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Modern Fault Diagnosis in Power Systems Based on 5G Networks

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ABSTRACT:

The future power system will be dynamic, requiring intelligent control, reliable protection, and fast communication. Modern concepts in power systems, such as smart grids, involve bidirectional power flow and two-way communication. Conventional protection schemes and fault diagnosis methods are unsuitable for future power systems. This study proposes a modern fault diagnosis that integrates 5G's reliable communication and AI. 5G's URLLC, mMTC, and edge computing can bring significant advantages to the applications of power systems. In this study, a concept of intelligent fault diagnosis is proposed, which utilizes 5G network and AI. This work is divided into two main sections. The first section develops an ML-based power system protection model on MATLAB, and the second section deals with simulating 5G communication network on OMNeT++. ML algorithm developed for power system protection achieved fault detection accuracy of 99% and isolated faults within 7ms. The standalone 5G network without edge computing server achieved round trip network latency of 20 ms.

Keywords: 5G Network, Modern Fault Diagnosis, SVM, ML, MATLAB/Simulink, OMNeT++, Smart Grid

Contents

Lis	List of Figures				
Lis	t of T	ables		6	
1	Intro	Introduction			
	1.1	Motiva	ation	9	
	1.2	Resea	rch objectives	11	
	1.3	Thesis	structure	11	
2	Com	munica	ation roles in power system and 5G networks	13	
	2.1	Comm	nunication Roles	13	
	2.2	Grid Ir	nfrastructure and Communication Technologies	14	
		2.2.1	Wired and Wireless Technologies	16	
		2.2.2	Fibre optics	16	
		2.2.3	Power line communication	17	
		2.2.4	ZigBee	17	
		2.2.5	WLAN	18	
		2.2.6	WIMAX	18	
		2.2.7	Cellular communication technology	18	
	2.3	Fifth G	Generation Networks (5G)	20	
		2.3.1	5G Architecture	21	
		2.3.2	Multi-Access Edge Computing and 5G	24	
		2.3.3	5G in Power Systems	24	
3	Мос	lern Fau	ult Diagnosis	27	
	3.1	Protec	ction issues and challenges	28	
		3.1.1	Blinding Protection	30	
		3.1.2	Sympathetic Tripping	30	
		3.1.3	Reach of Distance Relay	30	
	3.2	Evolution of protection schemes 3			

	3.3	Machi	ne Learning and Power Systems	32
		3.3.1	Machine Learning in Power System Fault Diagnosis	35
		3.3.2	ML algorithm in Modern Fault Diagnosis	38
	3.4	ML ba	sed Power system protection	38
		3.4.1	Datasets	39
		3.4.2	Machine Learning Algorithm	40
		3.4.3	MATLAB/Simulink Protection model	41
4	Syste	em Simı	ulations and Results	43
	4.1	5G Sin	nulators	43
		4.1.1	SyntheticNET Simulator	43
		4.1.2	OMNeT++	44
		4.1.3	NS-3	45
		4.1.4	MATLAB/Simulink	45
		4.1.5	OPNET	46
	4.2	Power	System Test Case with 5G Standalone Architecture	46
	4.3	Result	S	48
		4.3.1	5G Communication Network Results	49
		4.3.2	ML based Power System Protection Results	50
5	Cond	clusion		54
Bibliography 55				55

List of Figures

Figure 1	5G Key technologies Yrjola and Jette (2018)	10
Figure 2	NIST conceptal grid infrastructure López, Moura, Moreno, and Ca-	
macho	o (2014)	15
Figure 3	Cellular network evolution	19
Figure 4	Cellular network main component Peterson and Sunay (2020))	21
Figure 5	5G with UE connectivity process a) BS detect and connect with UE	
b) BS e	establish control plane connection between UE and Core c) BS estab-	
lish tu	nneling d) Tunneled over SCTP/IP and GTP/UDP/Ip e) UE handover	
f) UE r	nultipath transmission Peterson and Sunay (2020)	23
Figure 6	5G Network Architecture in power system Cosovic, Tsitsimelis, Vuko-	
bratov	ric, Matamoros, and Anton-Haro (2017)	26
Figure 7	Faults in AC overhead transmission system Eskandarpour and Kho-	
daei (2	2018)	27
Figure 8	Microgrid protection issues, challenges, and protection solution	
Patnai	k, Mishra, Bansal, and Jena (2020)	29
Figure 9	Microgrid operation protection schemes Patnaik et al. (2020)	31
Figure 10	IDT relay structure Sepehrirad, Ebrahimi, Alibeiki, and Ranjbar (2020)	32
Figure 11	Power system protection with 5G network and ML	39
Figure 12	Simulink power distribution line model	40
Figure 13	ML based fault sensing and isolation	41
Figure 14	OMNeT++ Test case network with SA	47
Figure 15	OMNeT++ BS and UE connectivity Process	48
Figure 16	Packet transfer from UE1 to internet	49
Figure 17	Packet transfer from internet to UE2	50
Figure 18	Packet generation by UE 1 (relay)	50
Figure 19	a) Decision boundaries b) 3D projection of target values	51
Figure 20	Simulink-ML load isolation output	52

List of Tables

Table 1	Communication technology comparison	19
Table 2	5G Simulator Comparison	46
Table 3	Communication network parameter and latency)	51
Table 4	Accuracy Scores	52

Acronyms

3GPP	Third Generation Partnership Project		
5G	Fifth Generation		
AI	Artificial Intelligence		
ANN	Artificial Neural Networks		
AR	Augmented Reality		
B5G	Beyond Fifth Generation		
BS	Base Station		
CN	Core Network		
DER	Distributed Energy Resource		
DG	Distributed Generator		
eMBB	enhanced Mobile Broad Band		
eNB	eNodeB		
EPC	Evolved Packed Core		
gNB	gNodeB		
HAN	Home Area Network		

- HIF High Impedance Fault
- ICT Information and Communication Technology
- IED Intelligent Electronic Device
- MEC Multi-Access Edge Computing
- **mMTC** Massive Machine Type Communication
- ML Machine Learning
- NAN Neighbourhood Area Network
- NG-Core Next Generation Core
- **NIST** National Institute of Standards and Technology
- NSA Non-Standalone
- PCA Principal Component Analysis
- PD Protection Device
- PLC Power Line Communication
- QoS Quality of Service
- RAN Radio Access Network
- SA Stand-Alone
- SVM Support Vector Machine
- TLA Three Letter Acronym
- UE User Equipment
- **UPF** User Plane Function
- **URLLC** Ultra-Reliable Low Latency Communication

VR Virtual Reality

- VM Virtual Machine
- **WAN** wide area network
- **WiMAX** Worldwide Interoperability for Microwave Access
- WLAN Wireless Local Area Network

1 Introduction

To fight rising global warming challenges, increasing energy demand, issues of power system reliability and stability, the concept of smart and reliable power system is introduced and realized as a solution. Power systems are gradually moving toward future and intelligent power systems. Traditional power systems are centralized and static in nature with radial configuration Hussain, Nasir, Vasquez, and Guerrero (2020). Basic architecture consists of generating units (electricity generators) at one end and loads (consumers) on the other. Power flow in a traditional power system is unidirectional and system topology is usually same all the time. On the other hand, future power system can be considered as more decentralized power system in which many distributed energy resources (DERs) such as wind, solar, and energy storages are integrated into the grid. For the future power systems to be environmentally friendly and producing green energy, many renewable generators are integrated. Other than producers and consumers, future power system creates roles such as prosumers and aggregators. Increase in penetration of DERs gives rise to many challenges in power system protection, control, reliability, and stability Cisneros-Saldana, Samal, Singh, Begovic, and Samantaray (2022). Bidirectional power flow, inertia less generation, and changing network topology are some of the challenges which needs to be considered.

1.1 Motivation

Due to the changing power system dynamics and increasing bidirectional power flow, modern protection schemes are needed. Frequent distributed generators connection and disconnection may affect settings of protection system and protection devices Telukunta, Pradhan, Agrawal, Singh, and Srivani (2017)Coster, Myrzik, and Kling (2010). Bidirectional power flow in future power system may cause increase in fault tripping of protection devices. Similarly, at Microgrid level sympathetic tripping and false operation of impedance relay can raise serious concerns regarding the protection of microgrid. To manage the future power system challenges, not only improved protection schemes are needed but advance information and communication technologies (ICTs) can play a vital role. Recent development in wireless 5G communication and its features such as ultra-reliable low latency communication (URLLC) and massive machine type communication (mMTC) can be of great advantage to the challenges of future power systems Patnaik et al. (2020).

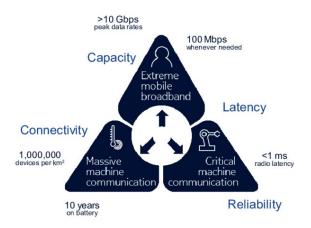


Figure 1. 5G Key technologies Yrjola and Jette (2018).

