PNNL-34658

5G Energy FRAME: The Design and Implementation of Data, Model, and Use Case

Year 2 Report

August 2023

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U.S. DEPARTMENT OF ENERGY

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Pacific Northwest National Laboratory
Richland, Washington 99354

Abstract

This report summarizes Year 2's work of Pacific Northwest National Laboratory's (PNNL's) 5G Fabricated Resource and Asset Management Encompassment for energy infrastructure (Energy FRAME) project, funded by the Department of Energy Office of Science's Advanced Scientific Computing Research (ASCR) Program.

In this report, the latest 5G equipment testing results are presented, along with two 5G-enabled AI/ML examples for grid applications; in addition, the workflow involving grid edge, cloud, and High Performance Computing (HPC) platforms is introduced, to support and interface the cross-domain simulation for power system transmission, distribution, and communication networks. Last but not least, the outlook for Year 3's work and the overarching impact of the 5G Energy FRAME on a multitude of stakeholders are provided.

Additional 5G performance data is now being shared through a publicly available weblink: *https://www.pnnl.gov/projects/5g-energy-frame/publications.*

Acknowledgments

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Acronyms and Abbreviations

AI	artificial intelligence
ASCR	Advanced Scientific Computing Research
AWC	Advanced Wireless Communication
CENATE	Center for Advanced Technology Evaluation
CNN	Convolutional Neural Network
CPU	central processing unit
DER	distributed energy resource
DOE	Department of Energy
EDM	Energy Data Marketplace
EIA	U.S. Energy Information Administration
ELW	Energy Learning Warehouse
Energy FRAME	5G Fabricated Resource and Asset Management Encompassment
GFL	grid-following
GFM	grid-forming
GnB	Next-Generation Enhanced Node B
GPU	graphical processing unit
HPC	high-performance computing
IBR	inverter-based resource
IoT	Internet of Things
LTE	Long-term Evolution
ML	machine learning
mMTC	massive machine-type communication
NSA	non-standalone
PMU	phasor measurement unit
PNNL	Pacific Northwest National Laboratory
SA	standalone
T&D	transmission and distribution
T&D&C	transmission, distribution, and communication
TCP	Transmission Control Protocol
UDP	User Datagram Protocol
UE	User Equipment
UPF	Use Plane Function
uRLLC	ultra reliable low-latency communication
vLAN	virtual local area networks
VM	virtual machine
WECC	Western Electricity Coordinating Council

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1.0 Introduction

The evolution of cyber physical system (CPS) has achieved new landmarks, including Smart Grid (SG), Electric Vehicle (EV), the fifth-generation mobile communication technology (5G), among many other crucial components of our modern society and social life. Now with the overarching decarbonization goals established domestically and internationally, it is important for all the energy stakeholders to reimagine the two main pillars for any CPS, the Bits (smallest component of Information in cyber domain) and Watts (fundamental unit of Energy in physical domain in support of Bits), and explore the benefits of the explosion of wireless/wired connectivity, accessible computing capabilities, and greener power grid. It might be that being intelligent for CPS may mean to have sustainable source of energy, unburdened communication, and highly efficient computing. To some degree, we can experience this everyday with the smart devices that we use and wear.

1.1 The Design of the Energy Data Model Convergence

The concept of Bits & Watts imprints a profound vision of the integrated landscape of 5G communication, data, and computing, as shown in Figure 1. To be more specific, the 5G-for-Grid (an integrated scientific computing domain enabled by 5G for power grid) applications requires the energy data model convergence. For example, the classical structure of power grid planning and operation for large interconnections, i.e., U.S. Western Interconnection, are orchestrated through both multi-year look-forward planning models and real-time control room operations with streaming data. Now with the emergence of Artificial Intelligence (AI) and Machine Learning (ML) technologies, as well as affordable cloud computing access at enterprise level, a holistic mechanism for grid model and energy data could be built with the extended connectivity and compute offered by 5G and cloud resources.

