLONAL selection algorithm, which is based on the immune system's clonal selection process [158]. These techniques have shown advantages over robust controllers in terms of less overshoot and settling time, which improves BEL controller precision. Additionally, several authors have investigated how to efficiently modify parameters with fuzzy inference systems, which can result in better tracking error reduction and learning performance [166]. The optimization of nonlinear parameters has also involved deterministic optimization techniques such as gradient descent methods [169] and steepest descent [144]. Moreover, model parameters have been updated using statistical methods like the least square estimator [170].

Although these methods show potential for enhancing BEL parameter adjustment in MG systems applications, it is important to remember that difficulties remain in accomplishing generalization in various MG

configurations. Research is still being done to find the best BEL parameter adjusting methods for real-world uses like MGs, and a systematic approach has not yet been developed.

3.4. Conclusions

This chapter gave an overview of the BEL model, outlining its key elements and several types of control systems applications. The use of BEL-based control systems has proven to provide benefits, such as enhanced performance highlighted by reduced complexity and computation time. Fast learning, quick response times, improved precision, resilience, and generalization are all made possible by this approach. In addition, we presented a comparison between BEL and the HCA of MGs, emphasizing how the BELBIC technique might enhance MG control performance. We discussed the potential advantages and disadvantages of this strategy for the control and protection of MGs after looking into control applications of the BELBIC method.

This chapter not only advances knowledge of BEL's principles and applications in MGs, but it also clears the path for comprehension of the integration of new paradigms and artificial intelligence techniques inspired by the brain into energy systems. As a result, we built a brain-inspired modeling framework for MG protection in the next chapter, considering the emotional learning system's insights and the function of the AMYG and its projections.

Chapter 4. Brain-inspired model framework for Microgrids.

This chapter proposes a theoretical framework for brain-inspired self-protective solutions based on the behavior and functionality of the AMYG. A comparison between the theoretical foundations and behavior of the AMYG and those of MGs is made to apply in MGs energy systems. In addition, a model is proposed that uses the inference process theory of the brain to complement the AMYG reaction.

4.1. Introduction

Power systems are currently experiencing a noticeable transition away from conventional relay-based systems and toward advanced virtual solutions and AI-based methodologies [5]. A growing deal of attention is being paid to software applications and AI techniques, even though most MG protection strategies currently in use rely on relay operation and control. With the use of these innovative techniques, MGs' operations might be dynamically managed during disturbances and outages, avoiding the necessity for large-scale relay deployments with constant settings. Furthermore, employing brain-inspired algorithms—which mimic cognitive functions—opens an exciting path for more accurate decision-making regarding the protection of MGs. AI and bio-inspired algorithms together could revolutionize the field of system protection for modern MG systems, enabling online learning and increasing energy efficiency in MG applications [171].

While the previous chapter showed how BEL was applied in the current methods to enhance energy management, stabilize frequency and voltage, and improve control strategies, the brain's intrinsic self-protective mechanisms, and inference learning are not used for MG protection. Brain-inspired algorithms hold enormous potential to enhance autonomous control and self-healing in MG systems by imitating the behavioral and cognitive processes of the brain. This is an opportunity to explore the potential of learning from the human brain to program adaptive protection relay settings or to employ virtual protection solutions to protect the MG.

This chapter's objective is to develop a brain-inspired model framework by analyzing the emotional behavior of the AMYG during the occurrence and extinction of fear. The AMYG is a key brain region that regulates emotional responses and protective reactions. It does this by identifying potential threats, assessing the emotional impact of various events, consolidating memories, and orienting reactions. It also offers a "panoramic view" of the internal and external environments, encouraging more flexible behavior. These instinctive actions or emotional reactions could offer the chance to develop a new AI-based defense system for MGs with improved intelligence for learning and decision-making, among others. To develop a conceptual framework that will promote understanding, spark creativity, and potentially result in the creation of new techniques for MGs, three main investigations are conducted: first, a study of the fundamental theory of brain AMYG behavior, its components, connections, and response to fear stimuli is performed; second, an analysis of the actual AMYG computational models that could be implemented in an energy system is conducted; and third, a parallelization between the fundamental principles of the AMYG and the MG protection system is presented.

Furthermore, a novel brain-inspired model on the brain's ability to infer events and evaluate prediction errors is introduced. Predictive coding theory serves as the foundation for this approach. In addition to the AMYG reaction, this model provides an inference method for locating and classifying faults by using the connection between the Th and cortex. Python is used to implement the model, and its inference response under fault conditions is used to validate its performance. This multidisciplinary approach provides a new model based on brain-inspired theories to support the MG protection and control system, bridging the gap between neuroscience models and applications in MG. Our findings could have an impact on the general field of MGs and indicate a step toward the adoption of a more biologically accurate brain-inspired algorithm in MGs.

4.2. Amygdala theoretical framework and physiological behavior

4.2.1. Foundations of the Amygdala theoretical Framework

A key component of the brain's subcortical networks that oversee identifying and reacting to dangers is the AMYG. Given that it collects sensory information from multiple brain regions and their extensive connections to cortical regions, the striatum, hypothalamus, and brain stem areas, it is also known as the “sensory gateway to emotions” [172]. These interactions are critical for defensive behavior processes, fear memory regulation and preservation, and the generation, consolidation, and storage of memories associated with emotional experiences and fear connections, including those associated with rewarding and unpleasant stimuli [173].

The AMYG is essential for memory consolidation, orienting reactions, assessing the emotional intensity of events, identifying threats, and controlling emotional responses, among other functions. It contributes to protective activities and the transitioning between defensive responses that people exhibit in reply to unpleasant stimuli. Therefore, a personal fear or anxiety reaction may be felt in response to aversive stimuli or in situations where a threat is perceived. One may decide to fight, run away, or freeze in such circumstances. Such affective reactions or innate tendencies might offer a chance to develop a new AI-based protection system with improved features, like the capacity to make decisions and learn about the state of the grid

Components of the Amygdala

The AMYG is essential for connecting environmental cues with defensive reactions. As seen in Figure 4.1, it is constituted of four central distinct bases.

- ❖ Lateral Amygdala (LA)
- ❖ Basal Amygdala (BA)
- ❖ Centro Amygdala (CeA)
- ❖ Intercalated Cell Cluster (ITC) is segregated into dorsal (ITCd) and ventral (ITCv).

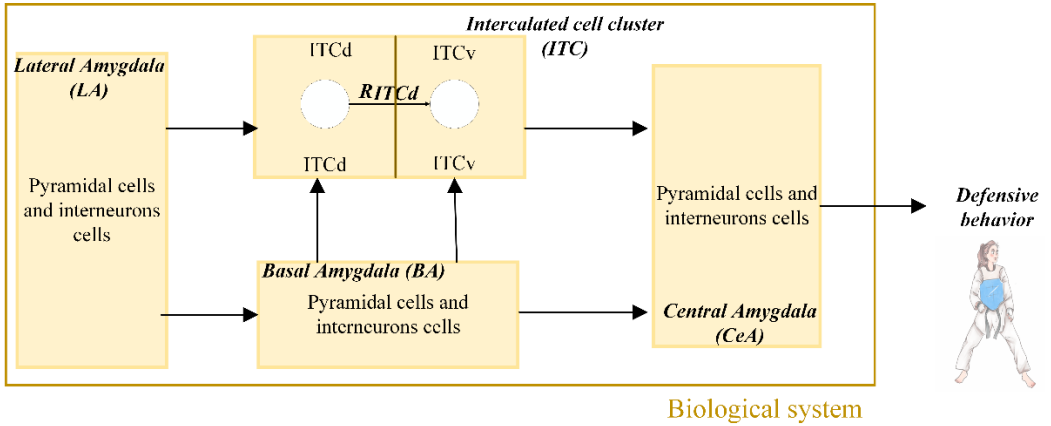


Figure 4.1 Main components of the Amygdala

A basolateral amygdala (BLA), which is distinguished by its almond form, is the whole name for the LA and BA. The ability to produce and transfer conditioned fear responses depends on these nuclei. The AMYG's output core is the central nucleus, most especially the central medial nucleus (CeM). Information processing involves transitional processes, which are performed by the BA and ITC clusters [173].

During auditory fear conditioning, the LA is essential to memory consolidation [174]. Fear extinction, context-dependent fear renewal, and contextual fear conditioning receive assistance from the BA. It is the main channel through which knowledge about conditioned stimulus (CS) and unconditioned stimulus (US) is transferred from LA to CeA, and it integrates contextual cues from the hippocampal region (HIP).

The ITC mediates feedforward inhibition on CeA neurons during BLA activity, hence controlling CeA excitability and functioning as an inhibitory source between BLA and CeA. The CeA is the last stage of AMYG processing and serves as a focal point for communication with the fear response mechanism. Additional divisions of the CeA include the Central Lateral Nucleus (CeL) and Central Medial Nucleus (CeM) subnuclei. CeM is inhibited by CeL through inhibitory inputs, which affects how the organism responds to conditioning, including freezing [175].

4.2.1.2. Key connections and projections of the Amygdala

The AMYG is an important hub for emotions, receiving projections and connections from the cortex, Th, hypothalamus, HIP, and other areas. We will

be focusing on the Th, Infralimbic cortex (IL), and HIP as these are the three main neural connections that enable us to mimic the behavior of fear acquisition and extinction. More information about the microcircuits and AMYG foundations can be found in [176], [177], [178], [179].

Particularly, the Th receives input from the visual and auditory systems among other sensory systems, acting as the entrance point for sensory information. Quick processing and transmission of the fundamental information (unaltered sensory qualities) from the sensory input (SI) obtained here to the AMYG and sensory cortex happens. After processing an input vector that includes components of both CS and US, the Th sends these signals in different directions to the AMYG, as explained in [173]. Additionally, the AMYG establishes connections and projections with the HIP and the IL. The IL is essential to the task of fear extinction and plays a crucial role in controlling reactions to threats. It accomplishes this by affecting ITC, which interacts with the BA to modify the excitation of neurons in the CeM.

