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Virtualized Intelligent Relaying of Smart Grid Over 5G Network

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***Abstract*—Integrating artificial intelligence (AI) and virtualization technology into power systems applications can facilitate the transition from conventional grids to smarter grids. Virtualization of grid application, including AI-based applications, near the edge of the grid reduces communication latency and promotes centralized or decentralized decision-making. The infrastructure of edge or cloud datacenters serves as a robust platform for deploying intelligent virtual applications within smart grids. In this paper, we propose a concept of intelligent virtualized relaying using 5G communication. The concept is demonstrated through a hardware-in-loop setup consisting of an MLP algorithm deployed on the edge server, a grid model in OPAl-RT, and UDP protocol communication of voltage and current information over the 5G network. In 5G communication, latency poses a challenge when a fault occurs in the power system and immediate decision-making is required. In this paper, we attempt to predict faults to overcome the latency barrier using the MLP algorithm. Our MLP algorithm achieved an accuracy of 99.9%, enabling it to predict faults based on pre-fault events, isolate the fault, and island the load with backup distributed generation (DG). Based on the results obtained from Test-1 and Test-2, the fault was predicted within 90ms and 200ms.**

***Keywords*—Virtualization,Intelligentization,5G, hardware-in-loop(HIL),Edge,Cloud,Datacenters**

I. Introduction

Relays are an essential component in power systems which are analogous to the eye of a human that senses an abnormality and triggers the body to protect the system. With time, relays have evolved from mechanical structured relays to digital physical relays. But as the grid is digitalized, the number of devices involved in digitalization are also increased. Similar to Moore's law. This increase in the massive number of physical devices, including relays, involved in protection, automation, and control of the grid is an economic and environmental concern.

In recent years, the concept of virtualization of power system functions has been introduced to deal with the exponential growth of physical devices in the grid. Virtualization itself is an old concept that is utilized to create multiple virtual device environments within a single physical device, therefore optimizing technical and environmental resources. An idea of using virtualization and cloud infrastructure to automate electrical systems is presented in [1].

Edge and cloud data centers can play a vital role in supporting the digitalization, virtualization, and intelligentization of power systems. Intelligent protection devices, such as artificial intelligence (AI) assisted relays, can be virtualized as a software application that receives information on the state of the grid, detects a fault in the power grid, and sends a signal to isolate a faulty region [2], [3]. This can be achieved by virtualizing multiple Intelligent Electronic Devices (IEDs) protection functionalities into one or more servers as proposed by authors in [4].

The architecture of the edge and cloud infrastructure can be categorized into centralized, decentralized, or hybrid infrastructure as shown in Figure.1. Edge servers close to physical equipment allow latency-critical tasks in which communication latency is challenging. On the other hand, cloud infrastructure is utilized to perform tasks that might require higher computational resources. An Edge-Edge based infrastructure will be a decentralized infrastructure with distributed edge servers performing distributed tasks [2]. Cloud-Cloud based infrastructure can be considered as a centralized infrastructure that communicates only important information. An Edge-Cloud infrastructure can be considered as an hybrid infrastructure [3] which utilizes the computational resources of a cloud and latency critical abilities of the edge server.

Communication infrastructure and communication delays are another concern for virtualization at cloud or edge servers. 5G and beyond cellular networks are capable of enabling virtualization, digitalization, and intelligentization in smart grids [5]. 5G and beyond 5G networks offer functionalities, such as network slicing