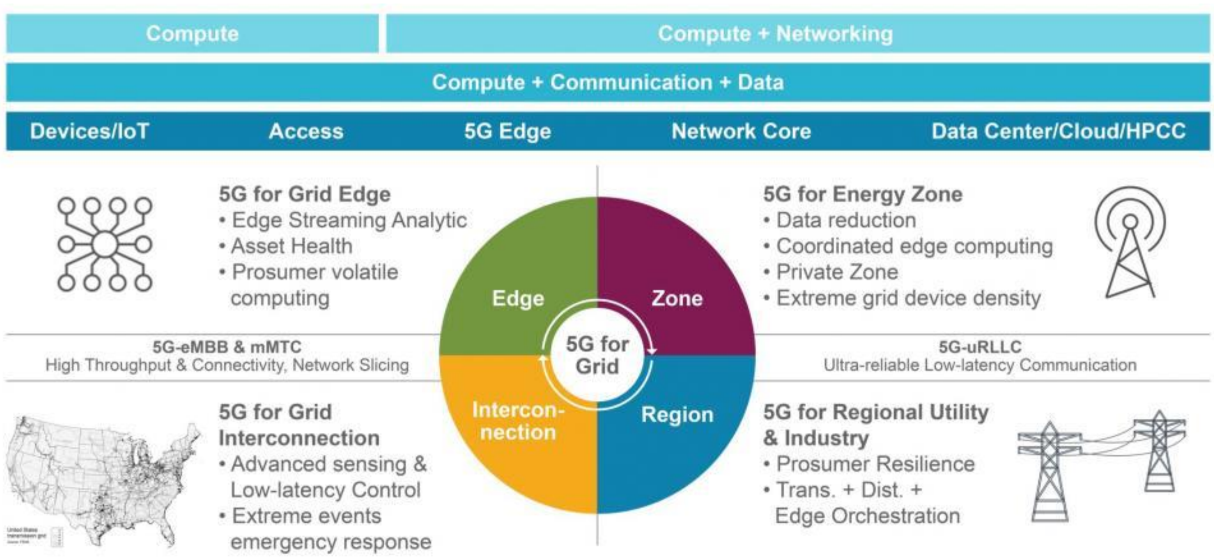


Figure 1 Integrated landscape of 5G communication, grid, and computing.

To achieve and implement the optimized energy data harvesting within the realm of 5G-for-Grid applications, it is important to develop the following two components: the Energy Data Marketplace (EDM), and the Energy Learning Warehouse (ELW).

1.2 Energy Data Marketplace (EDM)

Functioning as an EDM, its objective is to break the data silos among different groups of stakeholders, speed up information sharing across multiple domains and large geographical regions, and foster aggregated AI-based inferencing capabilities by utilizing distilled data from the edge devices and edge-based energy zones. EDM can host the data, model, and extracted data that is connected by 5G fabric, while it also presents a unified access for a wide range of stakeholders in the clean-energy future. More importantly, it may enable multilateral data sharing and exchange between participating stakeholders while preserving privacy through available encryption technologies, i.e., utilities, prosumers, microgrid and smart building operators, Distributed Energy Resource (DER) aggregators, energy service providers, smart communities, and researchers. The concept of EDM has been valued by a wide-range of stakeholders, several examples are Open Energy Data Initiative (OEDI) [1], Distributed Photovoltaic Protection (DPVProt) Modeling Tools shared online [2], Enhanced-IEEE-39-Bus-System-with-Inverter-based-Resources-on-Multi-Time-Scale-Platforms [3], and DOE Office of Electricity hosted *Big Data Synchrophasor Analysis* [4,5].

Furthermore, with a focal point on large-scale co-simulation of transmission, distribution, and communication networks, the data availability and quality can also be verified and validated through EDM; proper system architecture review and algorithm may help identify the bottleneck of data flow and potential need of real and virtual sensors [6, 7]. In addition, PNNL in-house tool GridApps-D™ has potential to support standards-based Application Programming Interfaces (APIs) and associated database for time-series data storage, query, analysis, and visualization [8, 9, 10]. In addition, the gateway will include not only energy infrastructure information but also cross-domain data (such as telecommunications) that is not commonly available in current tools [11, 12]. It is of great interests to explore a seamless integration of publicly available field asset infrastructure databases [13], geographical information, and weather forecast and event data, along with other aggregated energy data from the U.S. Energy Information Administration (EIA) website [14].

1.3 Energy Learning Warehouse (ELW)

The ELW platform supports continuous integration and delivery (CI/CD) of edge computing functions and ML models, as well as the efficient and flexible distribution/deployment of retrained edge computing models. ELW is highly interconnected with EDM, and they are complementary to each other to fully support the self-evolutionary applications at grid edge and edge-based energy zones.

This is particularly important for some of the ML models that rely on rarely available data, for example the high-resolution point-on-wave fault data of the electronic inverters in DERs [2,3]. The latest fault data from events could be extremely valuable for the generation owners and/or prosumers. Through EDM, these kinds of data could be shared in time and further adopted to update the ML model training database; once the training was completed, either at the cloud or other HPC platforms, the updated model parameters can be distributed accordingly to all the subscribed users for this specific energy learning model.

In summary, instead of simply collecting and redistributing a significant amount of data, this cloud-based platform, grid edge, and edge-based energy zones proactively aggregate the data and distills them into tangible and actionable information for further distribution.

It is also important to quantitatively evaluate the benefits of EDM and ELW; therefore, the team will leverage the co-simulation of power grid transmission, distribution, and communication networks, and perform Monte Carlo-based sensitivity analysis to derive performance profile for the proposed cloud-based platform. The engineering metrics for performance ranking include total energy not served, voltage and line flow violations, renewable generation curtailment, network and process delay, communication-caused grid equipment misoperations, and quantifiable computation time requirements for various grid optimization and control applications. The cross-domain interdependency node importance [15] and 5G testbed simulated data [16] can also be integrated to support the performance evaluation.

1.4 5G-enabled Workflow for Grid Analytics

For renewable grid integration throughout the electricity infrastructure, the ubiquitous use of inverter based resources (IBRs) has made the grid more difficult to operate under dynamic conditions; thus, there is a strong need to explore how IBRs will change grid dynamic behaviors, and examine how IBRs could be utilized to enhance power system operation and control.