It is noteworthy that cortical modulation arising from the IL can influence the balance between fear retention and rapid fear suppression by guiding the system to engage in a “rapid switch” or “cautious” fear mode [180]. Within the neurological framework, HIP functions as the center for processing relational, spatial, and contextual information. HIP is necessary for contextual fear training, which combines emotional reactions with environmental inputs [176]. Figure 4.2 shows the model for AMYG projections and connections.

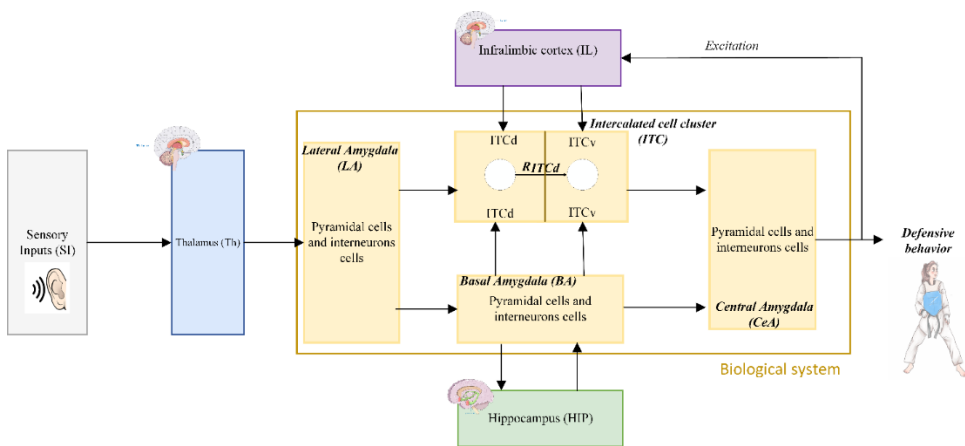


Figure 4.2 Amygdala’s connections and projections

4.2.2. Physiological behavior- Phases of fear condition and extinction

Three different phases are used to characterize the physiological behavior. First, the fear conditions set off a conditioned fear response, which makes AMYG neurons more reactive to that circumstance. Following that, during the fault extinction phase, the fear is decreased. Eventually, an encoded fear memory-enabling post-extinction or self-healing phase develops. The following will go into further detail on how each step operates.

4.2.2.1. Phase 1: Conditioning phase

Multiple excitatory and inhibitory circuits in the AMYG coordinately interact to cause the fear state [180]. For instance, rodents' avoidance responses to threatening stimuli can be either passive (freezing) or active (fighting). Pavlovian classical training, which links an emotionally neutral stimulus (CS) to a fundamentally unpleasant stimulus (US), is the source of this behavior [172]. This fear training explains how organisms learn to anticipate danger, enhances the AMYG neuron spiking in response to CS [181], and provides a direct path from the perception of dangerous stimuli to the activation of emotional reactions [182].

The LA's synaptic connections are significantly impacted by the pairing of CS and US in classical conditioning. The Th's synaptic inputs to LA neurons are amplified through fear conditioning. Different presynaptic and postsynaptic mechanisms help to achieve this enhancement, which in turn speeds up the transfer of information relevant to CS [181]. To put it simply, learning causes synapses on LA cells to become more powerful whenever the matching CS and the US are presented at the same time. Furthermore, synapses onto BA cells are potentiated when LA activity coincides with US activity. Moreover, synapses onto ITCd are potentiated when LA activity coincides with US activity. Lastly, when BA activity occurs in conjunction with the lack of a projected US, synapses in ITCv become potentiated [182]. A graphic representation of the fear response behavior can be found in Figure 4.3.

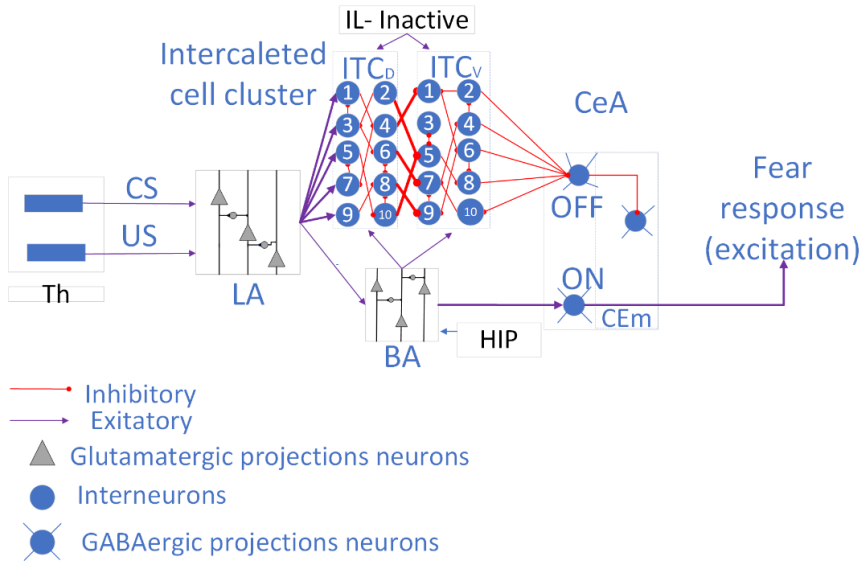


Figure 4.3 Fear response behavior of the brain – representation [172], [180]

4.2.2.2. Phase 2: Suppression of fear response

Fear conditioning may cause a range of responses in BA neurons, such as the emergence of fear cells (excitatory) and extinction cells (inhibitory) responses to the CS. Fear cells either lose their initial responsiveness or adopt an inhibitory response to the CS (orienting), while extinction cells upgrade an excitatory CS response after extinction training. Notably, fear cells may interact with CeM neurons, but extinction cells may selectively contact ITCv neurons [183]. The strength of the link between CS and US neurons should progressively decline following the acquisition phase. Over time, the fear response that the CS triggers will decrease as the connection weights between CS and US neurons decrease. GABAergic neurotransmitter neurons, in addition to BA, provide a different path for the retransmission of CS/US data from the LA to the Ce. BLA neurons are inhibited by projections that ITC cells return to the BLA [180].

IL’s cortical modulation can be utilized to intentionally modulate ITCd and ITCv to either promote or prevent extinction. When IL boosts ITCd activity and improves ITCv inhibition, the CeM may become more strongly disinhibited [174]. However, IL can improve CeM suppression by raising

ITCv activity. IL inputs are necessary to progressively decrease fear responses throughout the extinction phase [172].

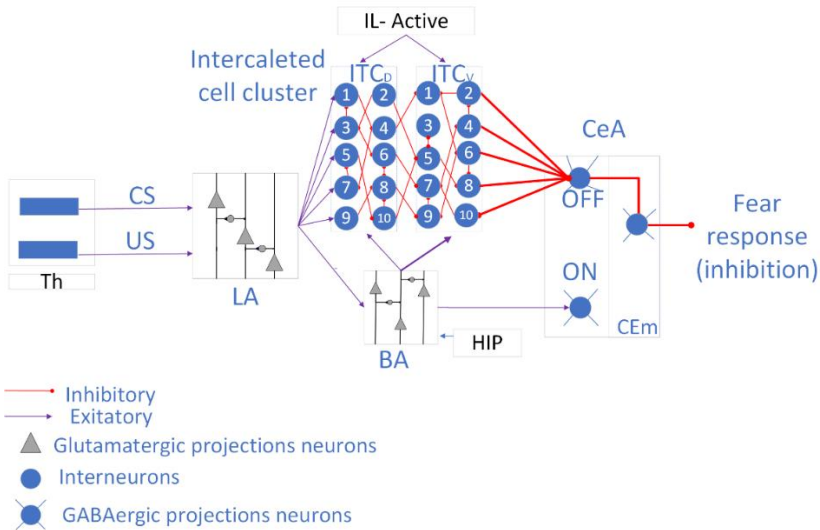


Figure 4.4 A graphic representation of the fear inhibition behavior of the brain [172], [180]

4.2.2.3. Phase 3: Fear response stabilization

Even after the initial phase of fear reduction is completed, the post-extinction phase entails purposefully returning to and interacting with the dreaded stimulus. This procedure aids in preserving the newly acquired knowledge and keeps the fear reaction from resurfacing on its own over time. In essence, it aids in reinforcing the idea that the stimulus that was feared is no longer connected to danger.

4.2.3. Amygdala models

Four main computational models of the AMYG can be found in the literature: biologically realistic models, rule-based, connectionist, and phenomenological spiking neuron models [172]. See [172] for additional details about these models. Rule-based models, such as the Mackintosh, Le Pelley, and Rescorla Wagner models, attempted to replicate behaviors observed in classical conditioning, but they failed to consider the processing of CS and US information. The biological evidence of pavlovian conditioning served as the inspiration for connectionist models, which are neural network models to analyze stability and oscillations using the integrate and fire

methods. Balkenius and Morén (2000) developed a model for emotional conditioning that centers on the AMYG, which serves as the location of fear extinction learning and the centrum of fear acquisition.

These models, however, lack a higher level of biological realism and treat the AMYG as a black box or homogenous structure. Recent models, such as phenomenological [184] and biologically realistic models [185], integrate complex AMYG circuitry, considering numerous areas and interactions [183], in contrast to older models that view the AMYG as a "black box." While the phenomenological model is useful for analyzing network dynamics and replicates the spiking behavior of neurons, it overlooks some biological constraints on brain processing and learning. The biological realistic models, which are the final model, are crucial for simulating complex behaviors like those of the amygdala. They respect biological constraints on learning and computation while addressing real-world neuronal features. One of the problems with these models is their complexity [172]. The main behaviors and connections used in this investigation are highlighted in Figure 4.5. Table 4.1 provides an overview of the principles, microcircuits, and physiological behavior of the AMYG nuclei, and the main afferent and efferent circuits of the AMYG nuclei have been compiled into Table 4.2.