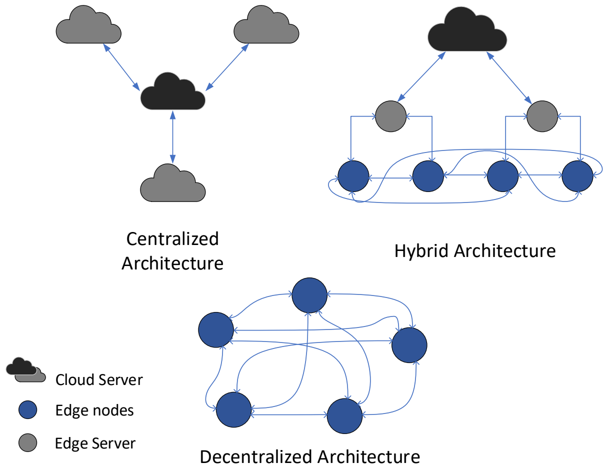

Figure 1: Edge Cloud Architecture

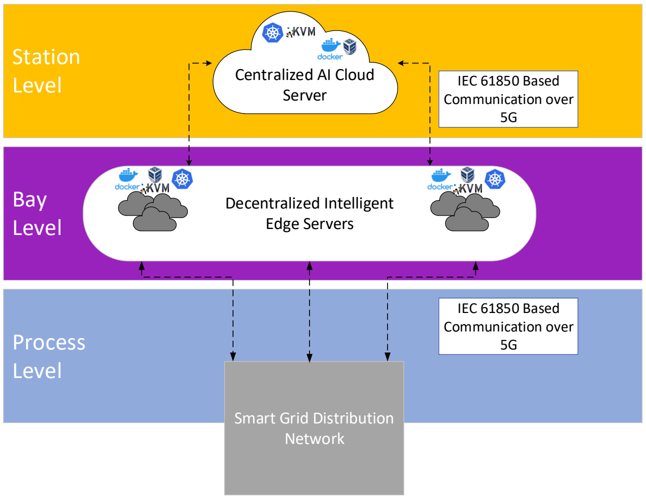

Figure 2: 5G Assisted Virtualized Relaying

and multi-access edge computing, which would assist in the optimization of data traffic transferred to and from edge or cloud servers. AI algorithms deployed on an edge or cloud datacenters as microservices will receive data traffic over 5G network and each network slice would accommodate a separate traffic for separate microservices. For example grid state traffic, in the form of IEC61850 sampled values (SV), could be transferred over a 5G network on one slice. Controlling or inter-trip IEC61850 GOOSE traffic could be transferred over 5G on another slice. By slicing, network resources are optimized and congestion in the communication network can be avoided.

This paper presents a novel concept of virtualized AI-based relaying of a smart grid over a 5G network. A multilayer perceptron (MLP) based algorithm is deployed on an edge server which receives grid three-phase current and voltage information. Based on the information received, the algorithm predicts a fault, triggers the circuit breaker, isolates the fault region, and sends an intentional islanding signal to continue to power the load by adding DG to the network.

This paper is divided into five sections. Section II gives a literature overview of the related research in intelligentization with the virtualization of smart grids. Section III discusses the methodology and experimental setup. In section IV results are analyzed and discussed, and conclusions are presented in section V.

II. Related Works

Implementing a single protection at a medium-voltage substation level would require hundreds of IEDs, and each IED would have its own cost of manufacturing, casing, and packaging. A virtualized protection relaying will reduce costs, complexity of the protection scheme, and motivate protection function optimization using intelligent software applications. Intel proposed two approaches in [6]. The first approach is to virtualize IEDs on individual virtual machines (VMs) without sharing virtualized functionalities. In the second approach, common functionalities are shared between virtualized IEDs. Similarly, ABB's softwarized version of SSC600 aims to virtualize protection and control functionalities to propose a centralized protection and control systems. Virtualization can be performed using technologies such as VMware or kernel-based virtual machines (KVMs).

A substation can be virtualized at the station level and at the bay level. Nokia presented a concept of transitioning from digital substation to virtualized substation in a white paper [7]. Different functionalities such as virtual IEDs, IEC61850 functionalities, protection functionalities (such as Intertrip protection), can be containerized at an edge or cloud datacenters as microservices, for example, using Docker containers. Communication can be established with IEC61850 standard using 5G network infrastructure as shown in Figure 2.

The author in [8] proposed a software-based virtualized platform (EPICS) to perform virtualized protection and control functions of a power grid. The proposed platform is based on Docker containerized microservices. Authors implemented line differential protection and distance protection as Docker microservices. These microservices were tested using a Real-time digital simulator (RTDS) in a hardware-in-loop (HIL) configuration.