With the 5G capability offered through PNNL facilities and research team, a 5G enabled workflow for grid analytics could be valuable to support the grid decarbonization planning and grid reliability assessment. Traditionally, aggregated IBR models at the transmission side are used to study the behaviors of IBRs in responding to faults in the systems. However, it is not sufficient because their behavior in the distribution systems is required to be modeled and simulated accurately, to have a complete high-resolution picture of the grid dynamic behavior. As a result, it is urgently needed to have an open-source based, scalable transmission and distribution (T&D) co-simulation platform, as shown in Figure 2. This co-sim platform can connect/emulate along with 5G state-of-the-art hardware equipment, and test application compatibility and performance, in particular the data flow, latency constraints and requirements, compute coordination, and the effectiveness of grid control actions. More importantly, this platform could simulate the behavior of large-scale IBR-rich power systems as well as the complex interactions between IBRs and the T&D network, and help us answer the questions, like "*how many grid-forming inverters can a synchronous-machine-dominated T&D system hold*", and "*how does low inertial physics affect grid resilience*"?

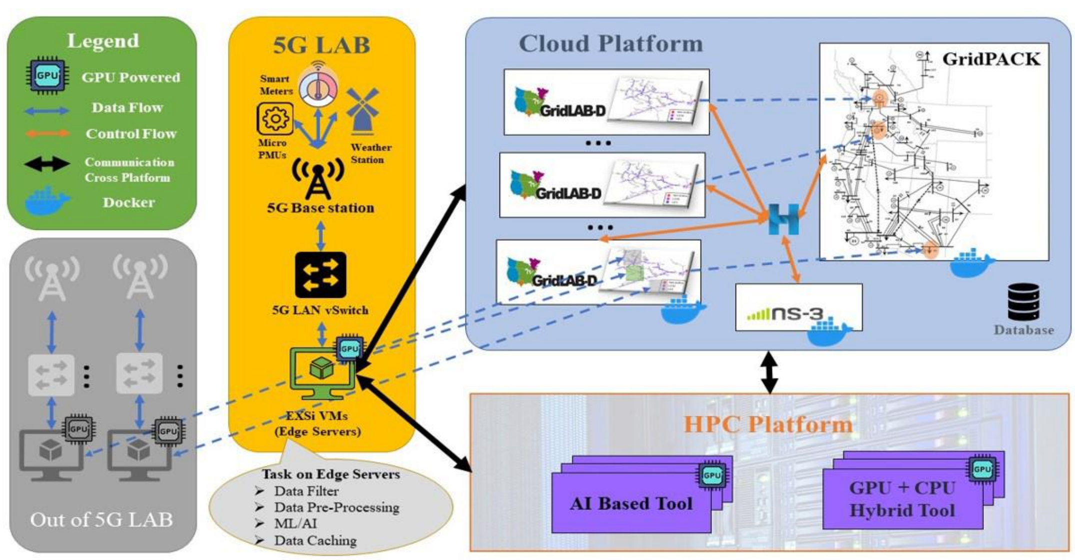


Figure 2 A conceptual view of the computing framework [17].

2.0 5G Hardware Testing and 5G Performance Metrics

The evolution of 5G architecture from the initial Non-Standalone (NSA) to Standalone (SA) is shown in Figure 3.

In NSA, the User Equipment (UE) is anchored to LTE core (EPC) switches to 5G core based on the availability to provide higher bandwidth. However, the NSA UE functions as LTE UE beyond the coverage area of 5G. The mobility is controlled by the LTE through intra-system handover. It may be noted here that UE maintains dual connectivity with both LTE and 5G Radio Access Network (RAN) simultaneously throughout the data transmission process. One challenge associated with the NSA is interference, the interference due to both LTE and 5G RAN reduces the overall performance [18]. The UE is anchored to the 5G core and LTE, when it is within and beyond the 5G coverage range respectively. In other words, SA operates either as a complete 5G or 4G system, instead of utilizing both as in the case of NSA. SA through its end-to-end (E2E) network slicing provides multiple services such as eMBB, uRLLC, and mMTC [18].