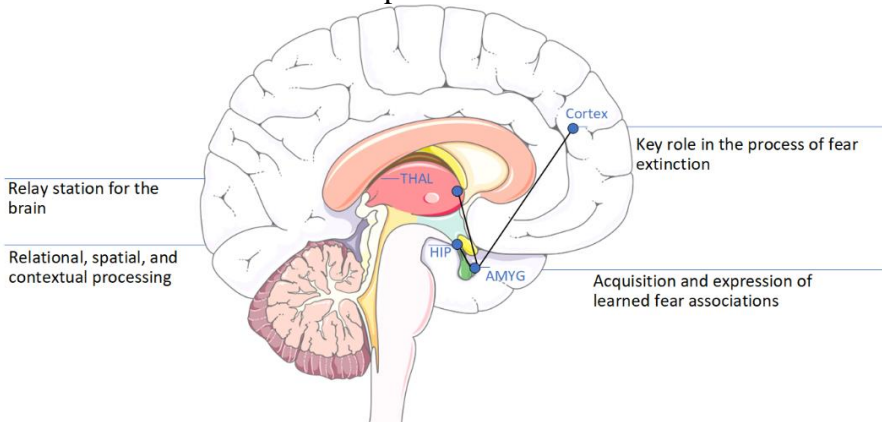


Figure 4.5 *Amygdala connections and key behaviors*

Table 4-1 *Amygdala nuclei’s physiological behavior, foundations, and microcircuits*

Amygdala	Functions	Microcircuits	Properties
LA	Formation and retention of fear-	Sensory afferents from sensory cortices and sensory thalamus	Enhance response of LA neurons to CS inputs

Amygdala	Functions	Microcircuits	Properties
	conditioned memories		
	Convergence of conditioning inputs at the cellular level	Projections to ITC and BA	Synaptic processes involved in fear learning
BA	Activity in context-dependent fear renewal, fear extinction, and contextual fear conditioning	Contextual information from the HIP	Associations with the US
		Projections to the CeA and ITC	The major route via which US and CS information is sent from LA to CeA
ITC	The control center of the AMYG, located at the BLA and CeA border	Receive projections from the IL cortex	Reduces conditioned fear response
	A crucial backup route for sending CS/US data from the LA to CeA	Inputs from the neurons in LA and BA	Control CeA excitability, by generating feedforward inhibition
CeA	The amygdala's output point	Obtains the projections from BA and the ITC cells	The interface to the fear response system. Generates fear behavioral responses
		Projects targeted at various brain stem areas	Playing a role in the generation of autonomic and behavioral fear responses

Table 4-2 Key afferents and efferent circuits properties of the AMYG nuclei

Name	Functions	Properties	References
THAL	The entry point of sensory information	Swiftly processes the sensory data received	[173]

Name	Functions	Properties	References
	Provide primary data to the AMYG and sensory cortex	Fast response to stimuli	[173]
IL	Regulate states	Used of neurotransmitters (dopamine, norepinephrine, and serotonin)	[180]
		Guide the system towards either a “cautious” fear mode or a “rapid switch” mode.	[180]
HIP	Hub for processing relational, spatial, and contextual processing	Transmit Information related to social or emotional contagion – Positive motivation	[176]
	Memory consolidation	Organize and obtain data about their environment and their location.	[186]

4.3. Predictive coding and inference learning

The brain uses biological inference to operate by making predictions and classifying perceptions [187]. According to the Bayesian brain theory, it operates as an inference machine [188] by updating beliefs and choosing actions based on sensory data using a hierarchical generative model. In a generative model, $p(o, s) = p(o|s)p(s)$ predictions are made by combining prior beliefs $p(s)$ and sensory data likelihood $p(o|s)$. This model infers hidden states that likely produced the sensory signals. This kind of inference is made possible within a generative model by predictive coding, which explains the neural connection between cortical hierarchies [188].

According to the predictive coding framework, perception results from hierarchical brain circuits exchanging predictions and prediction errors (PE) [189]. While bottom-up PE is produced by mismatched predictions and sensory inputs, predictions from higher cortical areas are conveyed top-down to suppress predictable sensory events. Lower cortical regions process sensory inputs, and higher regions perform associational functions [187]. Higher regions receive prediction errors via forward connections, while deep pyramidal cells send predictions via backward connections [190], [191], [192]. According to research by [193], it is this equilibrium between top-down (empirical prior predictions) and bottom-up (prediction errors) influences [193] that help suppress prediction errors in conventional neocortical microcircuits. Figure 4.6 presents a schematic representation of

the cerebral cortex's hierarchical architecture for predictive coding, as suggested earlier [193].

The microcircuit is reproduced in all of the granular cortices of the brain in this model [193]. Neurons in sensory cortices are arranged into six-layered columns (L1-L6). Data is transferred from lower hierarchy regions (such as thalamic projections) to the granular layer (L4) and from superficial layers (L2/3) to higher cortical columns. Prediction errors at every level are continuously computed by the synchronous operating system. See [193] for further information on these canonical microcircuits.

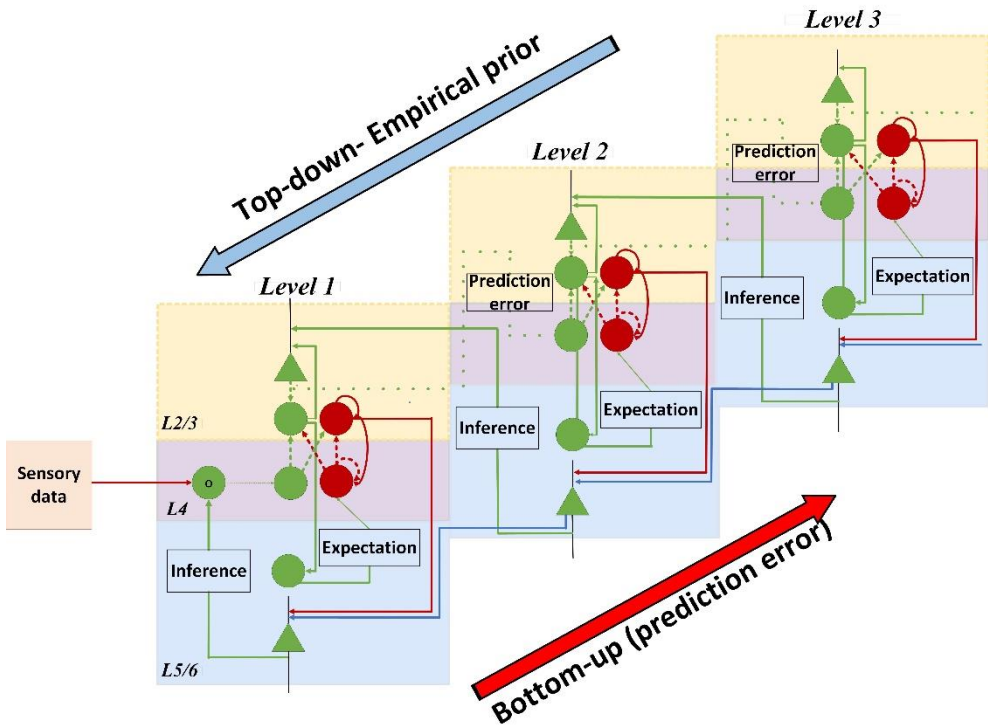


Figure 4.6 Canonical microcircuits - Cortex Hierarchical model proposed by [193]

Using the so-called oddball paradigm—which embeds deviant tones with a low probability of occurrence in a regular pattern of repeating (high probability)—predictive coding has been thoroughly studied in both human subject and animal work (see, for example, references[194], [195], [196], [197], [198]). These studies show that the brain can modulate prediction error precision, exerting a stronger influence on higher cortical layers, eventually,

all layers of the system converge on beliefs that reduce error [187], [199]. The inverse of variance, precision, represents the proportion of signal to noise and establishes the confidence in prediction error. Increased precision refines beliefs and decreases errors by increasing the influence of prediction error on cortical hierarchy levels [200].

Synaptic gain modulation, which is impacted by cholinergic neuromodulation, controls the accuracy of predictive coding [201], [202], [203], [204], [205]. Through this neuromodulation, higher processing stages and subsequent Bayesian updates are preferentially accessed by neuronal populations that report prediction errors, such as superficial pyramidal cells. This procedure is similar to adjusting the Bayesian filtering Kalman gain [187]

Predictive coding has been also investigated to enhance machine learning tasks including incremental learning and restricted data recognition because of its biological plausibility [206], [207]. An energy-based method that operates in two stages—weight update and inference—and minimizes a quantity known as free energy (F) can be used to explain predictive coding. The squared prediction errors $\bar{\epsilon}_l$ at each layer added together is the definition of F. The $\bar{\epsilon}_l$ at each level generate the updated assumptions about hidden conditions and related predictions at the above level. The concept of F explains how adaptive systems, such as the brain, minimize free energy through approximation-based actions and perception [208], thereby resisting disorder and maintaining order. Variational inference (VI), which seeks to reduce the difference between approximation and genuine sensory input distributions, is based on this fundamental idea. This idea is supported by predictive coding, which lowers prediction errors by minimizing free energy [208].

Predictive coding has been proven, for example, by the auditory cortex, which reacts more strongly to new tones than to noises that are repeated [209], [210]. Through the minimization of free energy, it reduces prediction errors by upholding previous assumptions about predicted features and updating these views with new observations. Usually, the normal distribution can be used to represent this.

$$p(s) = \mathcal{N}(s; \mu, \Sigma_s) \quad (1)$$

$$p(o|s) = \mathcal{N}(o; v(s), \Sigma_o) \quad (2)$$

In this case, \mathcal{N} represents the normal distribution, and μ, Σ_s denotes the prior distribution's mean and variance. $v(s)$ is a function that associates hidden states with observations and Σ_o denotes the variance of probability distribution. When a new tone (o) is detected by the system by computing the negative free energy in the way illustrated below, it deduces the most likely cause and the "true" magnitude:

$$F = -\frac{1}{2} \left(\frac{(o - v(s))^2}{\Sigma_o} + \frac{(s - \mu)^2}{\Sigma_s} \right) + C \quad (3)$$

where the constant C contains terms that are not dependent on the size (s) of the tone. By adjusting the function $v(s)$ and the mean μ by taking into account the new observation o , the system optimizes the negative F and decreases prediction errors. It is feasible to maximize the negative free energy (F) in the gradient's direction with regard to s :

$$\frac{dF}{ds} = \frac{o - v(s)}{\Sigma_o} v'(s) + \frac{\mu - s}{\Sigma_s} \quad (4)$$

While $o - v(s)$ shows the discrepancy between the actual observation collected (o) and the predicted observation depending on the estimated state $v(s)$, the term $\mu - s$ reflects the variation between expected μ and predicted s . Reducing precision-weighted prediction error is equivalent to maximizing the negative F for a given observation. Reducing the prediction error can be achieved by decreasing the variational free energy, which is connected to the free energy gradient, and the precision-weighted prediction error and may be expressed in equation (5) according to [193].

$$\mathcal{F} = D_{KL}[q(s|o; \phi) || p(s|o; \theta)] - \ln p(o; \theta) \quad (5)$$

This implies that learning model parameters or enhancing inference over states can lead to the minimization of free energy. Under the Predictive coding framework, a sensory system maximizes the negative free energy and minimizes prediction error, essentially adjusting its view of the environment based on sensory data [188].