AI algorithms can be used at an edge server or cloud data center to have a virtualized AI based smart grid fault detection system. A neural network based smart grid fault detection is proposed in paper [2] which also uses a framework for allocating computational and communication resources for edge devices to achieve maximum throughput and minimum delay. Three phase current and voltages were given to a Long Short Term Memory (LSTM) algorithm to detect faults in the system. The experimental setup is discussed in detail [3] in which authors considered using cloud-edge based hybrid fault detection system to solve the problem of large amount of data transfer and network delays. The authors used LTE 4G and a WiFi module to communicate data packets.

An LSTM based online fault detection, classification, and localization of faults is proposed by authors in [9]. To validate the accuracy of the AI model, the grid model and the AI algorithm are implemented on a real-time platform (OPAL-RT). The authors compared the accuracy of the ANN-based model with LSTM-based algorithm and concluded that the LSTM algorithm is either more accurate than ANN or both have the same performances in different types of faults.

An edge computing based fault location scheme is proposed for distribution grid in [10]. The framework proposed by the author for locating fault utilizes device layer for acquiring measurements, edge layer for determining faulty branch, and cloud layer for accurately estimating fault location using neural networks. These three layers can be considered as process layer which collects measurement, bay layer which uses edge computation, and station layer utilizing AI algorithms.

III. Experimental setup

This paper proposes a concept of virtualized intelligent relaying method of smart grid network during pre-fault events using 5G communication. To test the concept, an experimental setup is established that uses an intelligent virtualized relaying algorithm – Multilayer perceptron (MLP) model – to predict artificially applied pre-fault events that would cause a permanent fault in the power grid. These pre-fault events can be due to persistent earth faults or intermittent earth faults. A hardware-in-loop (HIL) concept is utilized to combine three areas:

- Power Grid Model in OPAL-RT.
- Private 5G physical communication network.
- AI Algorithm Deployed on 5G Basestation.

A. AI Algorithm Deployed on 5G Basestation

Multilayer perceptron is a class of neural network that consists of source nodes (forming input layer) and computation nodes (in hidden layers and output layers) [11]. In other words, it is a multi-layer neural network made up of perceptrons (neurons). Mathematically a single perception can be represented as in Eq.1 where, y represents the output unit, x_i is the i-th element of the input vector X , w_i is the i-th element of the weight vector W, and b is the bias term. Graphically our MLP consisting of several perceptron can be represented as shown in Figure.3.

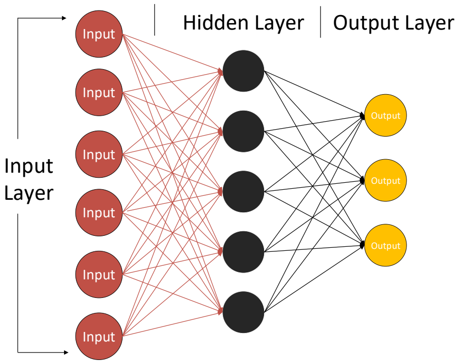

Figure 3: Multilayer Perceptrons

$$y = \text{ReLU}\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{1}$$

$$and, \text{ReLU}(x) = \max(0, x)$$

The input x represents three-phase voltages or current values which are measured near the main grid. w representing the weights are optimized by stochastic gradient descent algorithm used in MLP model. Rectified Linear Unit (ReLU) activation function is used which outputs the same value if a positive value is computed and for all negative values it will output (0). The MLP neural network acts as a binary classifier that decides between a fault predicted (1) and a fault not predicted as (-1).

The MLP model is deployed on the 5G Basestation, which provides 5G connectivity and acts as an Edge server. The edge server can be considered as virtualized intelligent relaying at the bay level. The edge server sends and receives UDP packets from both the client Raspberry PIs (RPIs). The MLP model at the edge server continuously receives three-phase current and voltage measurements. The model makes predictions based on the incoming values and sends the predicted values to the second RPI. The second RPI verifies the prediction signal and identifies whether the algorithm has predicted a fault or not. Once a fault is predicted, the second RPI sends a trip and intentional islanding signal to the grid over the 5G network.