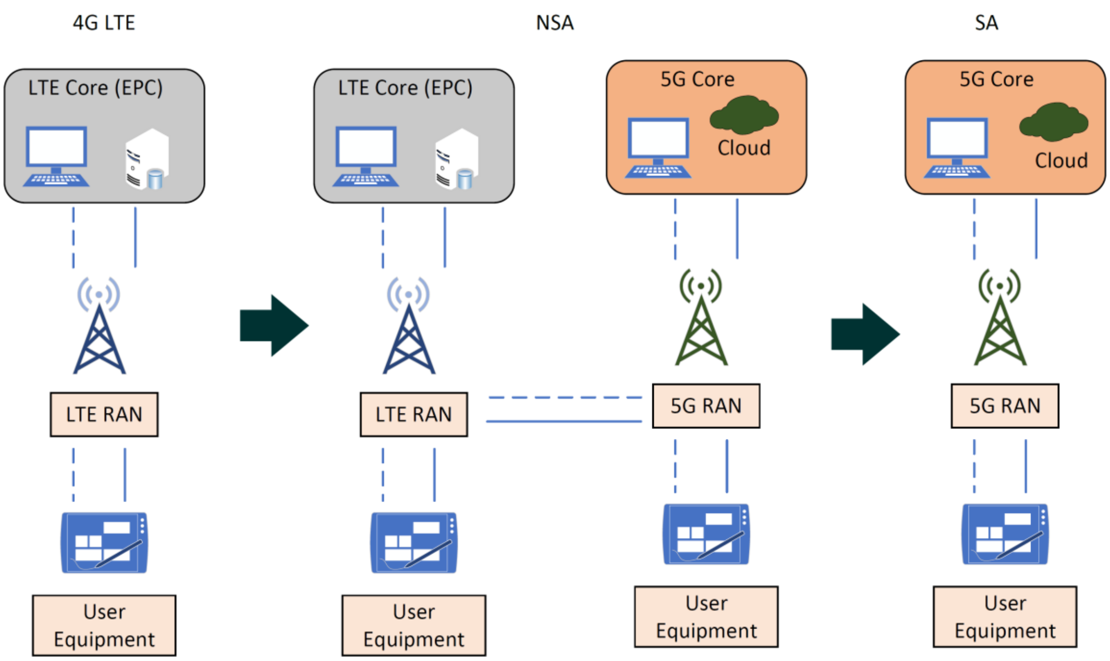


Figure 3 An illustration of 5G Non-Standalone and Standalone architectures.

Figure 4 presents the testbed for estimating the baseline performances of NSA network in PNNL AWC 5G Innovation Studio [19]. The studied testbed estimates only a few characteristics such as latency, Radio Resource Control (RRC) state transition threshold, and throughput; however, in the future this will be extended to determine other characteristics as well. The testbed comprises of two virtual machines namely VM-1 and VM-2 connected to the same host, each of these virtual machines is connected to different virtual network adapters with separate virtual local area networks (vLAN); and these two virtual machines are also connected via the 5G network. In this group of tests, the characteristics are assessed under NSA mode of 5G. The salient features of our proposed testbed are as follows. First, it represents an end-to-end system. Second, by connecting the two virtual machines to the same host it is feasible to measure the time-sensitive properties such as latency. Lastly, the performance data is available online for downloading [20].

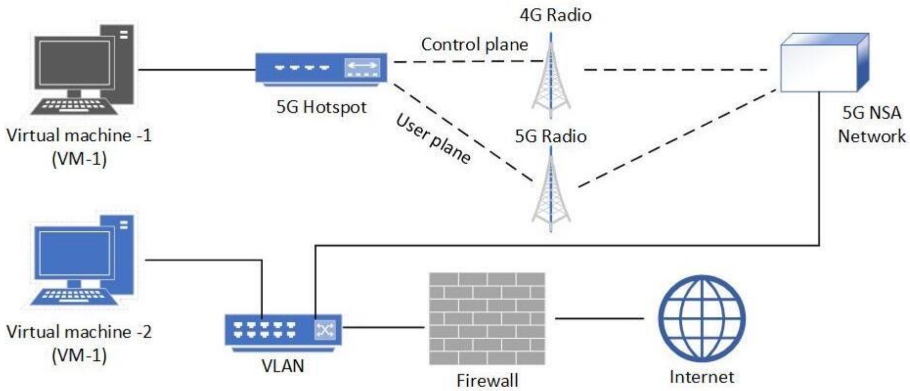


Figure 4 NSA Verizon system illustration.

For the appropriate estimation of the RRC state transition thresholds, it is imperative to determine the latency measurements corresponding to different sleep times, and the data was collected and the entire process is repeated for 50 times.

For a given sleep time, the first value from each iterations were extracted and plotted. From these plots it was evident that latency of the first message after a variable timeout period changes with respect to the RRC state of the system. In other words, there is a correlation between the latency measurement and RRC state. Based on observation and prior data analysis, a system is said to be in active, idle and inactive state, if the latency measurements are less than 100ms, lie within 150-450ms , and greater than 500ms respectively.

As a result, now we can identify the sleep time that makes the system achieve the above mentioned latency. After multiple trial and errors, it was concluded that sleep times of 1s, 10s, and 25s, allow the system to achieve those RRC states. To validate our assumptions, the latency measurements were once again collected with the studied sleep times.

As mentioned previously, the 50 iterations of latency measurements corresponding to three different sleep times were collected and plotted, using violin plots as depicted in Figure 5, Figure 6, and Figure 7. It may be noted that the first iteration corresponding to each sleep time is discarded due to two reasons. First, it is not possible to determine the time difference between the last sent message and the first ping of that iteration. Second, it is possible to control the variable timeout period between the messages passing through the 5G network. The run number in this paper refers to the iterations.

A simple examination of these figures provides the following inferences. Sleep time of 1s puts the system into active state as its latency measurements lie mostly in between 10-100ms. However, we can occasionally witness a spike in latency greater than 100ms and this shows the system slipped into inactive state. Similarly, sleep time of 10s puts the system to inactive state (latency greater than 100ms). The higher latency corresponds to the time taken for the system to return to active state. Finally, the latency measurements corresponding to the 25s sleep time indicate that the system is in idle state.

In the future, we intend to work on enabling support for concurrent devices. The objective is to test multiple devices simultaneously, by developing unique docker containers for the studied devices and establish communication between these containers. Some of the possible approaches to achieve this objective include, single-root input/output virtualization (SR-IOV) plugins and Cgroups (Control groups). The benefits of SR-IOV plugins includes but not limited to, faster communication between the docker containers, by reducing network latency and improving throughput, improved containerized network performance, and can be utilized in edge computing applications wherein low-latency and high-performance communication is needed. Similarly, Cgroups offers advantages not limited to optimal resource allocation, and network latency control for the docker container. With either of the two approaches the network latency and throughput will be studied under different load conditions and 5G configurations in our work.