Future smart communities will have millions of devices connected and communicating with each other. Integration of ICT in power grid will allow devices to have two-way communication which will enable grid's self-healing capability and active participation of customers Liu, Yang, Wen, and Xia (2021). Different possible communication technologies including ZigBee, WLAN, Cellular and fibre-optic can be used as a communication medium. Fibre-optic can be a solution, but its economic factor is one of the concerns. However, after looking from the economic perspective and considering requirements of future power system regarding massive device communication, low latency application, and possible plug-and-play opportunity, 5G technology is seen as a potential solution.

1.2 Research objectives

The objective of the research is to study 5G role in power system and more specifically in protection of future power system. By literature it is known that traditional protection schemes are not suitable for future power systems with bidirectional power flow and increasing DER integration Hussain et al. (2020) Patnaik et al. (2020) Telukunta et al. (2017) Gomes, Coelho, and Moreira (2019) Tetteh and Awodele (2019). Therefore, modern protection schemes need to be developed that can tackle protection challenges. In this research modern fault diagnosis scheme is proposed which utilizes wireless 5G as an essential component of the protection scheme. The research objectives can be categorized into following points: -

- 1. Power system application are low latency applications. Primary objective of the research is to compute 5G network latencies. With the help of Simu5G simulator, power system protection test case model is built, and latencies are computed.
- 2. Developing non-MEC based network design for user equipment (UE) communication with 5G
- 3. Studying possibility of modern fault diagnosis based on Artificial Intelligence (AI).
- 4. Developing power system fault dataset and Machine Learning (ML) algorithm for fault diagnosis.
- 5. Deploying ML algorithm in Simulink and testing by generating artificial fault.

1.3 Thesis structure

Forthcoming thesis is divided into three chapters. Chapter 2 introduces role of communication in power systems. It focuses on communication challenges and possible communication technologies that could be adopted. The chapter also presents details about 5G technology, its key features, and how it can solve future power system challenges. In chapter 3 the concept of modern fault diagnosis is presented. The chapter also reviews traditional protection schemes and progression to modern protection schemes. Since the proposed concept is based on utilizing AI, the chapter also discusses ML algorithm and fault classification technique. Implementation of developed algorithm on Simulink is also discussed in the chapter.

The final chapter 4 is based on computation of 5G test case latencies. In opening part introduction of 5G simulators are presented. A network design for modern fault diagnosis, without MEC server, is developed on simu5G simulator. In the end of the chapter results of Machine learning based fault isolation and latencies are presented.

2 Communication roles in power system and 5G networks

Shifting from traditional grid to a smarter grid require improvement in the power and communication infrastructure. Current power grid can be described as a unidirectional power flow system with a limited communication capabilities in small segments Wang, Xu, and Khanna (2011). A smarter grid-based infrastructure will allow bidirectional power flow and two-way communication between power grids and electricity customers. It is important to mention that to achieve a smarter grid, one of the key solutions is to design and develop smart grid communication infrastructure.

This chapter highlights the importance of communication in future power systems and presents possible communication technologies available. The chapter presents 5G network as a solution to future power system challenges, specifically in low latency application and massive machine type communication.

2.1 Communication Roles

In a power system operation, control, and management, communication infrastructure plays a critical role. Traditional power system utilizes communication infrastructure in limited boundaries. Ericsson (2002) classified communication role of traditional power system into three categories: -

- Real-time operational communication: It includes teleprotection and power system control of a traditional grid. In case of teleprotection the minimum latency of a communication system should be less than 12-20 ms Ericsson (2002). Whereas communication role in power system control includes communication in supervisory control (SCADA) or energy management system (EMS).
- 2. Grid administrative operational communication: This category of communication role does not demand strict real-time communication in a power system. The role

of communication might include administration of substation cameras, identifying fault location, and power grid security systems.

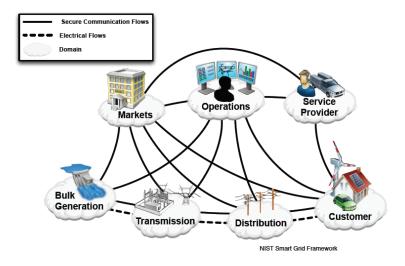
3. Administrative communication: - Which includes telephony or email communication.

For these communication roles as well as other possible future communication roles it is important that the communication media and the communication technology used is capable to fulfil the requirements of these communication roles. Moreover, the focus of this research work falls in the area of real-time operation communication, and specifically for communication in power system protection. In upcoming sections a brief introduction and comparison of the communication technologies is presented.

2.2 Grid Infrastructure and Communication Technologies

In a future power system, communication infrastructure will be a key component for reliable, efficient, and intelligent grid infrastructure. The concept of smart grid in future power system will have an additional digital layer added to it Deshpande and Raviprakasha (2015). A traditional power system is divided into four domains namely electricity generation, transmission, distribution, and customers. Energy flows unidirectionally between these four domains. Usually in a traditional grid there is no communication link between all these four domains.

National Institute of Standards and Technology (NIST) presented a conceptual model of smart grid in 2014. According to NIST a future power system can be divide into seven domains, with an additional communication or digital layer added to the grid infrastructure. These seven domains include four physical layers namely generation, transmission, distribution, customer, and an additional three upper domain layers providing an information communication infrastructure along with electricity services Liu et al. (2021). These three layers are named as electricity markets, service providers (aggregators, retailers or other),



and operations (managers of power flow).

Figure 2. NIST conceptal grid infrastructure López et al. (2014).

A traditional grid with the physical network can be considered as a body with which energy flows from one end of the network to the other end. However, traditional grid lacks reliable and flexible communication infrastructure. The addition of communication layer can be considered as adding the soul and mind of the power network. With the integration of advance information communication technology future power grid will have improved power quality, high reliability, and addition of intelligence in the power network with real-time information interaction, load management, electricity trading and many other services Liu et al. (2021).

According to Gungor et al. (2011), for information flow between power network two types of infrastructure is needed: - i) Flow of information from sensors and electrical appliances to smart meters, and ii) Information flow between smart meters and utility data centres. However, other possible infrastructure might include, for example, infrastructure for millions of Intelligent Electronic Devices (IED) communicating with each other and infrastructure to integrate edge computing in power system.

Developing communication infrastructure will require reliable communication technolo-

gies. Different communication technologies are available with medium of communication as wired communication or wireless communication. Each communication technologies have their own pros and cons but selecting which technology is suitable for grid application requires the technologies to be studied from technical, environmental, and economical perspectives. In upcoming sub-sections an overview of possible communication technology for future power system is presented by concisely going through the technical and economic perspectives of the technology.

2.2.1 Wired and Wireless Technologies

In wired technology communication between devices or transfer of data from one device to other is carried out through a wired-based technology. Two of the wired technology are commonly used in grid communication namely power line communication (PLC) and Fibre-optic communication.

On the other hand Wireless technology, as the name highlights, forms a wireless network and allows devices to communicate with each other. It is an alternative of wired technologies which does not require a wired connection and offers a plug-and-play option. Different wireless technologies are available which can be used for future grid applications including ZigBee, Wireless local area network (WLAN), Worldwide Interoperability for Microwave Access (WiMAX), and cellular networks.

2.2.2 Fibre optics

Fibre-optics communication uses optical fibre cables for communication. Information travel through fibres by means of light pulses. Fibre-optic is a reliable media of communication with high data rate and less communication interference. In smart grid fibre optics are used mainly in wide area network (WAN) and neighbourhood area network (NAN) Liu et al. (2021). It is mostly deployed for communication at control centre and substation. One of the most advantage feature of fibre-optics is that it provides low-latency com-

munication with high data rate over a hundred of kilometre free from electromagnetic interference.

However, along with its advantages it also has disadvantages. Fibre-optics are very expensive in terms of deployment and maintenance when compared with other wireless technology. Other disadvantage of fibre-optics is that in future power system millions of devices will need to communicate with each other and fibre-optics cannot introduce plugand-play feature. For communication of millions of devices many optical fibres would be deployed, which will not be a practical and economical solution.

2.2.3 Power line communication

Other type of wired-communication technology is power line communication (PLC). PLC utilizes existing power lines to communicate between devices by transferring data over the power lines. The data can be transferred with this technology as narrowband PLC (between 3-5 kHz frequency) with low data rate or broadband PLC (between 2 – 259 MHz) with medium data rate Liu et al. (2021). Benefit of PLC technology is that additional lines are not needed, and data can travel over existing power lines. Thus, being economical and offering a plug-and-play option. However, power lines have high electromagnetic interferences. Moreover, number of devices connected to the power line and distance between transmitter and receiver, both has negative impact on the signal quality Gungor et al. (2011).

2.2.4 ZigBee

ZigBee technology can provide wireless communication in power system with ultralow power consumption. It is based on IEEE 802.15.4 standard. It has many practical usages in industries, home and buildings automation, health care system and in electricity networks as well. Despite being economical communication technology, some of the constraints for ZigBee technology includes less security, less distance coverage, high latency, and less devices connection, which limits its application in power system.