Now, the question is how to use this Predictive coding approach in the energy system. We started by implementing Predictive coding by adhering to the

suggestion made by [211] to connect variational autoencoders (VAE) and predictive coding. An autoencoder is an unsupervised deep-learning technique and its objective as proposed by [212], is to anticipate a data item \hat{o} back from the system by learning strong, structured, compressed, or separated representations of the input. Keeping the ideas from Predictive coding and variational inference, variational autoencoders, or VAEs, are a kind of autoencoder that incorporates probabilistic components into the encoding and decoding process. A VAE generates new data points using learned distributions and compresses the input into a reduced-dimensional latent space, capturing the underlying structure. This fits with the paradigm of variational inference, aiming to minimize the discrepancy between the approximate distribution of the latent variables and their true distribution.

The VAE will function as the energy system's Predictive coding model in our approach, predicting fault conditions or pattern deviations in the voltage and current data and modifying its beliefs in response to observed deviations. Their computational efficiency is high, and they require less human feature engineering. Normal system behavior is transmitted to autoencoders, which then identify any deviation from that behavior as an abnormality. When it is impossible to characterize the anomaly using a mathematical expression, this detection technique works well. Autoencoders from a big input stage are used to compress and subsequently decompress the data. By comparing the input signal to both its compressed and decompressed versions—error signals—any irregularity can be identified. When the system is under assault, this mistake is greater; when it is functioning regularly, it is smaller. As a result, the system may continuously learn from and adjust to new conditions while retaining optimal performance. The brain-inspired model architecture for the energy system and how the VAE is included in the predictive coding framework is elaborated on in the next section.

4.4. Brain-inspired theoretical framework for Microgrids.

Various DG sources, ESSs, and interconnected loads are commonly found in an MG; these components are all controlled by protective, intelligent control systems. When there is a power outage, the MG's top priorities must be protecting people and power equipment and acting quickly to resolve problems that arise inside or outside the MG. When fear stimuli are perceived in the surroundings of the AMYG, it immediately initiates a protective reaction, which is modulated by the CeA according to the ratio of extinction

to fear. Adding AMYG capabilities to an MG system might entail starting protective responses, such as a trip signal that opens a CB.

4.4.1. Brain Amygdala in Microgrids – Conceptual integration.

This section seeks to draw comparisons between the components, connections, and behaviors of the AMYG and MGs.

4.4.1.1. Parallels in components and connections: Amygdala and Microgrids

❖ Sensory Inputs and monitoring signals

Through several ways, including sensory, olfactory, visceral, and internal state information, the AMYG processes SIs [152]. For control and operation management, on the other hand, an MG gets data from SI that includes a variety of sensors and measuring units that contain the system's electrical characteristics. Local memory is facilitated, and social behavior and environmental information are bidirectionally controlled by the circuitry between the HIP and the BA [186]. Contextual inputs in MGs could consist of data or information on the overall condition of the system, the external environment, previous fault data, and other pertinent factors.

❖ Thalamus-Sensory information relay and gateways

The Th is essential in enabling SI to be transferred to the AMYG. Regarding an MG, the Th may be linked to an agent classifier and a Gateway sensory system, which enable the MG to obtain real-time data from multiple sensors including voltage, current, frequency, and power. An interface is needed to access the apparent power and energy that smart meters can monitor. The temporal accuracy and control of the measurement can be managed by the gateway sensory system. Not only does this data need to be classified, but an expert algorithm-controlled agent classifier also needs to identify any abnormalities.

❖ Hippocampus-Memory center

The AMYG has connections with the HIP which serves as a memory center, and the circuitry between the HIP and the BA controls social behavior and contextual information [186]. In MGs, the memory center may be related to the EMS and databases that accumulate and analyze data forming a repository of knowledge about the MG's performance. Figure 4.7 summarizes the

relationship between the AMYG model and the previously described MG components.

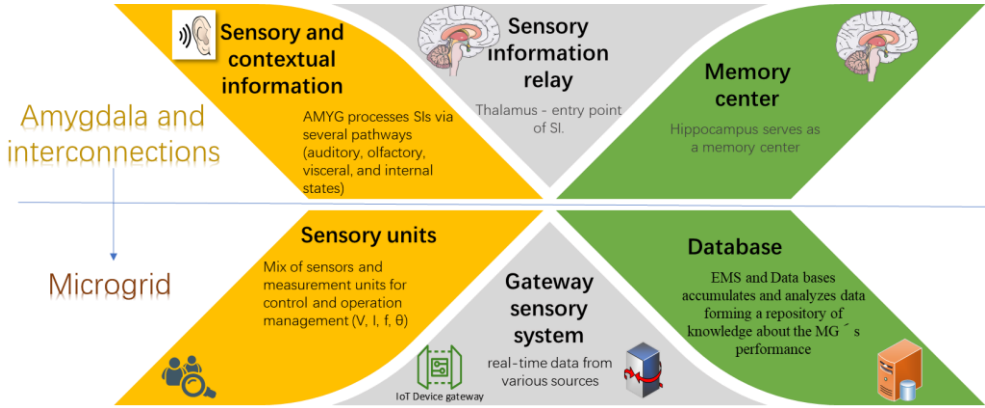


Figure 4.7 Linking concepts SI, Th, HIP

❖ *Amygdala- Defense response*

As a key component of the emotional response, the AMYG controls and guides the activation of defense mechanisms in response to potential fear stimuli. To detect faults and coordinate corrective actions during fault situations or system failures, protection systems in MGs are essential. To detect faults and coordinate corrective actions during fault situations or system failures, protection systems in MGs are essential. Essential components of MG protection systems are transformers, relays, and switchgear. A self-adapting system to return electrical parameters to pre-fault values is required to raise the efficacy of MG's fault detection. We observe analogies between the AMYG and MGs in the dynamics of detecting faults and subsequent prevention, and the AMYG's process of conditioning fear responses.

This conceptual connection becomes important when thinking about cutting-edge software-defined solutions such as the VPR since it can improve control algorithms and automation infrastructure while also reducing the physical size and complexity of protective systems. Both system cost and reliability may increase because of this innovation [5].

❖ *Infralimbic cortex – Regulatory hub*

The brain's prefrontal cortex, or IL, oversees rational thinking. IL inputs can be understood as outside factors that, depending on the emotional state and context of the system, influence the AMYG's reaction [176]. There might be a counterpart for this feature in MGs' EMS. To ensure the high-performance

operation of MGs, EMS serves as a regulatory center that continuously checks system conditions and controls real-time operation by optimizing power generation, distribution, and consumption. The link between the MG components, the cortex, and the AMYG is summarized in Figure 4.8.

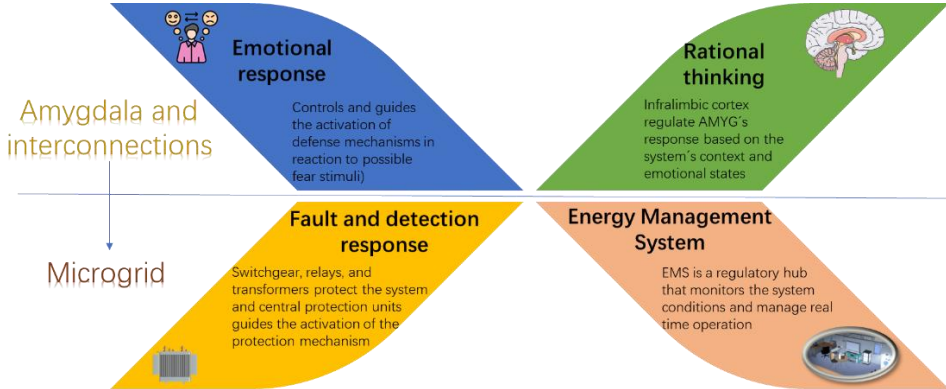


Figure 4.8 *Linking concepts IL & AMYG*

4.4.1.2. *Physiological perspectives: Modeling Amygdala behavior in Microgrids*

A relationship between the physiological behavior of the AMYG and its possible use in MG needs to be established. This part seeks to show a comparison between the MG protection system and the physiological behavior discussed in the preceding section. Synaptic weights on LA, BA, and ITCd increase throughout the fear condition and fear acquisition phases. This potentiation activates CeM, the network's output cell that triggers the fear response while inhibiting ITCv [172]. A comparable approach, analogous to how the AMYG receives information from the Th and produces a predicted fear response, can be used in the case of MG protection. It becomes required to duplicate AMYG operations within the MG to accomplish this behavior within the MG system. Data on voltage levels, frequency, and current flow can be processed by the MGC and sent to the AMYG equivalent. In addition to detecting real conditions (US) such as equipment failures or short circuit faults, this transmission involves the analysis of patterns of deviations (CS) associated with fault conditions such as overvoltage, overcurrent, frequency fluctuations, or temperature variations.

Fear response is decreased and CeM is blocked after fear extinction [172]. This indicates to an MG system that a defect must be quickly suppressed for the system to continue operating. After the fault has been effectively suppressed and corrected, the system moves into a post-extinction phase where there is no longer that fear condition. In this stage, the AMYG homologue within the MG should revert to its initial synaptic weights, free from any reactions associated with fear.