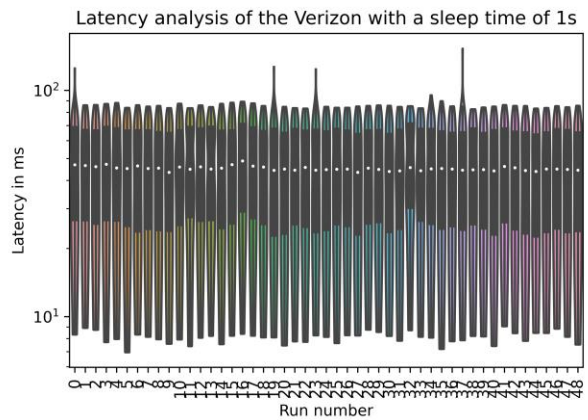


Figure 5 Sleep time of 1s.

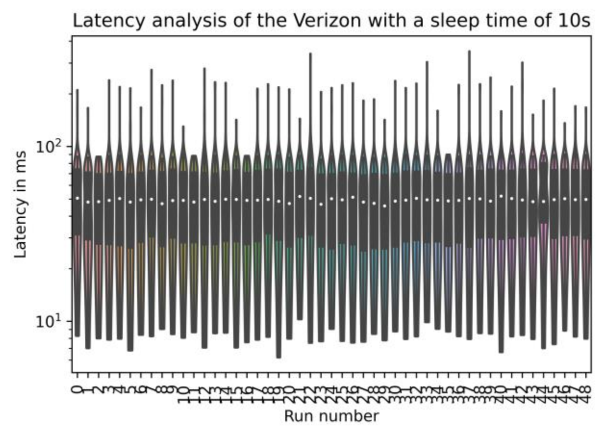


Figure 6 Sleep time of 10s.

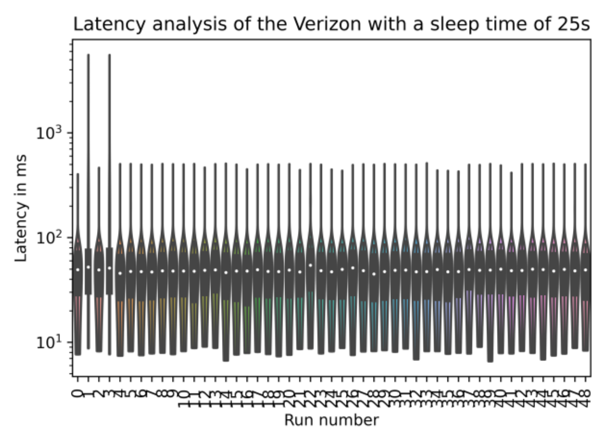


Figure 7 Sleep time of 25s.

3.0 5G-enabled Energy Data and Learning Examples

In this section, two 5G-enabled energy data and learning examples are presented, to showcase the state-of-the-art facility of PNNL's 5G testbed, and online AI/ML capabilities enabled by in-situ CPU/GPU compute offered by 5G hardware.

Through the successful simulation and execution of those two grid domain examples, the project team aims to present the connectivity and computing (especially for AI/ML) capability offered by 5G hardware and architecture. The claimed performance (esp. on latency) of 5G are critical to the feasibility of these envisioned examples. The goal of this task is to test the performance of these AI/ML applications with real 5G hardware under a realistic but controlled environment. Last but not least, these examples showcase a reference implementation process for other scientific computing problems and solutions, that can be simulated and demonstrated with 5G testbed and field deployments.

3.1 5G Testbed Example 1: PMU data anomaly detection

A phasor measurement unit (PMU) is a device in electrical power systems to measure and analyze electrical waveforms in real-time. It uses phasor measurement technology to measure the amplitude, frequency, and phase angle of electrical signals, and is able to capture high-speed data at high rates (up to several thousand samples per second, with reporting rates as 30 frames per second), to monitor and control the stability and reliability of electrical power system.

Figure 8 shows the combination of the testing hardware and software environment. This test consists of PMU streaming data generator, PMU data receiver, and edge application server. The emulators and software are deployed in three separate virtual machines (VMs) that operates on ESXI VM host.