B. Private 5G Communication Network

The communication between the virtualized intelligent relay on the edge server (bay level) and Opal-rt (process level) is established using private 5G connectivity. To link physical hardware with a virtual application running on an edge server, a 5G device or 5G modem is needed in between which can transfer the data from Opal-rt to the edge server and vice versa.

In our experimental setup, we have used RPI with a 5G hat to connect and communicate with the edge server and grid model running on OPAL-RT. The RPIs act as 5G modems and send the UDP packets to the edge server or OPAL-RT. Each RPI has its simcard, allowing it to connect and register with 5G basestation's access point network (APN). The 5G basestation is configured in a 5G standalone mode with 50 MHz bandwidth. More details about the connectivity and 5G basestation configuration can be viewed in this paper [12]

C. Grid Model with OPAL-RT

A simple two-way power-sourced grid model is developed with MATLAB Simulink which can power a load connected in between the two power sources. The load of 100kW/11kV can be powered from both the sources of 75kW/25kV at a distance of 20km and the distance of the load from each source is 10km. However, one of the sources acts as a main grid, and the other acts as a back-up distributed generation (DG). After a fault is predicted the DG is inserted into the grid and the main grid is isolated from the load. Therefore, forcing intentional islanding of the load to continue receiving power from the DG.

For testing in a HIL configuration, the grid model is loaded into the OPAL-RT and is configured to communicate the grid's voltage and current measurements. The communication between OPAL-RT and the RPI is established using UDP communication on specified ports. In this connectionless UDP communication the OPAL-RT can be considered as a server that sends measurements and receives trip/islanding signals from the two RPI and the edge server.

IV. Discussion and Results

The MLP binary classifier algorithm is made up of three hidden layers with 6 neurons in the input layer, 5 neurons in the middle layer, and 3 neurons in output layer as shown in Figure.3. The maximum number of epochs for which the Adam solver should converge is set to 500 and the L2 regularization parameter is set to 0.0001.

The training datasets of the MLP model are generated by a Simulink grid model. The datasets consists of more than 40000 values containing grid's voltage and current measurements during normal operation and fault scenarios. The datasets are divided into 80% and 20% for training and validating the model. After training the model with generated data, the MLP model achieved train and test accuracies of 99.99 %, and the cross-validation (CV) score was found to be 99.97%.

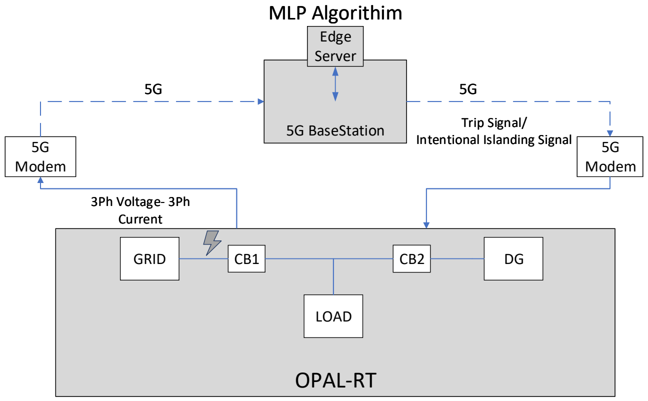

Figure 4: Experimental Setup

Model	Training accuracy	Test accuracy	CV score	loss
MLP-Classifier	99.999 %	99.985 %	99.97 %	0.006134

Table I: MLP Model Accuracies

The trained model waits for the three-phase voltage and current values. Once the MLP classifier receives a stream of UDP packets, it makes a fault prediction based on those values. Our MLP classifier algorithm was able to predict faults and we achieved a validation score of 100%. We experimented with multiple sets of tests with the MLP model and received training, test, and validation scores in the region of 99-100%. During all the tests the classifier was able to predict the fault. Results of two tests can be seen in Table II.We also conducted another set of tests during which no faults were applied and the MLP algorithm classified with 100% accuracies that no faults were present in the power grid.