4.4.2. Brain-inspired modeling description

To improve the AMYG biological model's accuracy and ability to represent higher-level behaviors, it is imperative to incorporate different AMYG nuclei, specifically LA, BA, ITCd, ITCv, and CeA. Furthermore, to depict their relationships and interactions with the Th, IL, and HIP, it would be necessary to emulate the theoretical behavior. Figure 4.9 illustrates how the MG system evolved from the AMYG concept. We simulate four brain regions in this model, including the Th, AMY, IL, and HIP, which are important for the development and expression of conditioned fear.

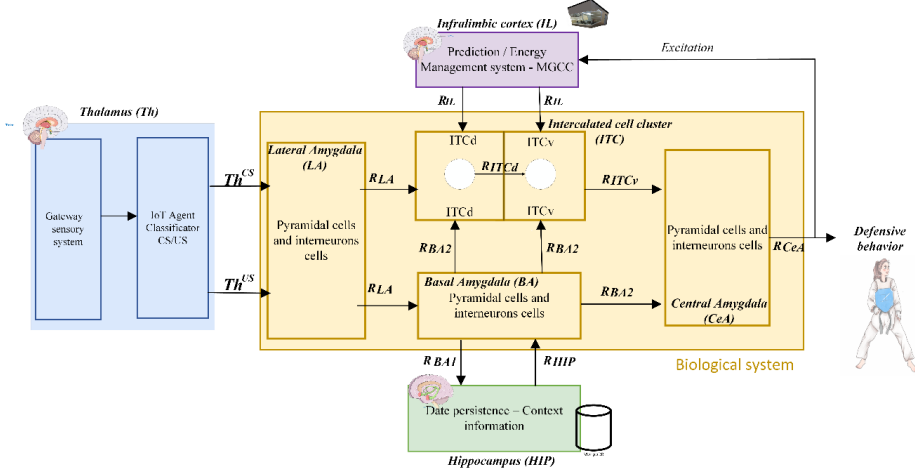


Figure 4.9 Amygala model architecture [172], [180]

The AMYG is the foundation of the system, and a biophysically realistic model is needed to accurately simulate their function during fear conditioning. Considering the spike time reaction, this biophysical model can be represented by a leaky integrated fire (LIF) model. Within the framework of the MG system, the LA serves as the main indicator of possible disturbance inside the MG. It quickly evaluates incoming signals from the MGC and protection devices to find any signals that might be dangerous. If this data

exceeds a threshold that has been set beforehand, it acts as an alert for the next processing step. In contrast, the BA acts as a central location for processing more complex sensory data. It might cause projections to reach the CeA and activate fear cells. On the other hand, it might cause projections to be sent to the ITCv and extinction cells to fire, which would decrease the fear response.

Measurements of the local or instantaneous current and voltage transformers are required by the model. Furthermore, a range of measures can be obtained for smart plugs or physical relays in the system, including frequency, and power (active, reactive, apparent). Although apparent power and energy can be measured by smart meters, access to this data needs to be through an interface. The temporal accuracy and control over the measurement can be achieved through the gateway sensory system. To activate the amygdala model, this model has a vector input of SI and monitoring data from the electrical system. As seen in Figure 4.10, this information must be communicated with the Th through a gateway.

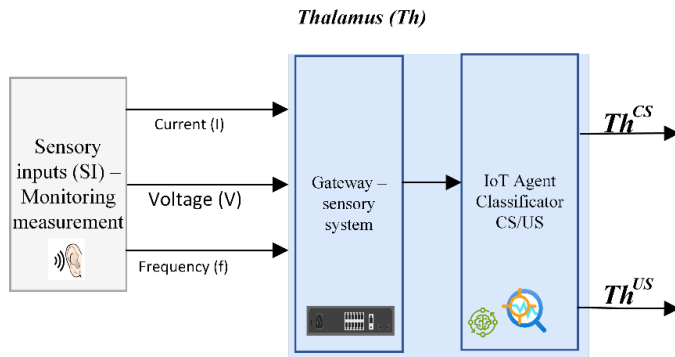


Figure 4.10 *Sensory Information and Thalamus Blocks*

The Th serves as an entry point for SI and classifier information, and it is replicated by an agent classifier governed by an unsupervised learning algorithm that sends a conditioned stimulus (Th^{CS}) signal related to overvoltage, overcurrent, frequency fluctuations alongside the detection of actual abnormal condition Th^{US} (unconditioned stimulus) related to an equipment failure or short circuit fault. After analyzing the SI from the Th, the AMYG produces the anticipated reaction, which is usually a fear response. The response is moved to the Output. CeA generates a reaction that is required to turn on the protection action and the CB. When the CS is delivered without the US, the AMYG model predicts a progressive decrease in the fear response. This would be equivalent to a power system gradually returning to normal functioning following the resolution of the fault.

As Figure 4.11 illustrates, the HIP functions as a context processor and memory. Before delivering notifications (RHIP) to the BA, it saves the actual fault conditions and checks them with system data. It also uses a database instance to keep the current context data. Furthermore, to update the stored sensory data, a forward loop is necessary.

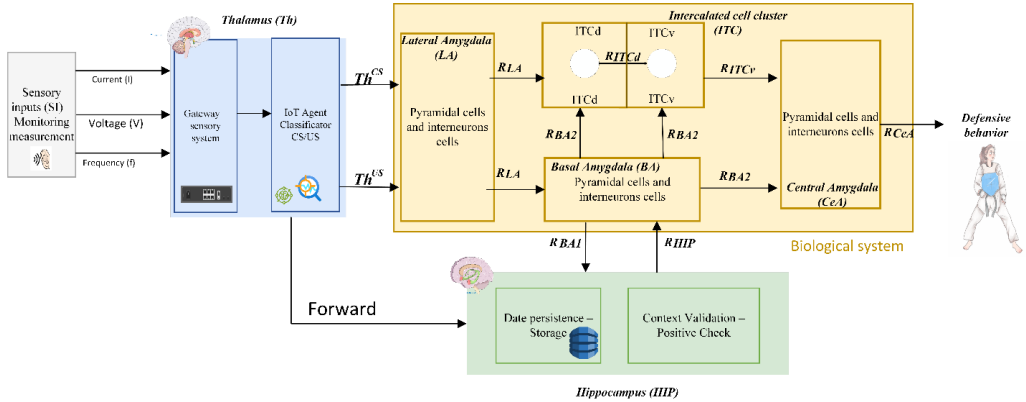


Figure 4.11 Hippocampus model - blocks and projections

To closely cooperate with the AMYG and affect the MG status selection, the microgrid central controller (MGCC) must imitate the IL. By encouraging the regulation of the cortex through the signal (RCeA) to the IL, this connection creates a feedforward loop that changes the state of the MG reaction. The Th transmits bottom-up (forward) information to the cortex, which then sends top-down (feedback) information to create a closed loop for defect classification and prediction. Figure 4.12 shows these connections as well as the complete model.

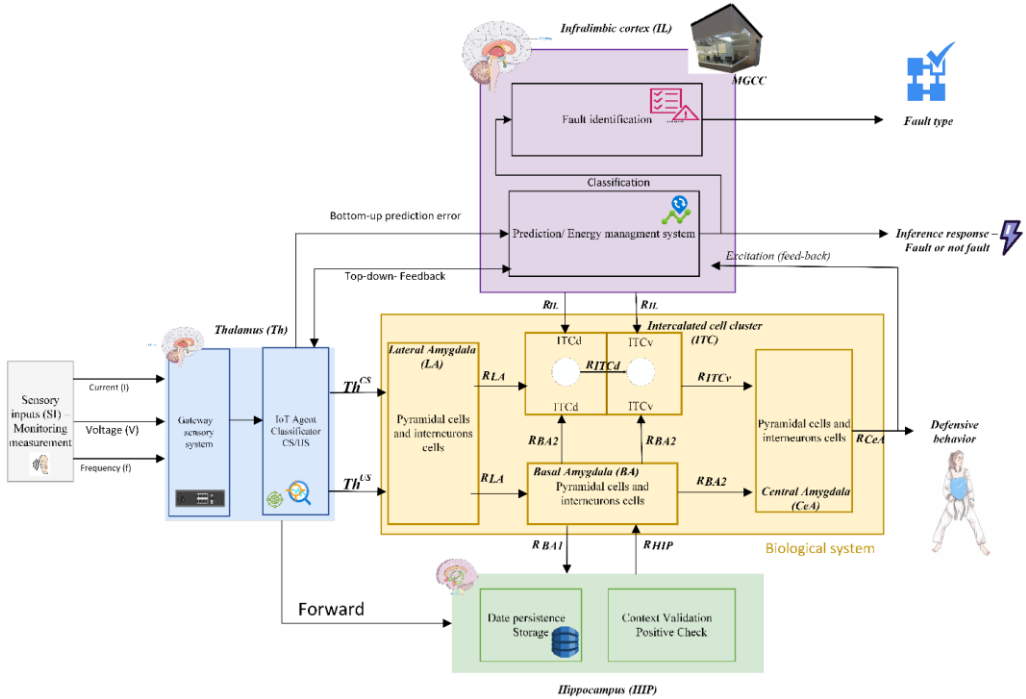


Figure 4.12 Brain-inspired architecture

4.4.2.1. Logical rules and subsystem description

Replicating the AMYG's expected behavior for fear conditioning and extinction as well as the inference response is made possible by the completion of all these blocks with logical interaction and intercommunication rules. Three alternative circuits or scenarios comprise the model: the post-extinction circuit, which is driven by cell recovery or self-healing, the excitatory circuit, which is led by the extinction condition, and the inhibitory circuit, which is led by the fear condition. Furthermore, to simulate the inference process outlined in the Predictive coding session, a second microcircuit linking the Th and the IL is added.