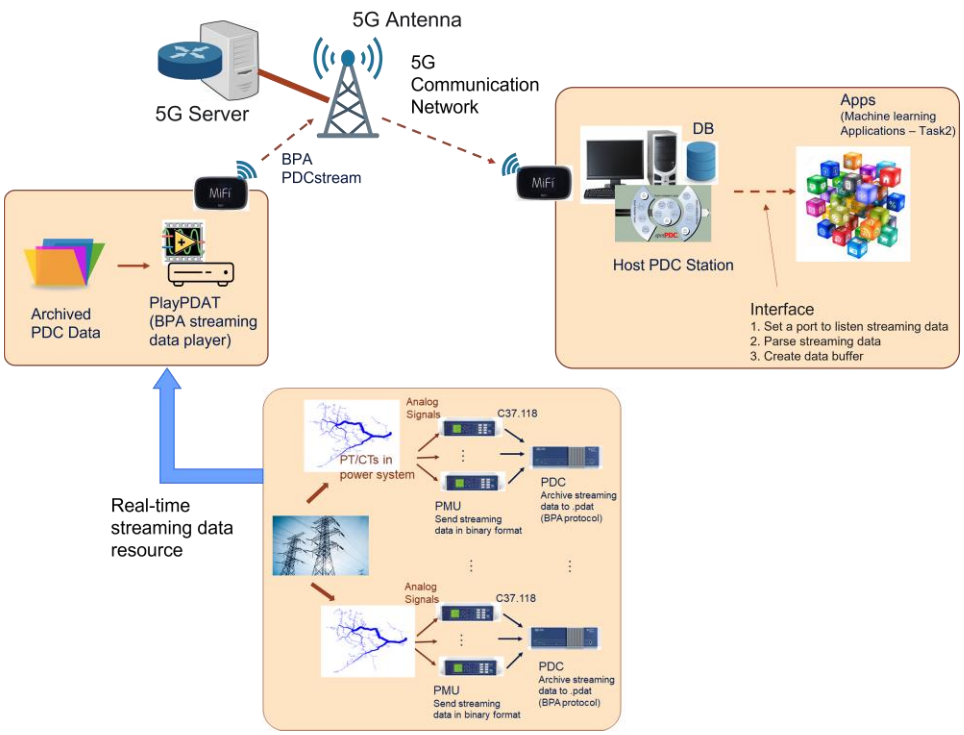


Figure 8 The simulation configuration for AI/ML example 1.

The three VMs (PlayPDAT VM, openPDC VM, and ML App VM) are operating on the same ESXI host. The VM clocks are synchronized by precision time protocol (PTP), also known as IEEE 1588. PTP is highly accurate for time synchronization that usually applied in industrial automation and telecommunications. The essential operation of PTP involves exchanging messages between a master clock and a set of slave clocks. The master clock sends synchronization messages to the slave clocks, which use the information to adjust their clocks to match the master clock. PTP demonstrates the capability to attain synchronization accuracy in the sub-microsecond range. This level of precision proves suitable for latency measurement in comparison to the reporting rate of PMUs at 60 frames per second (FPS), and the synchronization frequency of GPS at 1 pulse per second (PPS). Furthermore, PTP emerges as a preferred choice over alternative synchronization protocols, especially for field installations. It empowers hosts to synchronize with a shared time reference source, exhibiting notably higher precision within sub-microsecond range.

Each VM is connected to different virtual network adapters with separate virtual local area networks (VLAN). This ensures that the multiple VMs/nodes from different LANs are configured to communicate through the unique logical 5G network. The experimental network configuration of the ESXI VM host connected to AWC Verizon 5G NSA test network is shown in Figure 9. The setup of Verizon 5G NSA configuration provides a 28 GHz signal for the 5G user plane and an LTE anchor for the control plan. In AWC lab, the 5G antenna and Verizon server/router are connected via a single-mode optical fiber.

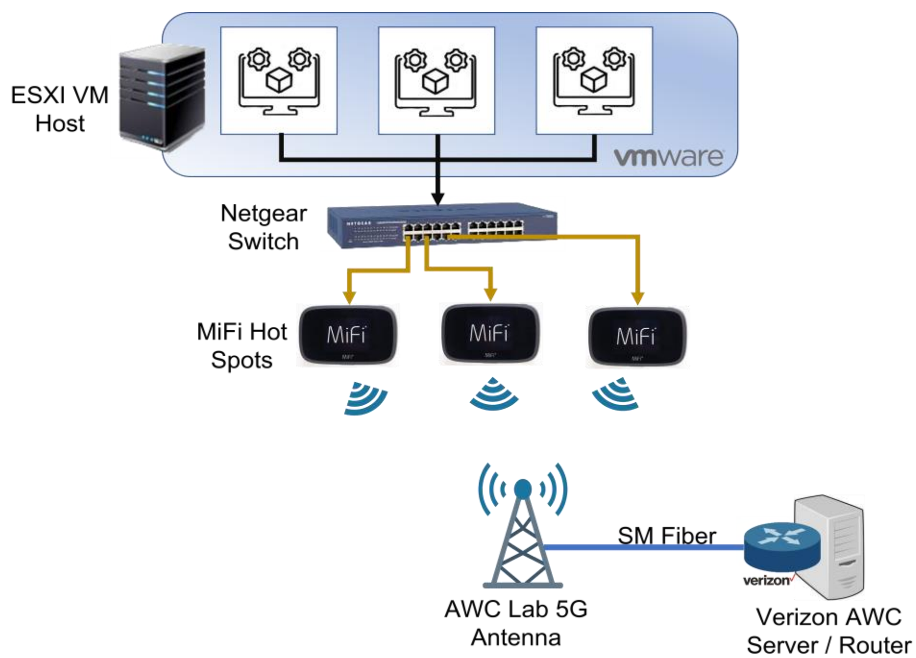


Figure 9 5G network configuration and VM settings for PMU, PDC, and PMU-based application.

The configured 5G wireless architecture has been tested in an online power system application for PMU-based anomaly detection. The anomaly detection (AD) algorithm was deployed on the edge device that listens the PMU streaming data. Once the data was received, a 5-minute moving window is used to train the dynamic regression model. The trained dynamic regression model is used to predict the frequency measurement values for the next 5 seconds. The prediction error can be computed using the PMU observations from data stream. For the short-term predictions, the prediction errors and training errors typically follow similar distribution.

However, when an immediate event occurs in short-term interval, the training and prediction errors differ since the training moving window no longer has the same trend as that of the prediction interval (event occurrence time). This behavior is captured by checking whether the exceedance probability of prediction error is 3.5 standard deviation away from the training error.