2.2.5 WLAN

WLAN is a wireless local area network technology which is based on IEEE 802.11 standards and is used mainly to perform point-to-point or point-to-multipoint communication within a home area network (HAN) Liu et al. (2021). Advantages of WLAN network includes low cost of deployment, plug-and-play option, latency in 15 ms, and medium-high data rate. However, disadvantages of WLAN include less area coverage, signal distortion by high-voltage equipment or signal interference, and up to 250 device connections for a single router.

2.2.6 WiMAX

WiMAX technology is capable to communicate similar to WLAN but with higher data rate, thousands of device connection, and longer distance communication. WiMAX is based on microwave access technology and follows an IEEE 802.16 wireless standard. It can provide point-to-multipoint connection and can be adopted as NAN or WAN. Disadvantage of WiMAX includes high deployment cost and high latency as compared to other wireless technologies.

2.2.7 Cellular communication technology

Cellular networks are also one of the technology available to play its role in power system communication. Due to its already existing infrastructure in most of the areas and network easily accessed, it can be an economical as well as practical solution. Cellular network evolved from 1G (first generation) to all the way up to 6G. These networks evolutions are governed by 3rd Generation Partnership Project (3GPP) standards, which unites 7 international telecommunication standards including ARIB, ATIS, CCSA, ETSI, TSDSI, TTA, and TTC.

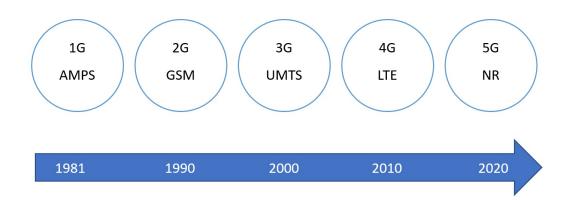


Figure 3. Cellular network evolution.

Cellular network infrastructure consists of four major parts including radio access network (RAN), core network (CN), operation and management, and user equipment (UE). Its base station deployed at various locations gives access to cellular networks and allows devices to communicate with ease. Moreover, recent advancement of 5G and B5G networks, including high data rate, mMTC and URLLC, can be of key importance for many smart grid applications. However, every technology has limitation, cellular networks also have some limitation. 5G networks can travel shorter distances and are significantly interrupted by physical objects such as huge building, walls, and towers. 5G networks also have other vulnerabilities such as identification attacks and battery drain attacks against cellular devices Shaik, Borgaonkar, Park, and Seifert (2019).

Table 1.	Communicati	on technology	comparison.
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Technology	Data rate	Coverage	Latency	Cost
Fibre-Optic	Very high	up to 100 km	3 us/km	High
PLC	High	5 km	5 ms	Medium
ZigBee (IEEE 802.15.4)	Very high	70 m	3 ms	Medium
WLAN (IEEE 802.11ac)	High	70 m	10 ms	Low
WiMAX	Medium	30 km	50 ms	High
5G	Very high	Few hundred meters	less than 1 ms	Medium

2.3 Fifth Generation Networks (5G)

5G is a fifth-generation technology for cellular networks. 4G (LTE-Advanced) was capable to provide high data rate and network performances, but cellular networks had some challenges which required further development. One of the main reason for development of 5G was to introduce cellular networks for industry and information of things (IoT) applications.

With an additional requirement of high data rate, industry demanded possibility of large devices interconnectivity and low latency communication over a wireless medium. Thus, it led to an introduction of triangle of 5G, presenting enhanced Mobile Broad Band (eMBB), mMTC, and URLLC Figure.1. eMBB deals with the applications which require high data rate such as streaming 8K videos, virtual reality (VR), and augmented reality (AR). For smooth running of these application, it also requires low latency communication. Whereas mMTC in 5G will allow around millions of devices to connect and communicate with each other within a single cell.

International telecommunication union (ITU) set requirements for 5G in International mobile telecommunication-2020 (IMT-2020). According to the requirements the peak data rate for uplink was set to be 10 Gb/s and for downlink 20 Gb/s. Latency for eMBB was set 4ms and for URLLC 1ms. Moreover, 5G would have mobility up to 500km/h in rural eMBB. Control plane latency was set around 10-20 ms. However, in current crowded and scarce spectrum, the requirement of data rate of 20 Gb/s is not feasible in low-band spectrum therefore 5G needed higher band spectrum to achieve this requirement.

Cellular network uses radio waves as a medium to transmit data. 5G network supports frequency spectrum in the region of mmWave, low-band, and mid-band. mmWave lies in frequency range of 24-72 GHz and can provide data rate up to 1-2 Gb/s Shahinzadeh et al. (2020) at shorter distances. For longer distance 5G uses a mid-band frequency spectrum which falls in the region of 2.4-4.2 GHz.

2.3.1 5G Architecture

Cellular network main components can be divided into two systems: RAN and Mobile core Peterson and Sunay (2020). RAN is responsible of managing radio spectrum by assuring that radio spectrum is used efficiently and provides required quality-of-service (QoS) to the users. Different sub-components are combined to build up RAN, main component of RAN is base station also referred as eNodeB (eNB) for 4G and gNodeB (gNB) for 5G.

Mobile core, on the other hand, provides connection to internet for data and voice services, ensures the QoS of the connectivity is met, track user's mobility to avoid service interruption, and monitors user's billing and charging Peterson and Sunay (2020). Mobile core is referred as Evolved Packed Core (EPC) in 4G and Next Generation Core (NG-Core) in 5G. Core act as bridge between RAN and the internet. Moreover, mobile core is also further partitioned into control plane and user plane.

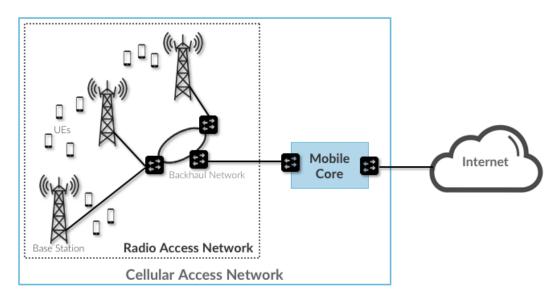


Figure 4. Cellular network main component Peterson and Sunay (2020)).

To interconnect gNB with mobile core a Backhaul Network is used to establish a connection between RAN and mobile core. Backhaul is typical wired connection. It is an important part of the RAN; however, it is implementation choice, and it is not prescribed to implement Backhaul network according to 3GPP standard Peterson and Sunay (2020). The connectivity services of cellular network are provided to the UE. A UE can be a moving device or stationery object, depending upon the type of application. Previously UE were name assigned to mobile phones and tablets, but recently objects such as car, drones, industrial machines, intelligent electronic devices (IEDs), robots and many other devices are also referred as UE when these are connected to cellular networks. These UE connects to a base station when a wireless channel is established for a UE. The connection remains established until channel is released if UE remains idle for a period of time. In second step each base stations forwards a signaling traffic after base station establishes "3GPP control plane" connectivity with the UE and Mobile core. In third step for each active UE, base station establishes tunnels. After tunnel is established, base station forwards packets of control plane and user plane between Core and the UE. However, these packets can be tunneled over SCTP/IP and GTP/UDP/IP Peterson and Sunay (2020).

In case of a moving UE, a base station also coordinates a soft handover of the UE between neighboring base stations. However, during UE handover, base station might also coordinate with multiple base stations for a multipoint transmission to a UE. The entire process of connection of UE to handover can be seen in Figure 5.

A 5G network can be deployed in multiple ways which can be summarized into Peterson and Sunay (2020): -

- 1. Stand-Alone (SA) 5G
- 2. Non-Standalone (NSA) (4G + 5G RAN over EPC)
- 3. Non-Standalone (4G + 5G RAN over NG-Core)

These different 5G deployment methods allow transition from 4G technology to 5G technology. In NSA over EPC, 5G base station is deployed along with 4G base station. 5G base

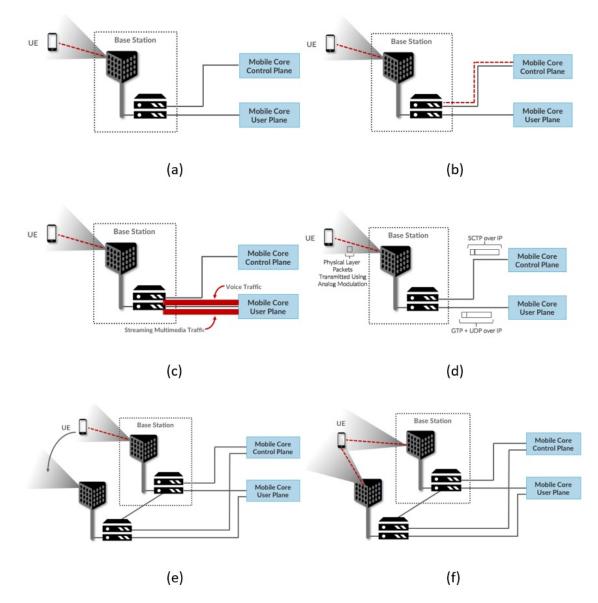


Figure 5. 5G with UE connectivity process a) BS detect and connect with UE b) BS establish control plane connection between UE and Core c) BS establish tunneling d) Tunneled over SCTP/IP and GTP/UDP/Ip e) UE handover f) UE multipath transmission Peterson and Sunay (2020).

station is responsible for carrying user traffic and the 4G base station forwards control plane traffic between UE and 4G Mobile Core. Non-Standalone over NG-Core uses 5G Mobile core along with 4G base station. On the other hand, stand-alone has only 5G technology deployed in the field.