- ❖ **Amygdala:** The LA, BA, ITC, and CeA components are represented by the four blocks that make up the biophysical system known as the AMYG. Biophysical Hodgkin-Huxley (HH) and LIF models could be used to effectively characterize the fundamental mechanisms behind fear learning. Since the action response must occur faster in the protection system, the LIF models concentrate on the spike time rather than on the structure of the action potential [213]. As a result, they may be used in the

model to guarantee a quick reaction.

- ❖ **Thalamus:** it functions as a relay station in the brain, filtering and analyzing sensory data prior to it reaching the cortex. This is simulated by detecting peaks in a signal, identifying the most common values (modes), and analyzing deviations from these modes. Just as the Th filters out irrelevant or less significant information, this subsystem filters and analyzes significant deviations in the signal, which could be analogous to how the Th processes sensory inputs and highlights important stimuli.
- ❖ **Infralimbic Cortex:** This subsystem makes use of the VAE. As the brain's IL is important in decision-making and behavioral responses to changes, we emulated its capabilities in this instance by performing signal segmentation and anomaly identification. Data segmentation into overlapping windows, which are then normalized and put into the VAE, is the first step in the process. To learn a compact representation of the signal windows, the VAE is defined using an encoder and decoder architecture. The latent space's mean and logarithmic variance are output by the encoder, which is made up of intermediate dense layers. In latent vectors, a sampling function produces results. From these latent vectors, the decoder reconstructs the input. Next, an Isolation Forest classifier is applied to the encoded data to find any anomalies.
- ❖ **Hippocampus:** A local storage is utilized in this subsystem to store memories and retrieve them when the model is operating.
- ❖ **Sensory inputs and monitoring measurement:** Utilizing voltage and current measurements is implied by the monitoring signals. Several failures that occur in an energy system are included in the model by using a common data set.

4.4.3. Analysis and validation of the concept

This section describes the initial results and validation of the proposed model's concept, which uses the Th and IL link to predict and recognize the fault type. The proposed system's schematic is presented in Figure. 4.13. Metrics are computed using statistical methods in conjunction with peak identification analysis in the relay-functioning Th block. The IL block is executed to find outliers in the input signal if metrics are higher than a

predetermined threshold. The threshold is defined to be 1.0 which is considered the normalized value of the identified maximum and minimum levels (peak mode) of the measured signal. Peak modes and anomalies are stored in a local database to expedite the identification process in subsequent repetitions. In this manner, the system detects the outliers ahead of time if measurements are higher than the threshold and the mode and outliers match those recorded in the database. On the other hand, the system recognizes that there are no errors if the metrics are low.

The process of the Th block is described by Algorithm 1. The first step in the process is to determine positive values. Similarly, it ensures that negative peaks are detected by inverting the signal and using the same threshold. The algorithm takes into account missing values and determines the mode, or most common value, of both positive and negative peaks. A point is defined as being sufficiently away from the modes when the threshold is reached. These far-off points are evaluated using the mean squared error (MSE), which stands for significant deviations. This procedure is similar to how the Th functions in the brain, where it analyzes and filters sensory data, highlighting important inputs and removing less important elements. The formula for calculating the MSE is given below.

$$MSE = -\frac{1}{n} \sum_{n=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

Where y_i is the i -th sample's actual value and \hat{y}_i is the projected value, and n is the entire amount of samples of a data dataset.

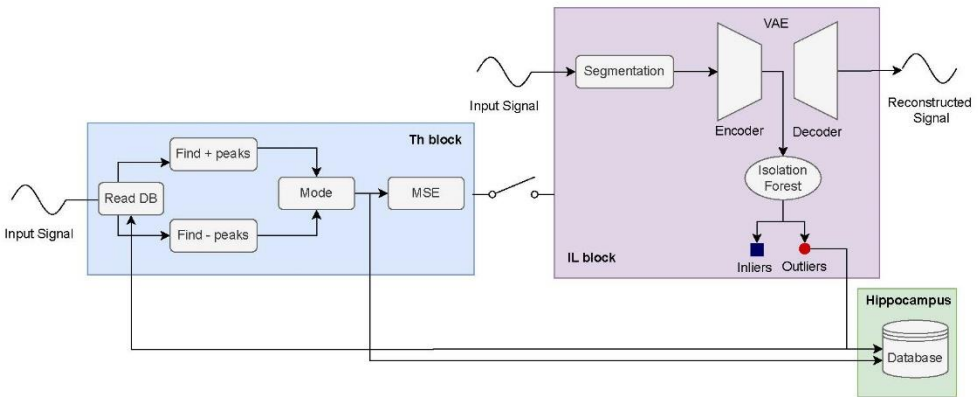


Figure 4.13. Schematic of the proposed system for validating the TH-IL interaction

Algorithm 1 Th block: Peak Detection and MSE Calculation

```

positive_index, _ = find_peaks(signal, height = 0.1)
negative_index, _ = find_peaks(-signal, height = 0.1)
positive_peak = signal.iloc[positive_index]
negative_peak = signal.iloc[negative_index]
positive_mode = mode(positive_peak)
negative_mode = mode(negative_peak)
if not numpy.isnan(positive_mode) then
    positive_diff = (positive_peak - positive_mode)2
    mse_positive = positive_diff[positive_diff >
    threshold].mean()
else
    mse_positive = np.nan
end if
if not np.isnan(negative_mode) then
    negative_diff = (negative_peak - negative_mode)2
    mse_negative = negative_diff[negative_diff >
    threshold].mean()
else
    mse_negative_far = np.nan
end if

```

The IL block consists of an isolation forest classifier that utilizes unsupervised learning to extract features from the latent space to detect the outliers, as well as two feed-forward neural networks (FFNN) that function as the encoder and decoder of a VAE. Figure 4.14 displays the VAE's structure. This model uses a sampling function to reconstruct the signal using two hidden layers of 256 and 128 neurons, whereas the decoder uses the opposite combination. Equation 10 explains how the VAE is trained with a loss function that combines the Kullback-Leibler (KL) divergence and the reconstruction loss (RL) given in the following equations.

$$RL = MSE(x, \hat{x}) \quad (7)$$

$$KL \text{ Loss} = 1 + \log(\sigma^2) - \mu^2 - \sigma^2 \quad (8)$$

$$= \frac{1}{2} \sum_{i=1}^N KL_i \quad (9)$$

$$VAE \text{ loss} = RL + KL \text{ Loss} \quad (10)$$

Where the original input is denoted by x and the reconstructed input by \hat{x} . The latent space variables' mean and standard deviation, sometimes known as logarithmic variance, are denoted by the symbols μ and σ . The term in the KL divergence computation for each latent space dimension is denoted by KL_i .

In order to overcome the difficulties caused by significantly divergent magnitudes that negatively impact classification accuracy, data are segmented and normalized using the scikit-learn Python library's MinMaxScaler function before entering the VAE. Equation 11 describes this function.

$$MinMaxScaler(x) = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (11)$$

Where the feature's maximum and minimum values are, respectively, $\max(x)$ and $\min(x)$. Larger values, regardless of their units, tend to be given more weight by the ML model if feature scaling is not done. Python was used to implement the proof of concept, and Tensorflow was used as the backend.

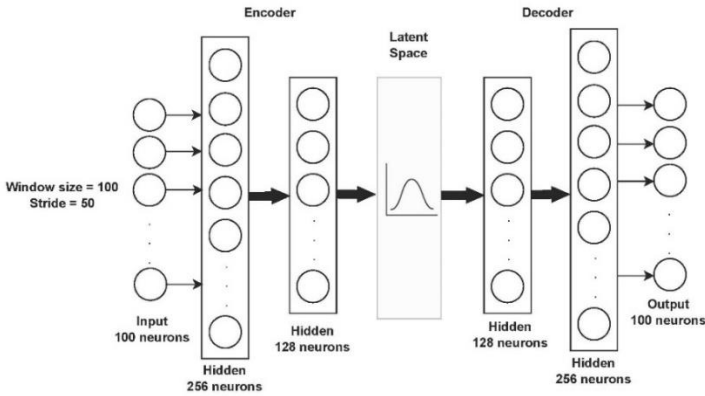


Figure 4.14 VAE architecture. Latent Space dimension (Z)=10

The Isolation Forest works by isolating observations in the dataset to identify anomalies. It constructs multiple decision trees randomly, where each split in the tree is chosen at random. The procedure entails choosing a feature and a divided value between the feature's maximum and minimum values. Data points that are uncommon and odd are called anomalies or outliers. They are segregated closer to the tree's root, which results in shorter routes. By averaging the path lengths across many trees, the Isolation Forest assigns an

anomaly score to each observation. Points with shorter average path lengths are considered anomalies, as they are more easily isolated. This method is efficient and effective for detecting outliers in high-dimensional [214].

4.4.3.1. Results

We used single-phase example data from https://github.com/pnnl/oedisi_transients.git to train the VAE and Isolation Forest models [215]. This project provides a data-driven algorithm that is containerized and trains a transient algorithm inside a Docker container using a dataset on a desktop. The trained model, training and testing results, and plots are copied from the Docker container to the local workstation after the training and testing procedures have been completed. We specifically chose the examples from IEEE123 that included fault types 1, 2, and 3-phase failures [215].

The Th block findings are displayed in Figure 4.15. In this instance, the peak modes at 15000A and -15000A, respectively, are positive and negative. This means that the IL block is activated for all points above the threshold by computing the MSE and using that result. For the positive peaks, the mean MSEs were 5430788.19, and for the negative peaks, they were 1582784.34. Since this is the initial iteration, the HIP database is empty.