Anomaly Detection Results

Figure 10 showcases the detection of the anomaly at the edge device, using the PMU data stream that is being received via 5G network testbed. It can be observed that one-step ahead forecast values (curve fitting results on the training data) are very close to the original observations in the order of 3rd decimal in frequency attribute (inset in Figure 10). This shows that the dynamic regression model provides a satisfactory goodness of fit during the training. Furthermore, when the event occurs on the 148-th second (vertical black dashed line), it can be observed that the five step ahead forecast (prediction values for next 5 seconds) is very close to the trained values before the 148-th second. However, at the 148-th second, the historical record event observations are far away from the predicted values. This difference in predicted values and the anomalous observations, results in a large prediction error that are not like the training moving window errors. As discussed in the Data section, the threshold for successfully detecting anomalous events is set at the 3.5 standard deviation.

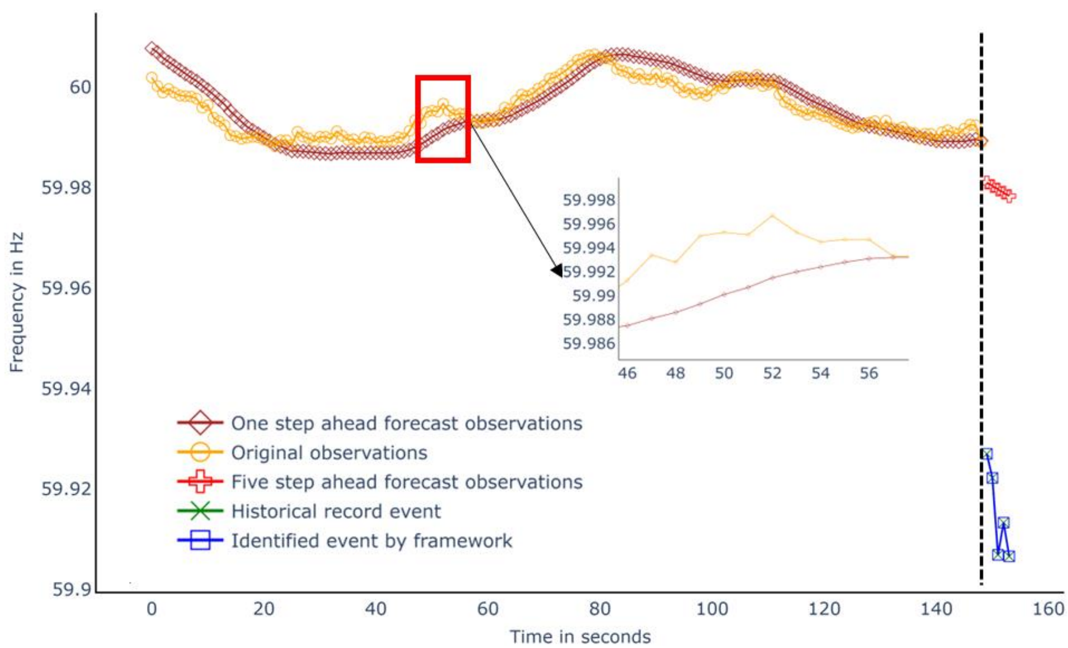


Figure 10 Detection of anomalous event at edge device using the PMU data stream via 5G network testbed.

3.2 5G Testbed Example 2: Learning-based Protection for PV

3.2.1 Background and Motivation

The complexity of the power distribution system increases significantly as the penetration of DERs continues to rise. Conventional protection schemes based on simple voltage, current, or frequency thresholds are expected to become less reliable. [21] proposed a new fault detection method for systems with high-penetration PV based on machine learning. A convolutional neural network (CNN) was trained to identify the fault zones (which would then trigger appropriate protection actions) based on high resolution current and voltage waveforms. The proposed method was tested on the EPRI J1 feeder using only local measurements, and achieved an accuracy of 95%.

In this project, we explored notable technical gaps that need to be addressed before similar protection schemes can be deployed in the field and used online in operation settings.

The availability of computing power at the protection relays
For learning-based protection relays to be deployed in a large scale, the cost must be affordable enough to access sufficient computing power, especially to run the learning algorithms at an acceptable latency. A potential solution is to employ 5G-enabled edge computing, which brings significant computing power to edge devices (e.g., protection relays), and can be accessed via Ultra-Reliable Low Latency Communications (URLLC) at millisecond-level latency.

The performance of the CNN with streaming data
Most methods proposed in the literature has only been tested with data generated/collected in advance with well-aligned fault onset time. For these methods to be employed in practical operation, their performance, in terms of both accuracy and latency, must be validated with realistic streaming data.

In this task, we will perform realistic tests in a 5G operational setting for the aforementioned learning-based protection scheme. More specifically, we assume 1) the high-resolution waveform data is being streamed from the measurement device to the edge computing server over the 5G network, 2) the CNN algorithm is triggered when new data becomes available and trip/no-trip decisions are made, and 3) the decisions are sent to the actuating relays. We will measure the communication delays at each step, the computational delays at the edge server, and the end-to-end delay between fault occurrences and actuating decisions.