2.3.2 Multi-Access Edge Computing and 5G

Multi-Access Edge Computing (MEC) is considered as an emerging technology for 5G and Internet of Things (IoT). With MEC technology 5G can bring cloud computing at the edge of the RAN. Cloud computing at the edge of RAN will provide computational and storage resources at RAN Liu Y, Peng, Shou, Chen, and Chen (2020) which will result in increased computation and reduce latency for the end users. In case of a cloud computing far from edge, the data would have to travel all the way to the cloud and return, which increases the latency of communication.

MEC typical features includes proximity, low latency, high bandwidth, real-time insight into radio network information, awareness of user's location, mobility support, and more security and privacy protection Liu Y et al. (2020). It can be a solution to many applications which either require low latency communication or are time-sensitive applications such as Augmented Reality (AR), Virtual Reality (VR), smart grid, and power system protection. However, to practically integrated MEC with 5G and IoT some key technologies are required namely Cloud Computing, Software-Defined Network, Network Function Virtualization, Information Centric Networking, Virtual Machine (VM) and containers, Smart Devices, Network Slicing, and Computational Offloading Liu Y et al. (2020).

This research study proposes a concept of utilizing MEC servers of 5G for power system fault diagnosis. More details are discussed in chapter 3.

2.3.3 5G in Power Systems

Authors in Garau et al. (2017) presented distributed monitoring and control of smart grid based on 5G and 4G network. According to authors a smart grid architecture can be categorised into centralized architecture, hierarchical architecture, and decentralized architecture. The authors conducted research on centralized network management (with LTE) and distributed network management (with 5G) and compared between the two management systems during fault management in smart grid.

A communication network performance in power system can be evaluated based on energy consumption, communication cost, processing requirement, bandwidth requirement, traffic and financial cost. Authors in Garau et al. (2017) highlighted benefits of decentralized network management over centralized network management by performing analysis of these scenarios by combining DIgSILENT PowerFactory, Omnet++, MATLAB, and Pyhton software tool.

Mostly power system protection and control schemes are developed with wired communication technologies, however this could be challenging, economically and technically, for future power systems. Authors in Hovila et al. (2019) introduced 5G application in line differential protection. To validate communication performance and protection system a test setup was developed by the authors featuring wired (fibre connection) and wireless (5G) communication technology. Wireless technology included 5G test network located in Espoo, Finland with core network and cloud network located in R&D premises of Nokia. On the other hand, the line protection scheme was the protection scheme developed by VTT's Microturbine laboratory. By a connection with 4G/5G modem R-SV and R-GOOSE messages were sent over mobile network.

A 5G based architecture control and protection application of smart distribution grid, using edge computing, is also proposed in literature Zerihun and Helvik (2019). According to the proposed architecture in Figure **??**, the aim is to virtualize and transfer some control function at the edge of cloud in 5G. Logical nodes in IEC 61850 are proposed to be kept near field devices (sensors and actuators) and decision making functionalities on protection IEDs are moved to edge cloud. For substation protection end-to-end network slice is taken into consideration which is isolated from rest of network. According to authors, for establishing 5G communication network architecture, main components required includes Field Devices, Radio Links, gNB, Edge Server, VM, Virtual Machine Monitor (VMM), SDN Controller and communication link.

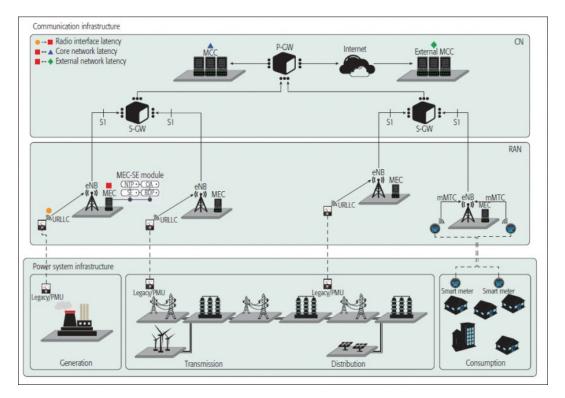


Figure 6. 5G Network Architecture in power system Cosovic et al. (2017).

5G and B5G networks are evolving communication technologies that are considered suitable for real-time and mission-critical applications of future smart grids. 5G's mMTC and edge computing provide a suitable environment for smart grid to implement distributed monitoring and control applications Cosovic et al. (2017). Authors in Cosovic et al. (2017) presented detailed discussion of benefits of 5G environment based distributed state estimation in smart grids. The authors concluded that 5G technology is capable of provide an ideal arena for development in future distributed smart grid services.

3 Modern Fault Diagnosis

In a normal condition, power systems operate under balance conditions but due to an insulation breakdown between conductors or physical contact due to an accident can result in imbalance in power system dynamics which is referred to as occurrence of a fault. Faults can be divided into symmetrical and asymmetrical faults. In 3-phase AC power system fault can occur between phase-ground (P-G), Phase-Phase (P-P), or 3-Phase fault. Similarly, DC faults in DC power system can be represented as pole-to-pole or pole-to-ground fault Figure 1. Such faults change the dynamics of power system and causes disturbances in the system stability. To minimize the harmful impact of faults on the system stability and equipment life, protection schemes and protection devices are used to isolate the fault before any damage has occurred.

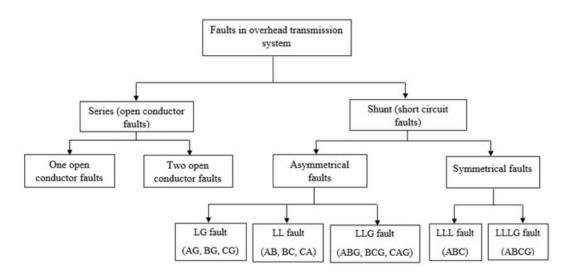


Figure 7. Faults in AC overhead transmission system Eskandarpour and Khodaei (2018).

For modern concepts of smart grid such as integration of micro-grid which involves bidirectional power flow and two-way communication, conventional protection schemes or fault diagnosis methods cannot be considered as suitable for future power systems. Conventional protection schemes are suitable for traditional power systems which involves a unidirectional power flow and unchanging network architecture throughout power system. In case of bidirectional power flow and varying network typologies, modern fault diagnosis needs to be studied.

Micro grids are important fragments of smart grid which can also be considered as a small-scale design of large power systems. For the customer to be an active part of the smart grid, micro-grid allows the integration of DERs at distribution level Patnaik et al. (2020). It does not only increase the reliability of the system but allows the participation of prosumers in energy market. A microgrid can generate enough power that could supply energy to its nearby load. It can be operated in grid-connected or Islanded mode. During its grid connected operation it exchanges power with the main grid. Excessive power produced by the microgrid is exported to the main grid and when the microgrid has deficiency of power, it imports electricity from the grid. Hence, this leads to a bidirectional power flow in a microgrid.

An intelligent or smarter grid can be considered as future power system which integrates Intelligence, modern communication, and cyber technologies (including cyber physical system & cyber security). Artificial Intelligence technique provides powerful tools for fault control and fault diagnostic in future smart grids Bose (2017). In this chapter a power system fault diagnosis is presented by using Machine Learning, a sub-branch of Artificial Intelligence (AI). In this research, by integrating AI and 5G cellular network, modern fault diagnosis scheme based on 5G network is proposed.

3.1 Protection issues and challenges

The bidirectional power flow disturbs the protection setting of the system and protection devices (PDs). The distributed generators in microgrids, contributing to fault current, can cause irregular operating time of the PDs which will lead to loss in protection coordination. Moreover, the increasing number of DGs of different sizes will generate fault current of different levels which might also disturb protection coordination. This dynamic nature of smart grid with DG integration and islanding/grid-connected topology can have an impact on current magnitude and direction which might result in miss-coordination of

protection devices Patnaik et al. (2020).