The fault can be categorized into pre-fault events and post-fault (permanent fault) events. In a pre-fault event, a persistent phase-ground fault for short duration (10ms) is applied every 100ms. These persistent faults lead to an unstable grid and a permanent phase-to-earth fault in the grid as shown in Figure.5. The MLP algorithim predicts the pre-fault condition which

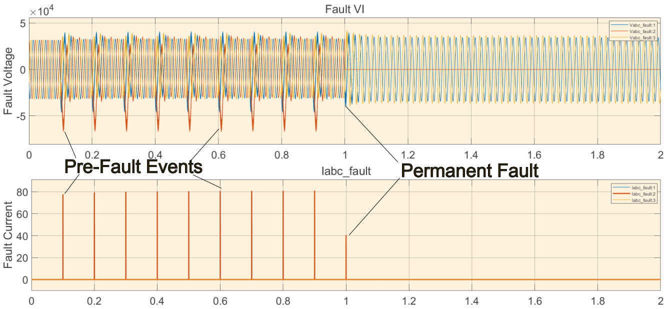

Figure 5: Fault Events

can be due to a persistent fault occurring at regular intervals or an irregular intermittent fault. After recognizing a pre-fault event, the algorithm predicts the fault and sends a trip and islanding signal to the OPAL-RT system. This signal is used to isolate the grid and intentionally island the load.

In this paper, experiments are conducted in which OPAL-RT is set to software-synchronized mode. Every 50 milliseconds (50 ms), OPAL-RT sends three-phase current and voltage measurements to the edge server via an RPI with a 5G hat. The application running on the edge server receives a high stream of UDP packets and makes predictions based on these UDP packets. It is worth mentioning that the latency of our private 5G communication is in the region of milliseconds [12], which can vary depending on the type of 5G deployment. All the experimentation results are obtained for 5G standalone deployment.

Results from Test-1 are shown in figures 6, 7, 9, 8. The first cycle of pre-fault event can be seen in Figure 6. These pre-faults (or persistent earth faults) occur every 0.1 seconds and lead to a permanent fault in our simulation if not isolated within 1 second. In Test-1 the MLP algorithim recognized the pre-fault event and predicted the fault within one cycle i.e. within $100ms$. After isolating the fault the load is intentionally islanded with the DG and continues to receive power as shown in Figures 8,9.

Similar results are obtained in Test-2 as well. However, in Test-2 the MLP algorithim was able to predict permanent fault in second cycle of pre-fault event i.e. within $200ms$ as shown in Figure 10.

Tests	Validation Score of Predicted Data	Time Taken
Test 1	100%	$\approx 90ms$
Test 2	98.75%	$\approx 200ms$