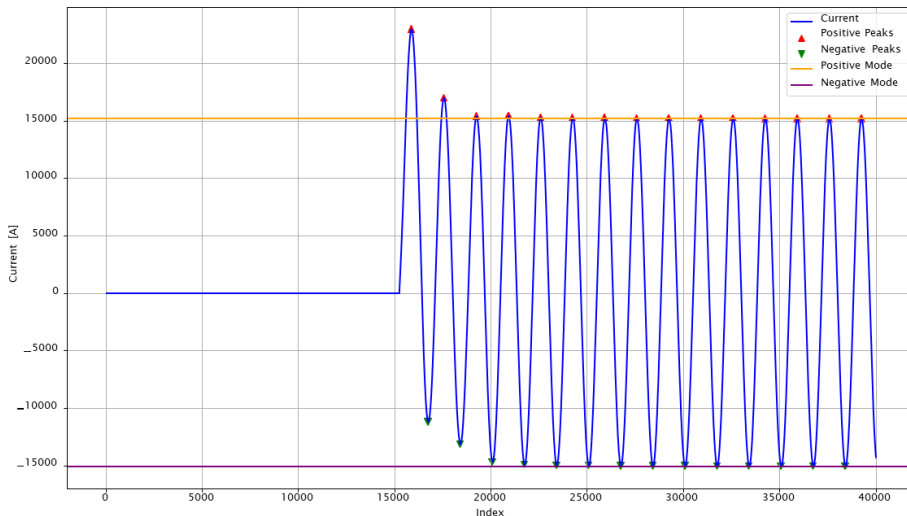


Figure 4.15 *Thalamus block result*

Subsequently, the IL block locates the odd data points and records them in the HIP database together with the related positive and negative peak modes.

The outcomes are displayed in Figure 4.16. Visual examination reveals that not all data points are appropriately classified by the Isolation Forest. Nonetheless, irregularities can be detected by the system. Here, an alert is triggered to notify users of the issue. We disregarded any data points that were equal to zero in this section because they might have included irrelevant or missing information that could have distorted the results. By taking this step, the reliability and precision of the results are increased because only significant, non-zero numbers are taken into account.

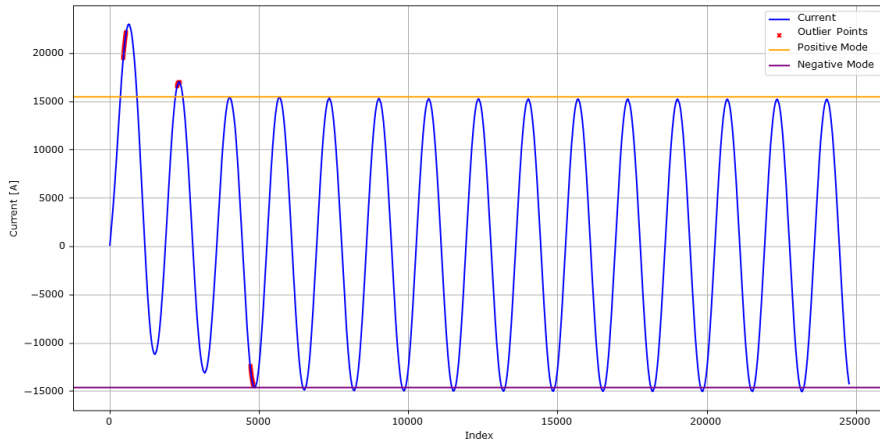


Figure 4.16 *IL block results*

Using information from an additional case of fault generation, we conducted a second experiment. The outcomes of the Th block's first stage are displayed in Figure. 4.17. The mean MSEs in this instance were 87398761.77 for the negative peaks and 20869115.85 for the positive peaks. As a result, as seen in Figure 4.18, the IL block both activates and detects the abnormal signal. As in the previous case, not every outlier is properly categorized. On the other hand, users receive the caution alert just as quickly.

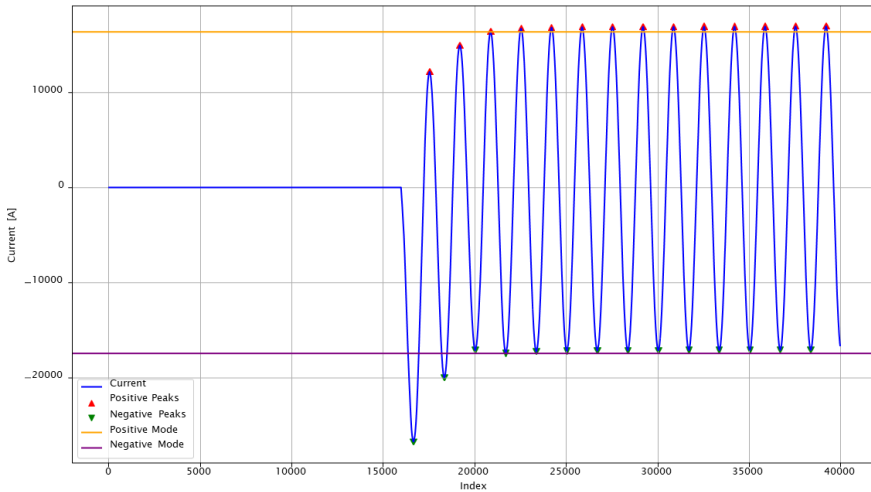


Figure 4.17 *Thalamus block results during second validation*

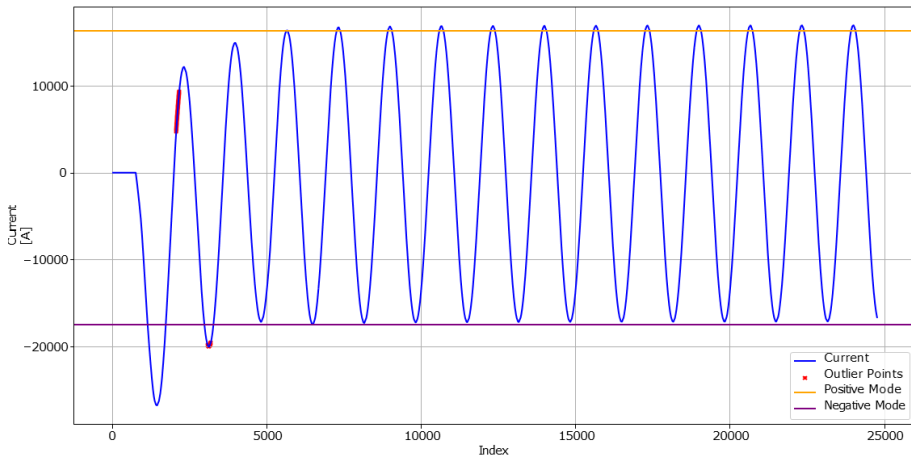


Figure 4.18 *IL block results during the second validation*

It is noteworthy to mention that the system will take some time for it to detect patterns in the data that enable it to identify the peaks and modes when operating in real-time with the current configuration. But this delay will be most noticeable in the initial iterations when the database is empty. To address this problem, the system needs to be initially configured with predetermined positive and negative peak modes that allow the MSE of the incoming data points to be determined. Future work will primarily concentrate on addressing this constraint in addition to enhancing the reliability of the VAE and the Isolation Forest classifier. One way to improve is to run a sensitivity analysis on the primary hyperparameters. This proactive

method demonstrates that brain-inspired modeling is a promising path for protective systems, despite the initial setup requirement.

4.5. Conclusions

This chapter aimed to apply our understanding of AMYG behavior and function to the control and protection of MGs. We explored the relationships, elements, and theoretical foundations of the AMYG and illustrated how its physiological behavior may be used to detect and prevent fault events in MGs using fear and extinction scenarios. Furthermore, we used variational VAEs to study the brain's inference and prediction processes in MGs and explained the mathematical foundation of predictive coding theory.

We described the brain-inspired model in detail and suggested the requirements for applying this strategy in MG protection. This approach places a major focus on logical subsystems and rules to specify how it operates within an MG. We found that LIF spiking neural networks may be used to model the AMYG block, generating spike reactions in response to fault conditions. The Th functioned as an expert system, screening and evaluating data before it reached the cortex, while the VAE represented the IL for signal segmentation and anomaly identification. The HIP region served as a local database for the storing and retrieval of anomalous data.

To demonstrate that this theoretical approach is applicable, we created a proof of concept. By simulating the inference process between the cortex and the Th, this idea can detect unusual data points. Positive and negative peak modes are identified by the Th subsystem. When a location surpasses a threshold, the MSE is used to trigger the IL subsystem. The HIP database contains the relevant peak modes for anomalous data points in the IL block. While supporting the theoretical approach, this proof of concept is not yet comparable to more sophisticated artificial intelligence techniques. Incorporating the amygdala's reaction for immediate system reactions and improving the existing model requires additional effort.

Developing an MG protection system based on AMYG, and its connections is an emerging subject of research. To provide a comprehensive understanding of how multiple brain regions collaborate to make inferences and influence fear memory development and expression, this technique needs to be extended to large-scale biophysical networks and their connections and

circuits with the HIP and IL investigated. To strike a balance between accuracy and computational feasibility, the model's level of complexity may need to be adjusted.

Comprehending both domains deeply is necessary to translate neural models into useful power system control. Working with specialists in both power system engineering and control and neuroscience would therefore be very advantageous. We aim to further enhance the potential of MG, including self-healing, flexibility, and reliability, by mimicking its functions and connections within the MG framework. However, to do so, we must first determine which MG components to model and which ones could have properties like those of the brain components that require modeling.

Chapter 5. Closing remarks.

This chapter describes the contributions made by the thesis and summarizes its key findings. There is also discussion on the potential future developments and endeavors to further advance this field of study.

5.1. Overall conclusion

The fundamental concept guiding our research was outlined in the introduction of this thesis. To prevent power outages and guarantee quick reaction during failures, we underlined the need for effective protection methods in distribution systems. We provided a summary of traditional protection schemes, including international standards and devices utilized in distribution grids, DERs, and MGs, as well as an explanation of the concept and classification of power failures in physical components. The idea of MGs was then presented, along with a description of their protection issues, including various forms of power outages, islanding faults, fault location and detection, cyberattack issues, and the traditional protection methods developed to deal with these issues. We emphasized the role of communication and AI in improving protective strategies, enabling automatic reactions, and assisting MGs in adapting to their dynamic and evolving environments. Furthermore, we presented the recently emerging field of networked microgrid protection, going over its advantages, topologies, architectures, and new challenges.