To develop microgrid's reliability and stability, protection of microgrid is an important element. Traditional or conventional protection schemes are not suitable to protect future power systems. In Figure 8 the author has demonstrated all possible microgrid related issues, challenges, and protective solutions. Some of the protection challenges which are related to microgrid grid-connected mode of operation are further discussed in the following sub-sections: -

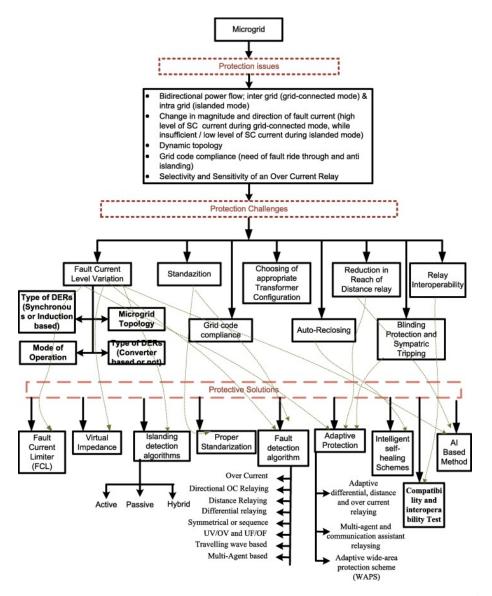


Figure 8. Microgrid protection issues, challenges, and protection solution Patnaik et al. (2020).

3.1.1 Blinding Protection

During a fault if the location of DG is in the middle of fault point and feeding station, the fault current which is sensed by the upstream protection device will be of lower level. Due to which the upstream protection device will not respond to the fault and thus will result in delay tripping or no tripping at all. This blinding protection usually occurs at high impedance areas Patnaik et al. (2020).

3.1.2 Sympathetic Tripping

In this type of tripping the protection scheme loses its selectivity and leads to isolation of connected DG unit or healthy feeder. One such case would be elevated level of fault current initiated from DG due to high resistive triple-line-ground fault at load feeder Patnaik et al. (2020).

3.1.3 Reach of Distance Relay

Impedance relay is triggered when it senses a fault within its reach (maximum distance). In case when DG is connected to the system, the distance relay might not operate on its assigned zone. Because when the fault occurs downstream of DG control center the upstream relay will detect extremely high impedance than real impedance which affects relay grading, and the relay does not operate in the specified zones Patnaik et al. (2020).

3.2 Evolution of protection schemes

Relays and circuir breakers are two main components of the protection system which are the brain and the body. Relay act as a brain which senses disturbances and signals the body (PD) to take certain actions. In the paper Tetteh and Awodele (2019) the author presented an overview of protection schemes of power system and their evolution throughout the time. The author discussed earlier works such as classification and identification of three-line currents using fuzzy logic, fault classification and identification on transmission line using wavelet and fuzzy based systems, Integrated protection system based on fuzzy inference rules, and adaptive multi agent protection relay coordination technique.

MG protection schemes can be divided into three branches namely differential, distance and over-current protection Venkataramanan and Marnay (2008). However, Patnaik et al. (2020) presented classification of all microgrid protection strategies and protection coordination method that are present in literature Figure 9

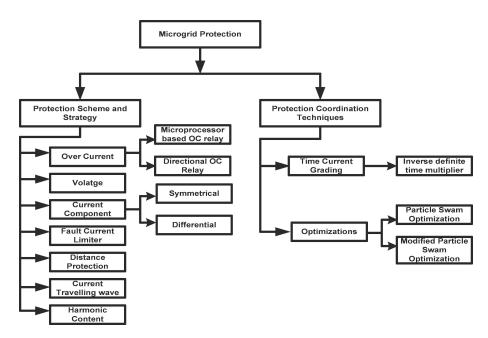


Figure 9. Microgrid operation protection schemes Patnaik et al. (2020).

In recent work, an intelligent non-model-based differential relay is presented for controlled Islanding of microgrids Sepehrirad et al. (2020). One of the issues of differential protection is that it requires real-time adaptive and selective based differential relaying for fault detection and tripping Sepehrirad et al. (2020). The proposed intelligent Decision Tree based differential relay can identify proper tripping timing with respect to different microgrid operation and topologies. According to the proposed scheme for Islanding scenario Figure 10, the electrical voltage and current signal are processed during faulty events. By using intelligent decision tree algorithm, effective signals are selected to be used for differential protection relay design.

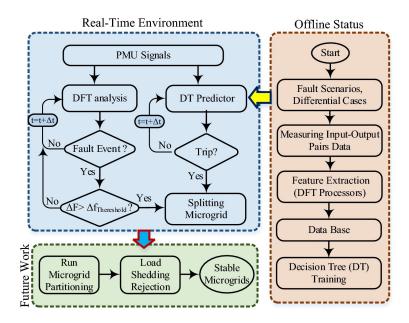


Figure 10. IDT relay structure Sepehrirad et al. (2020).

The future power system will be of dynamic nature which will require intelligent control & protection and fast communication. It is important to mention that for the protection of smart grids, grid intelligence, and fast & reliable communication will play a key role. Recent development in cellular communication and its features such as ultra-reliable low latency communication(URLLC) and massive machine type communication (mMTC) can be of great advantage to improve the communication lag and reliability of the protection system Tetteh and Awodele (2019).

3.3 Machine Learning and Power Systems

Machine learning (ML) is a branch of Artificial Intelligence. As the name suggest, in ML the machine algorithm tries to learn from data or by experience. Based on that learning

the ML model predicts or takes necessary actions. Primary purpose of adopting ML in different areas of application is that it provides automatic learning from a raw data and produces results which can be implemented in decision making process Miraftabzadeh, Foiadelli, Longo, and Pasetti (2019).

Machine learning tasks can be divided into four types namely, i) Supervised learning ii) Unsupervised learning iii) Semi-supervised and iv) Reinforcement learning. Main difference between these four learning is that in supervised learning the output (target value) is given to the model. Whereas, in case of unsupervised and reinforcement learning output are not shown to the model. Reinforcement learning further utilizes the concept of reward and punishment to train the model without the need of input/output data. Semi-supervised learning on the other hand contains some labelled output data and large amount of unlabeled data. To adopt which task depends on the data and the research problem.

Supervised ML can be applied to problems which require classification or regression. Classification deals with categorizing data into output classes and predicting the class of data. Classification can be in the form of alphabet-based classes or numerical class. Later is special type of regression in which data is classified in number classes. ML classification can be either linear or non-linear classification depending up-on the data distribution. Different type of classifiers such as deterministic or probabilistic classifiers can be used. An example of classification problem could be to predict whether the image is an image of "oranges" or "mangoes". It can also be binary classification where the data belongs to a class "0", "1" or "2".

Regression, on the other hand, in its simplest definition can be defined as a method to predict numerical output from a given data. It is also known as curve fitting in which the algorithm tries to fit data with the curve. The idea behind regression is to fit available data to a certain formula which will be good for data modelling; or by rephrasing it, in regression an approximate mathematical model is build which is suitable for the input/output relationship. Based on the mathematical modelling of data, regression can be divided into Parametric regression and Blackbox regression. One example of regression problem could be to forecast energy demand.

Growing application of machine learning can be seen in power system control, security, forecasting, fault diagnosis, and many other applications. Alimi, Ouahada, and Abu-Mahfouz (2020) Presented a comprehensive review of machine learning techniques developed for power system stability and security application. The research highlighted ML-based methodologies, achievements, and limitations of classifier design. There are four major power system security and stability domains where mostly ML techniques are deployed namely in SCADA network, Power quality disturbance (PQD) studies, Voltage stability assessment (VSA) and transient stability assessment (TSA).

Different ML algorithms such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), Decision Tree (DT) or other algorithms are used based on their performances. In Sung and Ko (2015) an interactive machine learning integrated load control scheme is proposed for improving performance and reliability of load scheduler and reducing peak power demand. To adjust the load scheduler SVM algorithm was used to accurately predict demand. Lassetter, Cotilla-Sanchez, and Kim (2018) used ML SVM algorithm to predict whether re-connection of microgrid to the main grid would lead to stability or not, based on real-time phasor measurement units (PMU) values. For training the ML model, the author created training dataset for different scenarios by using power system dynamic simulator. Based on these values the model was trained and it predicted whether the power system would lead to instability or stability when a microgrid will be reconnected to the power system.

In Zhao, Shang, and Sun (2019) the author proposed that by accurate classification of power quality disturbances, the power quality of a power system can be improved and governed by using time-frequency domain multi-feature and decision trees. Wavelet transform and S-transform were performed to extract features from power quality disturbance signals. Based on the extracted features, decision tree classifier algorithm was applied to accurately classify power quality disturbances.

One of the challenging areas of power system is the power outages. In literature ML models have also been used to accurately predict power outages after disturbances. There are number of factors involved which can result in power outages such as environmental factor, power line faults, or equipment damage. In Kankanala, Das, and Pahwa (2014) the author used ADABOOST algorithm to estimate power outages based on weather data. It evaluated the effects of wind and lightning on power outages in overhead distribution system. In Eskandarpour and Khodaei (2018) power outages due to extreme weather event, such as hurricanes, was used as one of the features to train a SVM model and predict power outages.