Table II: Fault Prediction Results

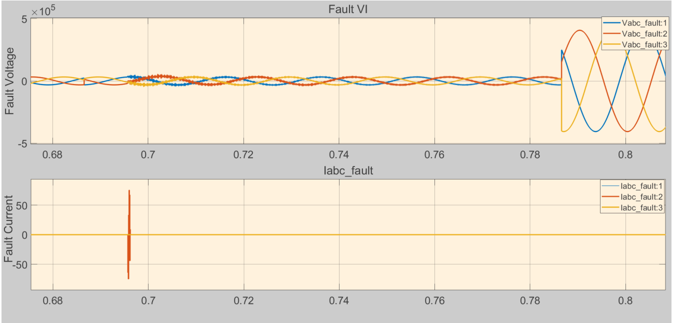

Figure 6: Test-1 Pre-fault Event

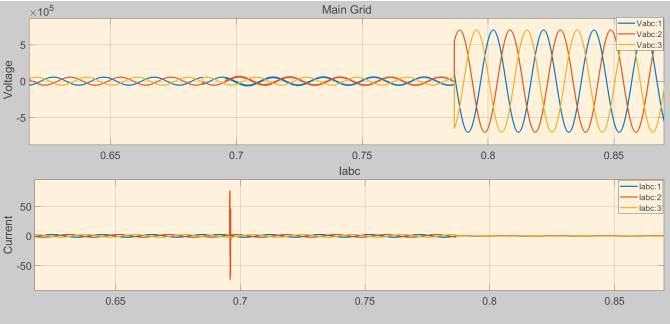

Figure 7: Main Grid

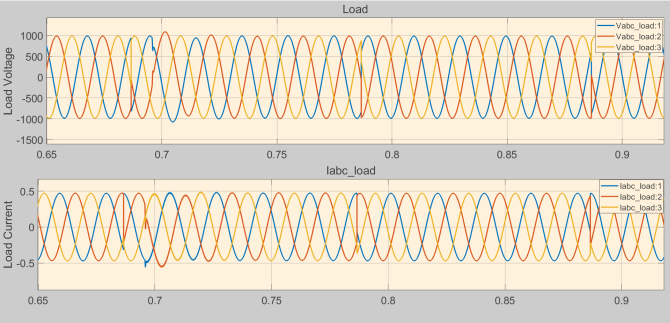

Figure 8: Load

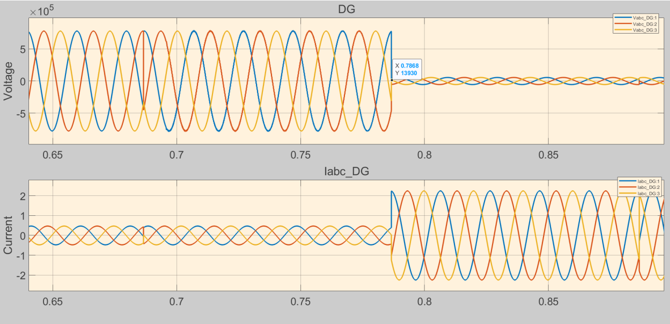

Figure 9: Distributed Generation

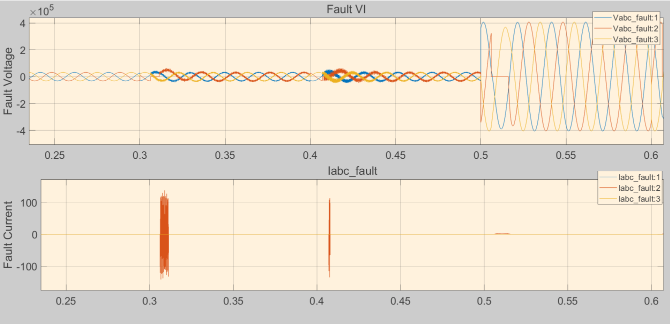

Figure 10: Test-2 Pre-Fault Event

Real-time taken during the complete process can be broken down using eq.(2). The total real-time consumed during the whole process can be divided into five parts:-

1) Latency of the OPAL-RT to send voltage and current measurements (T_{OPAL})
2) 5G Uplink time from RPI to edge server (T_{UL})
3) Time taken by AI algorithm at edge server to predict (T_{AI})
4) 5G downlink time from edge server to RPI (T_{DL})
5) Time taken by sending RPI to process and send isolation and islanding signal (T_{signal})

$$\text{Total Time} = T_{\text{OPAL}} + T_{\text{UL}} + T_{\text{AI}} + T_{\text{DL}} + T_{\text{signal}} \qquad (2)$$

V. Conclusions and Future Work

A. Conclusions

In conclusion, a virtualized layered feed-forward neural network (MLP) based relaying is proposed which communicates information over 5G network. A HIL setup is implemented which sends voltages and current information to an edge server over a 5G network. An MLP algorithm deployed on an edge server identifies and isolates faults, if the grid is under the influence of a fault. The MLP algorithm accurately identifies a fault and a signal is sent to the OPAL-RT which isolates the faulty region and island's the load with a back-up DG. UDP protocol is used for communication in this test setup, however, in the future we plan to implement using IEC61850 standard.

The proposed concept promotes the digitalization of electric grid by integrating intelligent algorithms, virtualization technologies, and wireless communication networks. Virtualizing grid applications using intelligent algorithms and wireless networks increases the situational awareness and efficiency of the protection algorithms, and supports developing a more environmentally friendly and smarter digital grid.

B. Future Work

In future we plan to implement microservices with Docker and Kubernetes with some practical test cases such as islanding detection, control of microgrids, virtualized differential protection, and other test cases. We also plan to develop a dashboard which will empower users with intuitive visualizations and enabling informed decision-making. Graphical representations will provide valuable insight into the way data traffic is communicating in real time.

Acknowledgement

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