Then, we investigated the implementation of a decentralized advanced protection system based on MAS in response to the current challenges of data latency, information uncertainty, computational complexity, and protection scalability that call for more advanced protection strategies. During faults, the proposed method seeks to prevent maloperation by comprehending MG topological changes and providing the appropriate protective device settings. Based on the type and number of distributed resources available, as well as the MG operation modes, relay settings need to be adjusted, according to our analysis. It also emphasized how important it is to have an in-depth understanding of the system and the necessity of an adjustment matrix tailored to each operation scenario. To locate any relay malfunctions that were undetectable in offline simulations, real-time simulations proved essential.

Several approaches for MG protection were discussed in Chapter 1 and the papers A, B, and C; however, issues with communication infrastructure, complexity, and reliability still exist. This motivated us to investigate different methods of protection. Improving AI methods by leveraging the knowledge from neuroscience and brain research is a new area of development. By comprehending the brain's self-defense processes connected to emotions and fear circumstances, it is possible to increase AI computational speed and efficiency. According to our research, novel MG protection techniques may be influenced by the brain's emotional learning mechanisms, especially those involving the amygdala. After examining current models that are motivated by emotions and how they are used in MGs, we concluded that the BEL model is a good candidate for secondary MG control. Nonetheless, further research is required to create strategies for protection that mimic the brain's natural defense processes.

The outcome of our research published in Paper D supported us in developing a theoretical framework that was inspired by the amygdala's function in triggering defensive responses in reaction to emotional stimuli and the inference process based on predictive coding theory (Paper E and F). We explored the essential processes and connections required to model the AMYG as well as the mathematical foundations of incorporating predictive coding into MGs. Since the brain functions as an interconnected system, it is necessary to replicate the activity of other brain sections in order to correctly imitate the AMYG's reaction. In addition, we developed a demonstration of the concept to validate the interactions between the Th and the cortex, demonstrating its potential applicability. Nonetheless, additional testing of this model with all subsystems operating together in simulations and real-world applications is still necessary. Even though this area of study is still in its early stages, we tried to lay the groundwork for establishing the concept and we hope it sparks ideas and encourages the development of novel brain-inspired approaches to MG control and protection.

5.2. Contributions

❖ **Comprehensive overview of fault location methodologies in Smart Grid and Microgrids.**

A thorough review of fault location and detection methods for SGs and MGs is presented, with a focus on integration in MGs and priority factors such as locating faults for different MG configurations, communication systems, and energy storage considerations. This

analysis highlights the need for advanced protection strategies by identifying the shortcomings of the existing fault identification, detection, and isolation strategies. The review offers solutions to protect systems against power outages while investigating protection approaches based on knowledge-based signal processing, and traveling waves, and addresses the difficulties of locating faults in different types of MGs, communication, and energy storage systems.

❖ **Comprehensive overview of Networked Microgrids protection.**

This comprehensive overview highlights the benefits of the NMGs to improve the dependability and adaptability of the distribution system that includes multiple DERs and provides a detailed exploration of protection schemes for protecting these systems. The lack of detailed assessments of the difficulties, solutions, and improvements in NMG protection is addressed in this overview. It presents various NMG topologies, and difficulties in connecting MGs, and looks into potential solutions. These challenges are presented comparatively, and suggested solutions are evaluated concerning simplicity, selectivity, scalability, dependability, and speed in a radar chart. Finally, this work underscores the necessity of a deeper understanding of NMG protection and offers a basis for further study and advancement in this area of smart grid technology.

❖ **Developing an efficient decentralized protection scheme to identify topological changes.**

It was found that in decentralized systems, the MAS model is efficient. Real-time simulation testing demonstrated that the proposed methodology enhances the implementation of these agents, resulting in more dynamic protections. Although this advancement offers more dynamic protections, more intelligence is necessary for proper operation to enable effective decision-making, operational autonomy, and fault monitoring and diagnostics. To establish system reliability, more RTSim tests are required, including those related to the communication systems.

❖ **Comprehensive overview on Brain-Inspired modeling for microgrid protection and control considering Emotional Learning.**

Although brain-inspired algorithms have been used to control MGs, a thorough analysis of their advantages and disadvantages has not been

provided. An overview of brain-inspired models, their applications in the electrical and industrial domains, and a general emotional framework for hierarchical control involving several brain regions are presented in this thesis. It opens the opportunity for the eventual incorporation of emotional learning paradigms in MGs by improving understanding of BEL concepts and applications.

❖ **Developing a brain-inspired artificial intelligence theoretical framework for Microgrid control and protection.**

A brain-inspired AI theoretical framework based on the amygdala's fundamental behavior is developed. To simplify implementation, this thesis draws comparisons between the MGs and the connections, projections, and components of the amygdala. A comprehensive theoretical model featuring intricate parts and operations is showcased and a proof of concept has been established to illustrate the applicability of these brain-inspired behaviors to MGs. Even though this model is still in its early stages, it offers a solid framework for research in the future and performance evaluations in comparison to existing AI and machine learning models.

5.3. Future work

This thesis proposes a promising framework for enhanced MG protection using brain-inspired artificial intelligence. However, as this field is still developing, several challenges need to be resolved. The potential future research directions identified in this thesis are listed in the following:

1) *Development and assessment using simulation software.*

MATLAB/Simulink modeling and simulation environment may be used to implement the brain-inspired AI-based protection to assess its efficacy in MG protection. This might include using the AMYG's spike reactions in fearful situations to cause the MG to react to the protection device. Neural insights can also be used to improve several areas of MG protection, including the ability for the system to self-repair following errors, manage protection measures during blackouts, predict the types of errors, and promptly trip circuit breakers in the event of a malfunction.

2) *Expansion to large-scale biophysical networks*

To create a protection system for MGs inspired by AMYG, it is necessary to expand to large-scale biophysical networks. Future studies should examine the circuits and connections between the interlinking cortex and the HIP to offer a comprehensive understanding of how different brain regions collaborate to regulate the expression and formation of fear memories. Since contextual information from past experiences can affect when the fear response develops, the inclusion of the HIP is essential for modulating fear responses. To balance computational efficiency and accuracy, the model's complexity may need to be adjusted.

3) ***Enhance sensitivity and perform comparison with established generative algorithms***

Future work will concentrate on raising the sensitivity of the critical hyperparameters in order to improve the reliability of the VAE and Isolation Forest classifier. The performance of this model might be improved by using a different generative algorithm. Furthermore, by incorporating knowledge from predictive coding and neuroscience, there might still be potential to enhance these models for practical application.

4) ***Networked Microgrid (NMGs) protection scheme implementation***

This brain-inspired framework must be incorporated into appropriate NMG protection plans. Testing the effectiveness of protection methods made resilient to dynamic topologies and communication failures should be the focus of future studies. The creation of standards and rules will direct users in the selection of suitable protection plans. Selectivity, adaptability, dependability, speed, high-speed communications, modularity, precision, and economy of cost are a few of the factors that these guidelines ought to consider. Hybrid protection methods that incorporate both DC and AC should also be included. For NMGs to be implemented and operated successfully, protection measures must be reliable, secure, and affordable.

5) ***Real-time testing and Smart Algorithms***

Future works ought to concentrate on putting this theoretical approach—which implements the amygdala reaction—into practice and assessing the protection methods' real-time simulation. In addition, it would be beneficial to provide useful guidelines that would aid in comprehending and utilizing the model in real MGs. The

creation of reliable, safe, and commercially feasible protection methods is necessary for the installation and functioning of these software solutions. Thus, it is obvious that further study into brain-inspired techniques is required. Additionally, research should look into online techniques and tactics based on bio-inspired algorithms and generative algorithms, including emotional learning, multi-agent systems, VAE, and predictive coding, in order to increase the flexibility and self-reliance of future power systems' autonomous restorative capabilities.

6) *Multidisciplinary studies to develop decentralized and brain-inspired protection algorithms.*

To create more brain-inspired algorithms, future research on adaptive protections should be carried out by interdisciplinary teams with knowledge of electrical protections, telecommunications systems, neuroscience, and intelligent algorithm programming. Making adaptive relay prototypes will be essential in the future. The creation of strong and efficient decentralized protection systems will be ensured by this cooperative strategy.

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Part II

Papers

Part II: Papers

Paper A

Fault Location for Distribution Smart Grids: Literature Overview, Challenges, Solutions, and Future Trends

Jorge De La Cruz, Eduardo Gómez-Luna, Majid Ali, Juan C. Vasquez, and Josep M. Guerrero

The paper has been published in the Journal *Energies* 2023, 16(5), 2280.
<https://doi.org/10.3390/en16052280>.

Part II: Papers

Paper B

Adaptive Multi-Agent-Zonal Protection Scheme for AC Microgrids

Jorge De La Cruz, Eduardo Gómez-Luna, John E. Candelo
Becerra, Juan C. Vasquez, and Josep M. Guerrero

The paper has been published in the
Proceedings European Conference on Power Electronics and
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Part II: Papers

Paper C

Review of Networked Microgrid Protection: Architectures, Challenges, Solutions, and Future Trends

Jorge De La Cruz, Ying Wu, John E. Candelo Becerra, Juan C. Vasquez, and Josep M. Guerrero

The paper has been published in the
Journal CSSE Journal of Power and Energy System 2024, vol. 10,
no. 2. <https://doi.org/10.17775/CSEEJPES.2022.07980>

Part II: Papers

Paper D

Brain Modelling for Microgrid Control and Protection: State of the Art, Challenges, and Future Trends

Jorge De La Cruz, Sen Tan, Diptish Saha, Najmeh Bazmohammadi, Juan C. Vasquez, and Josep M. Guerrero

The paper has been published in the
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<https://doi.org/10.1109/MIE.2024.3374234>.

Part II: Papers

Paper E

Brain Amygdala Modelling for Microgrid Control and Protection

Jorge De La Cruz, Najmeh Bazmohammadi, Juan C. Vasquez, and
Josep M. Guerrero

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Part II: Papers

Paper F

A Brain-Inspired Framework for Advanced Microgrid Protection and Control: A Theoretical Step Toward Self-healing Systems

Jorge De La Cruz, Patricia Fraco, Eduardo Gómez-Luna, Najmeh Bazmohammadi, Juan C. Vasquez, Manuel S.Malmierca, and Josep M. Guerrero

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