3.3.1 Machine Learning in Power System Fault Diagnosis

Faults are likely to occur in any functioning system which can damage the system and make it unreliable for operation. Important thing for system reliability and stability is that the fault is diagnosed, located, and isolated. Similarly in a very complex power system it is essential to diagnose the fault and isolate it before any harm to power system stability and equipment.

In literature many reviews and implementation of AI application in fault diagnosis are present. According to Prasad, Belwin Edward, and Ravi (2018), classification of faults in power system can be performed using three techniques: -

- 1. Prominent Techniques: They are wavelet approach, ANN approach and Fuzzy logic approach.
- Hybrid Techniques: It includes Neuro-Fuzzy Technique, Wavelet & ANN Technique and others.
- Modern Techniques: Are the techniques implemented for fault analysis in power system using SVM, Genetic Algorithm, PMU-based protection scheme, Principal Component Analysis (PCA) based framework and many other techniques.

Authors in Mishra and Rout (2018) presented a microgrid protection scheme using ML technique. According to authors the proposed microgrid protection scheme is more robust than conventional overcurrent relay operation for faulty events. In first step three phase current signal of the respective buses is passed through an empirical mode decomposition method. By using Hilbert-Huang transform important features are computed from decomposed signal, which are then applied to three different ML classifier algorithm namely naive bayes classifier, support vector machine and extreme learning machine. Output result of classifier represents the detection and classification of microgrid faulty events. The proposed protection scheme was tested for different types of faults (symmetrical, asymmetrical), different microgrid structure (radial, mesh) and microgrid mode of operations (islanded and grid connected).

ANNs are also one of the classifiers which is applied for detection and classification of power system faults in literature. Jamil, Sharma, and Singh (2015) applied feedforward Neural Network with backpropagation algorithm in the process of three phase power line fault detection and classification. Datasets used for training and validating the ANN model was obtained by simulating on MATLAB/Simulink a model of 400kV/50Hz three phase power line with two generators located at both ends. The length of the transmission line was considered 300 km and various types of faults were applied at different locations of transmission line. The authors presented results for both fault detection and fault classification using ANN.

Disturbances caused by fault are crucial to be detected to enhance performance of microgrids. Panigrahi, Rout, Ray, and Kiran (2018) has introduced a technique for microgrid fault detection and classification. For the detection of faults in microgrid, consisting of wind turbine and diesel generator, Wavelet transform, and Wavelet packet transform is used. To classify the faults a hybrid technique, Neuro-Fuzzy method is implemented. Analysis and assessment of the proposed approach was conducted on MATLAB/Simulink environment.

Increase in complexity of power system increases the rate of occurrence of faults in

power systems. Therefore, for rapid fault identification an adequate intelligent systems are needed which can identify faults. Kumar, Bag, Londhe, and Tikariha (2021) utilized machine learning algorithm for classification of faults. Current and voltage values were taken from IEEE-14 bus standard system which was simulated in MATLAB/Simulink for normal, symmetrical, and unsymmetrical fault scenarios. By training SVM algorithm different types of faults in power systems are classified with higher accuracy. In the proposed technique, faults are analyzed using transient data, features are extracted with wavelet packet transform and redundant features are removed to improve the accuracy of the model.

In Goswami and Roy (2019) MATLAB/Simulink simulated faults were classified. The Simulink model consisted of 90km power transmission line and the faults were applied at each 10km of line length. Based on the Simulink model, fault datasets with three phase RMS voltage and current values were generated and total 11 types of faults classes was considered. Three ML algorithm including Decision Tree, K-Nearest Neighbors and SVM were applied for the classification of faults using python and scikit-learn library. According to the results presented by the authors, SVM algorithm outperformed the other two algorithms

Sarwar et al. (2020) Proposed power distribution network High Impedance Fault (HIF) detection and isolation. Data from voltage and current sensors are used, which are applied to data driven techniques such as Principal component analysis (PCA), Fisher discriminant analysis (FDA), and multiclass-SVM, to detect and classify HIF. According to authors PCA can detect HIF but cannot classify HIF. Fisher discriminant analysis can classify and detect HIFs. However, better results are obtained using SVM for fault detection and classification.

Gururajapathy, Mokhlis, and Illias (2017) presented a review of most of the techniques which are deployed and commonly used in locating and detecting faults in power distribution system with distributed generators. According to author the fault location method can be categorized into conventional method and AI-based method. Conventional methods require less computational time but are inaccurate for larger power systems. Albased method has higher accuracies for larger power systems. After comparing between different AI algorithm including ANN, SVM, Fuzzy logic, Genetic algorithm (GA), the authors concluded that SVM algorithm is more widely used due to its successive progress in recent years. But none of any single AI algorithm has the capability to solve all problems based on specified conditions. Moreover, in this research SVM algorithm is considered for applying fault diagnosis in power system protection model.

3.3.2 ML algorithm in Modern Fault Diagnosis

The concept of modern fault diagnosis is to integrate intelligence and reliable communication. By using 5G communication and ML algorithm modern fault diagnosis scheme is proposed which can be a solution to future power system challenges such as false tripping due to bi-directional power flow. The concept of modern fault diagnosis can be seen in Figure 11 in which the ML algorithm can be deployed in MEC server. Incoming sensor values will be given to the ML model deployed in MEC server, which will detect and classify the occurrence of fault. If fault is detected the MEC server will sent trip signal to the actuator. Upon receiving a trip signal, an actuator will isolate the faulty region by tripping the circuit breaker.

3.4 ML based Power system protection

In this research a ML based protection method is proposed to isolate a fault once the fault is recognized by the ML algorithm. To train a ML model, three phase current and voltage datasets are generated by a MATLAB/Simulink model. The Simulink model consists of a 150kV 3-phase power source, 20km power line and load connected on the other end Figure 5.

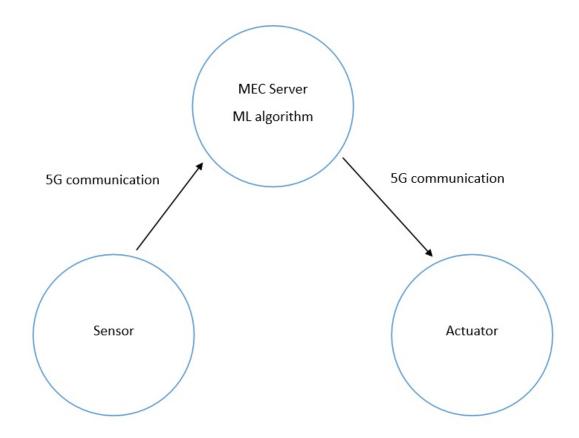


Figure 11. Power system protection with 5G network and ML.

3.4.1 Datasets

Fault datasets are generated by artificially generating different types of faults on the power line. Four different types of faults namely Ph-Ph-Ph, 3-Ph-G, 2-Ph, and 2-Ph-G faults were generated. The measurement of Load voltages and currents are exported into a CSV file to which a machine learning classifier is applied.

The dataset contains 48007 data values with target value "O" or "1" which mean that either there is no fault (O) or the fault has occurred (1). Total six values of measurement (RMS current and voltage of each phase) are input data (features of ML algorithm). Before training the SVM model, the datasets are pre-processed by applying random permutation and dividing into train, test, and validation sets. The train and testing datasets are used during the training and testing phase of ML model. Once the model has been trained and tested, a separate validation dataset is used to verify the performance of the model.

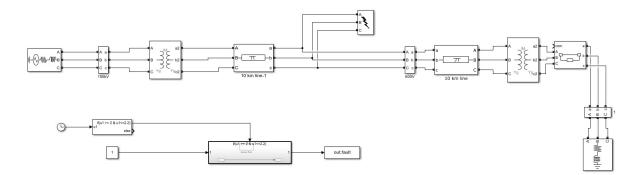


Figure 12. Simulink power distribution line model.

3.4.2 Machine Learning Algorithm

A ML algorithm for power system fault diagnosis is developed in this research using SVM. SVM is a data driven technique. Due to its generalization abilities and less vulnerable to dimensionality, it is used for detection and classification of faults Sarwar et al. (2020). It can classify samples by creating hyperplane, also known as decision boundaries, which separates one class from other Vaish, Dwivedi, Tewari, and Tripathi (2021).

SVM is a kernel method which uses kernel function to map two points from an original space into higher dimension Xie, Alvarez-Fernandez, and Sun (2020). In other words, it uses kernel function to transform non-linearly separable samples into separable samples by converting it into higher dimensions which are more likely to be separated Vaish et al. (2021). In this study, ML SVM classifier algorithm is used to classify the faults.

SVM classifier is developed in MATLAB and Python. For visualization of data samples and decision boundaries, Python is used. However, implementation of SVM Classifier on Simulink is carried out using MATLAB based SVM classifier. The results of both the classifiers are also presented in Results section.

For visualizing dataset decision boundaries and possible linear separation, PCA is used in Python. PCA is a dimensionality reduction or data compression method, however, in fault diagnosis it operates as pattern recognition Vaish et al. (2021). Both the SVM models are developed by using same model parameters. Radial basis function is used by the SVM classifier to identify the decision boundaries for classes. The C parameter value is kept 1. It informs the SVM model about the amount of flexibility in misclassifiying training samples. Higher C-value will select a smaller-margin hyperplane which will limit the amount of support vectors. Conversely, lower C-value will cause SVMoptimizer to have larger-margin in hyperplane. Selecting C-value depends upon the training dataset and respective classes.

3.4.3 MATLAB/Simulink Protection model

To classify the fault and isolate the load from faulted line SVM model is developed in MAT-LAB and applied in Simulink. The SVM Simulink block takes three phase load current and voltage as input values and predicts the output, which means the block predicts whether the fault has occurred or not. As soon as the model predicts the occurrence of fault, it signals the actuator (circuit breaker) to isolate the load. The SVM model can be labeled as an intelligent relay which senses the fault and signals the circuit breaker to isolates the load.

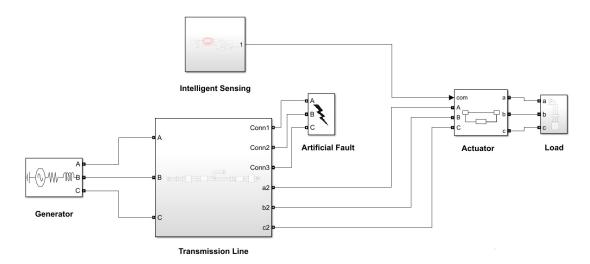


Figure 13. ML based fault sensing and isolation.

Since 5G will be used as medium of communication and the ML model will be deployed

at 5G's MEC server, it is important to study latency of communication. The next chapter presents 5G simulators, results of latency and ML based protection of MATLAB/Simulink model.

4 System Simulations and Results

One way for evaluation of network performance is by simulation of communication networks. The results obtained with simulation might not be as realistic as in practical cases, but it gives an overview of how the system will preform and react under certain conditions. Cellular networks are complex communication system in which each component has an impact on network performances. By software modeling of these component and complex systems an analysis can be made about the operation and interaction of such systems in real-world environment, which also minimizes cost and risk involved in implementation. Therefore, in this chapter simulation of 5G network for power system protection test case is presented. The chapter also introduces 5G simulators and results of ML based power system protection and communication latencies.

4.1 5G Simulators

5G Simulations software provides an analysis of how the 5G network and component interact in the real-world environment. By means of 5G simulation software one can compute latencies, simulate cellular networks including mmWave/NR and LTE, perform pathloss and interference modeling of mmWave, ad-hoc network, multi-hop network, vehicular ad-hoc network (VANET), antenna design and many other applications. There are many 5G simulators available for the researchers, but which simulation software is suitable depends upon the application and need of a researcher. Some of the well-known 5G simulators include SyntehticNET, Omnet++, ns-3, OPNET, OpenAirInterface, 5G-K, Matlab/Simulink, Vienna-5G and so on.

4.1.1 SyntheticNET Simulator

SyntehticNET simulator is developed by Al4networks Lab which is a python-based simulator and conforms with the 3GPP 5G standard Zaidi, Manalastas, Farooq, and Imran (2020). Since it uses python platform, it can integrate ML libraries of python and is also considered as the first simulator which is built to test AI network automation Zaidi et al. (2020). It has other key features including detailed handover process implementation, integrating edge computing, propagation modeling, and support for 5G standards. However, as per the author's knowledge SyntehticNET simulator is not an open-source software.

4.1.2 OMNeT++

OMNeT++ (Objective Modular Network Testbed in C++) is a discrete event network simulator which is written in C++ platform. Under academic license it is an open-source software and free to use and modify. OMNeT++ can be used for wireless and wired computer network simulation. Most recent release of OMNeT++ allows integration of Python to perform data visualization and plotting outputs. It models a communication network by compiling initialization file, network descriptive file, and message file. OMNeT++ allows networks to be modeled by combining reusable network components, also known as modules. It provides many other functionalities including protocol modeling, modeling of queuing networks and distributed hardware systems, performance evaluation of complex systems, and many other features.

Simu5G is an evolution of SimuLTE 4G simulator which is developed on OMNeT++ framework to simulate 5G networks. It is a library of OMNeT++ and allows simulation of data plane of mobile core and RAN. Moreover, it is also compatible with other libraries of OMNeT++ including INET (TCP/IP based network modeling) and Veins (for VANETS). For packets to be send from a UE to gNB or for communication between vehicles, application layer can be developed by writing the code in C++ language. Moreover, it is also based on 3GPP specification, but it does not model control plane function.

4.1.3 NS-3

NS-3 simulator is based on NS-2 and is licensed under GNU GPLv2 license Bouras, Gkamas, and Diles (2020). It is also an open-source software available free for research and development purposes. It is a discrete-event network simulator and provides a simulation engine to perform network simulations. NS-3 is developed on C++ platform and uses Python language. Main features of NS-3 includes C++ & Python scripting, Virtualization support for virtual machines, software integration, support for 4G network by LTE protocol stack, inclusion of evolved packet core, and support for 5G network simulation by mmWave simulator module. Bouras et al. (2020).

However, some of its weaknesses, mentioned by Bouras et al. (2020), are lack of credibility, lack of active maintainers, lack of documentation and community for fixing bugs.

4.1.4 MATLAB/Simulink

MATLAB is a powerful tool and programming platform which is used by engineers and scientists to design products and systems. MATLAB is based on its own MATLAB languages which is matrix-based language. It can be used to analyze data, develop algorithm, create models and applications.

Simulink, integrated with MATLAB, is a block diagram environment which can be used for applications in the area of automotive, aerospace, industrial automation, signal processing and communication network modeling. 5G Toolbox in Simulink provides opportunity for modeling, simulation, and verification of 5G network systems. 5G Toolbox is also 3GPP compliant which allows functionalities such as simulating effects of RF designs and interference, configure and simulate 5G NR communication link, and generate waveforms.

4.1.5 **OPNET**

OPNET (Optimized Network Engineering Tools) is also a simulator available at commercial level and is part of Riverbed Modeler. It is useful in studying communication applications, protocols, and networks. With its GUI a user can develop network topologies and application layers and implement them using object-oriented programming. OPNET offers three main functionalities namely modeling, simulating and analysis. Moreover, some of its strength also includes fast discrete event simulation engine, less simulation runtime, and fast graphical results upon network simulation.

Along with its benefits some of OPNET's disadvantages are Bouras et al. (2020): -

- 1. Supports lesser nodes for a single device.
- 2. In case of long ideal period simulation is inadequate.
- 3. Powerful GUI but complicated to use.

 Table 2. 5G Simulator Comparison.

Simulators	License Type	Platforms
SyntheticNET Simulator	-	Python
OMNeT++	Open source (for research and academics)	C++
NS-3	Open source	C++ and Python
MATLAB/Simulink	Not open source	MATLAB
OPNET	Commercial	C/C++

4.2 Power System Test Case with 5G Standalone Architecture

In this research work a communication network is developed for power system protection test case to compute latencies of 5G standalone network. OMNeT++ is considered in this study because it is open source, have easy to use GUI and developed Simu5G library to run modified test cases.

Power system protection test case will have two main IEDs: - 1) Sensors (Relays) 2) Actuator (Circuit breakers). With 5G network both the devices can communicate with each other. Voltage and current values can be sent from an intelligent relay to an actuator through gNB. The AI algorithm, deployed in the cloud, will be able to identify if the power system is running in normal condition or if a fault has been detected. If a fault is predicted by the AI algorithm, cloud will send a fault signal (similar to a GOOSE message) to an actuator to trip the circuit breaker.

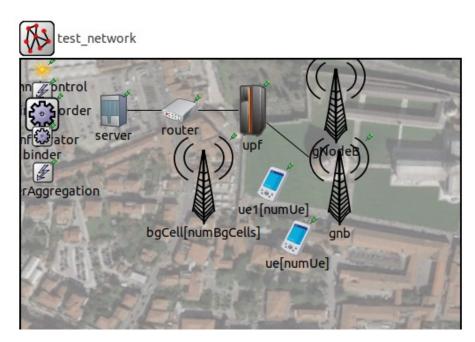


Figure 14. OMNeT++ Test case network with SA.

Above Figure 14 shows a simple architecture of single relay and actuator communication, labeled as ue (relay) and ue1 (actuator). Each UE has a separate network interface card (NIC) through which it connects and communicates with the 5G base station. Data from the UE travel all the way through radio waves to base station, user plane function (UPF), router and to the servers. The relay would send measurement of voltage and current in the form packet to the cloud far from the edge. The server represented in the Figure 14 will have ML algorithm deployed which will process incoming packet measurement values and predict occurrence of fault. An application layer is developed at the server which accepts incoming packets from relay and send another packet to the actuator containing

information to whether trip the circuit breaker or not.

Simu5G follows similar process of UE connectivity as mentioned in Figure 5. When simulation is run, the gNB first tries to detect the UEs and their availability. If UEs are available for communication, BS sends a signal and establishes a connection between UEs and Core. The core in the Simu5G is represented by UPF. Upon successful establishing of connection the process of tunneling begins. The packets transferred across the network using SCTP/IP and UDP/IP protocols. Since in power system test case the UEs are stationary object, therefore there would be no handover process and the communication would continue in similar fashion.

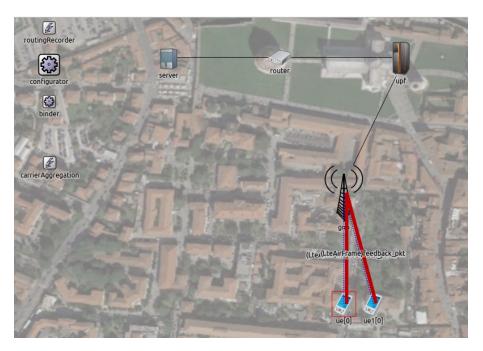


Figure 15. OMNeT++ BS and UE connectivity Process.

4.3 Results

The result section is divided into two parts. First section presents the result obtained by 5G SA network simulation by OMNeT++/Simu5G. Second section present the results of

ML algorithm and protection of power system distribution model by ML on MATLAB/Simulink.

4.3.1 5G Communication Network Results

A SA non-MEC based network is simulated with two UE communicating over 5G network. After the connectivity has been established between UPF and UEs by gNB, the UE (sensor) will start to send packets containing information of voltage & current measurement to the destination address. However, to send and receive these packets in OMNeT++/Simu5G the application layers of these modules need to be programmed.

The UE (sensor) application layer is programmed in a way that it continues to send the measurement packets to the internet server. The server application layer is programmed to receive the measurement packet, destroy it, and send a new alert packet to the second UE (actuator). The second UE (actuator) application layer is also developed which receives incoming packets from the internet server.

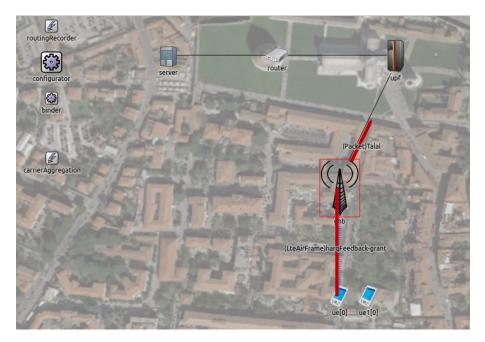


Figure 16. Packet transfer from UE1 to internet.



Figure 17. Packet transfer from internet to UE2.

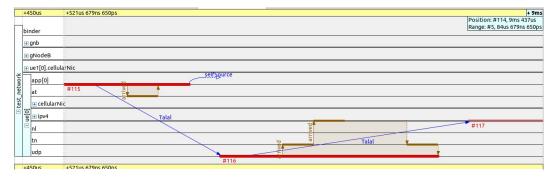


Figure 18. Packet generation by UE 1 (relay).

Both the UEs were approximately 150m away from the gNB with carrier frequency of 4GHz and the simulation was run for 20s. The Table 3 below shows the latency obtained for these specifications for a communication round from UE 1-to-Internet-to-UE 2.

4.3.2 ML based Power System Protection Results

In this study two SVM ML models are developed. For visualizing the data and decision boundary, python-SVM model is used and MATLAB-SVM model is used for deploying in

Table 3. Communication network parameter and latency).

Test case	Distance from gNB to UE 1 and UE 2	Carrier frequency	Latency
SA Non-MEC	150m	4GHz	20ms

Simulink to isolate the fault in power system distribution model. In python, the PCA-SVM based ML model was able to accurately diagnose the occurrence of fault. PCA was applied to reduce six-dimensional data to two dimension which was passed to SVM algorithm which accurately classified the diagnosis of power line faults.

By visualization of data and decision boundaries of SVM classifier, using Principal component analysis (PCA) and projecting target values, it is observed that the data values cannot be linearly separated in 2-dimension and 3-dimension Figure 19. Therefore, to non-linearly separate the target with high accuracy, radial basis function kernel is considered. In Figure 19a the red dots represents fault target value "1" and surrounding blue dots represents no fault class "0". Similarly by looking in three dimension space Figure 19b yellow dots are the target value "1" (fault class) and purple dots shows no-fault region "0".

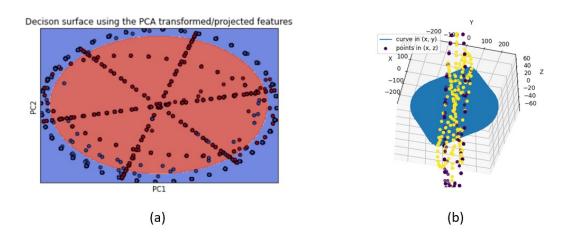


Figure 19. a) Decision boundaries b) 3D projection of target values.

By looking at the results, both the models achieved high accuracies. These accuracies are obtained using SVM scoring function. Each scores are obtained with three datasets, train-

Table 4. Accuracy Scores.

Models	Training score	Test score	Validation score
MATLAB-SVM	0.9960	0.9987	0.9941
Python-SVM	0.9769	0.9840	0.9808

ing set, test set and validation set. Each dataset has separate values and are not mixed with each other to verify the accuracies. However, the classes are not able to linearly separate in 2-D and 3-D. Therefore, RBF kernel function was applied to non-linearly separate samples. It can be proposed that by increasing SVM dimension to higher dimensions, the SVM model might be able to linearly separate data samples.

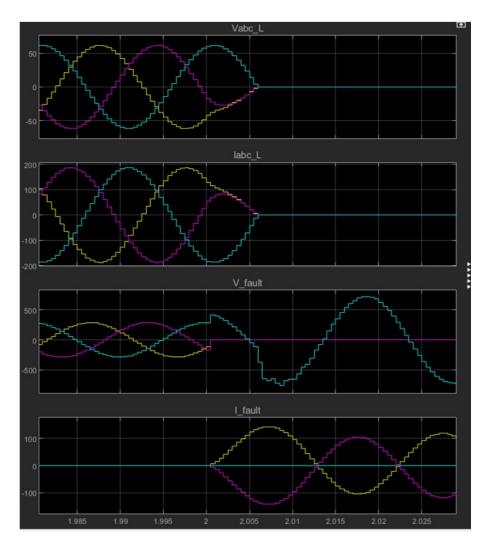


Figure 20. Simulink-ML load isolation output.

The SVM model on MATLAB/Simulink was tested by applying different types of line faults including 3-ph, 3-ph-g, 2-ph, and 2-ph-g. The ML model isolated the load within 7 milliseconds after the artificial fault was generated. The fault was generated at 2 second and the algorithm isolated the load from generators at 2.007 seconds. Moreover, the ML model was also tested without applying any fault to test maloperation of the ML model and its was able to accurately identify that the fault has not occurred. When ph-ph fault is applied the ML algorithm was able to recognize the fault and isolate the load after 6ms of occurrence of fault. In the Figure 20 Vabc-L, Iabc-L, V-fault and I-fault represents load voltage, load current, fault voltage and fault current respectively.

5 Conclusion

To conclude, in this research work a modern fault diagnosis concept is proposed which utilizes intelligence of ML and reliable communication of 5G Network. This study work also highlights the importance of 5G's key features including URLLC, mMTC and edge computing. The research work is divided into two parts:- 1) Developing 5G communication network to compute latency 2) Developing ML algorithm for fault diagnosis in power system.

A 5G standalone communication network is developed on OMNeT++ by simulating communication of two UE over gNB. The latency for the designed network was computed to be 20ms. However, in future, a MEC-based SA 5G network can also be simulated which will have lower latencies, as per literature.

In second part of the study two SVM models are trained with the same dataset generated in MATLAB/Simulink. Python-SVM model is used to visualize the dataset and observe the decision boundaries. Whereas, MATLAB SVM model is deployed in Simulink to identify occurrence of fault and isolate the load. Four different artificial faults (3ph, 3ph-g, 2ph and 2ph-g) were generated and the MATLAB ML model was able to isolate the load within 7 milliseconds. MATLAB-SVM model achieved an accuracy of 99% and PCA-SVM ML model, which was used to visualize the data, achieved an accuracy of 97%.

One of the future work would also be a practical implementation of proposed modern fault diagnosis schemes by deploying ML algorithm at 5G's edge server and providing IEDs to communicate over 5G network. Modern fault diagnosis can be a step toward reliable and stable future power system. Incorporating modern communication technology (5G/B5G) and artificial Intelligence will allow to take a step toward a more efficient and smarter power systems. Since traditional protection schemes are inefficient for future power systems, advance efficient protection schemes are needed which can accurately diagnose and isolate faults within the defined period.

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