3.2.2 System Setup

Compared to the synchrophasor data anomaly detection application, the protection scheme requires a safer and lighter protocol, to reduce latency and bandwidth utilization through the operational data network. In order to achieve this goal, we adopted IEEE P2664, namely Streaming Telemetry Transport Protocol (STTP) [22], at the application layer and UDP at the transport layer, for streaming the high-resolution point-on-wave (POW) data. STTP also offers a secure and lossless data compression options in the proposed application, so it can efficiently transport the streaming power system data over Internet Protocol (IP) networks.

The simulation setup for learning-based PV protection is as follows:

- Hardware:

  a) AWC 5G infrastructure: This includes AWC 5G antennas, the Verizon AWC server, and MiFi spot, all of which are used for building the 5G network.

  b) EXSI server: This server creates the simulation environment comprising two EXSI virtual machines (VMs), where one VM hosts OpenPDC for publishing the high-speed POW data, while the other is an STTP subscriber for receiving the streaming data and triggering PV protections.

- Software:

  a) OpenPDC: OpenPDC is an open-source tool developed by the Grid Protection Alliance (GPA). The software is utilized in this task to stream the high-sampling rate POW data.

  b) ProtectionSubscriber: This tool is deployed at the application VM and it facilitates the subscribing function for receiving and processing the high-speed POW data with a high sampling rate.

  c) CNN-based protection application: This application offers real-time remedial action scheme (RAS) for PV protection. The tool is developed using Python.

3.2.3 Progress, Findings, and Lessons Learned

IEEE 1547-2018 [23] allows distributed energy resources (DER) to ride through voltage disturbances, ending any de facto reliance on tripping as a voltage violation. Many new protection technologies for addressing these issues rely on communications, e.g., learning-based protection, which can be evaluated through test cases as shown in Figure 11.

This example demonstrates the use of 5G infrastructure in supporting CNN-based learning control applications, with high-fidelity and high-volume streaming sensor data from distribution grids. Figure 12 shows the configuration and data flow of the proposed framework.

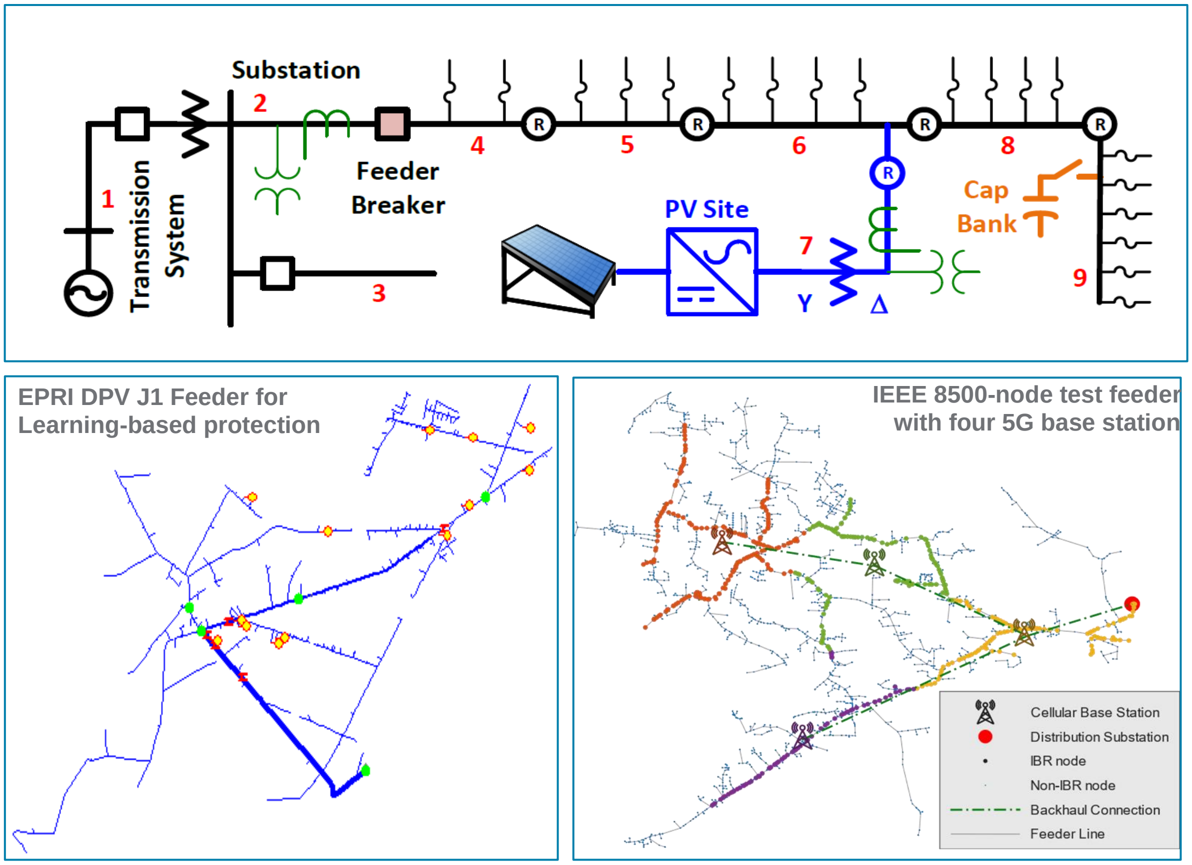


Figure 11 The learning-based protection for PV and two applicable test systems.

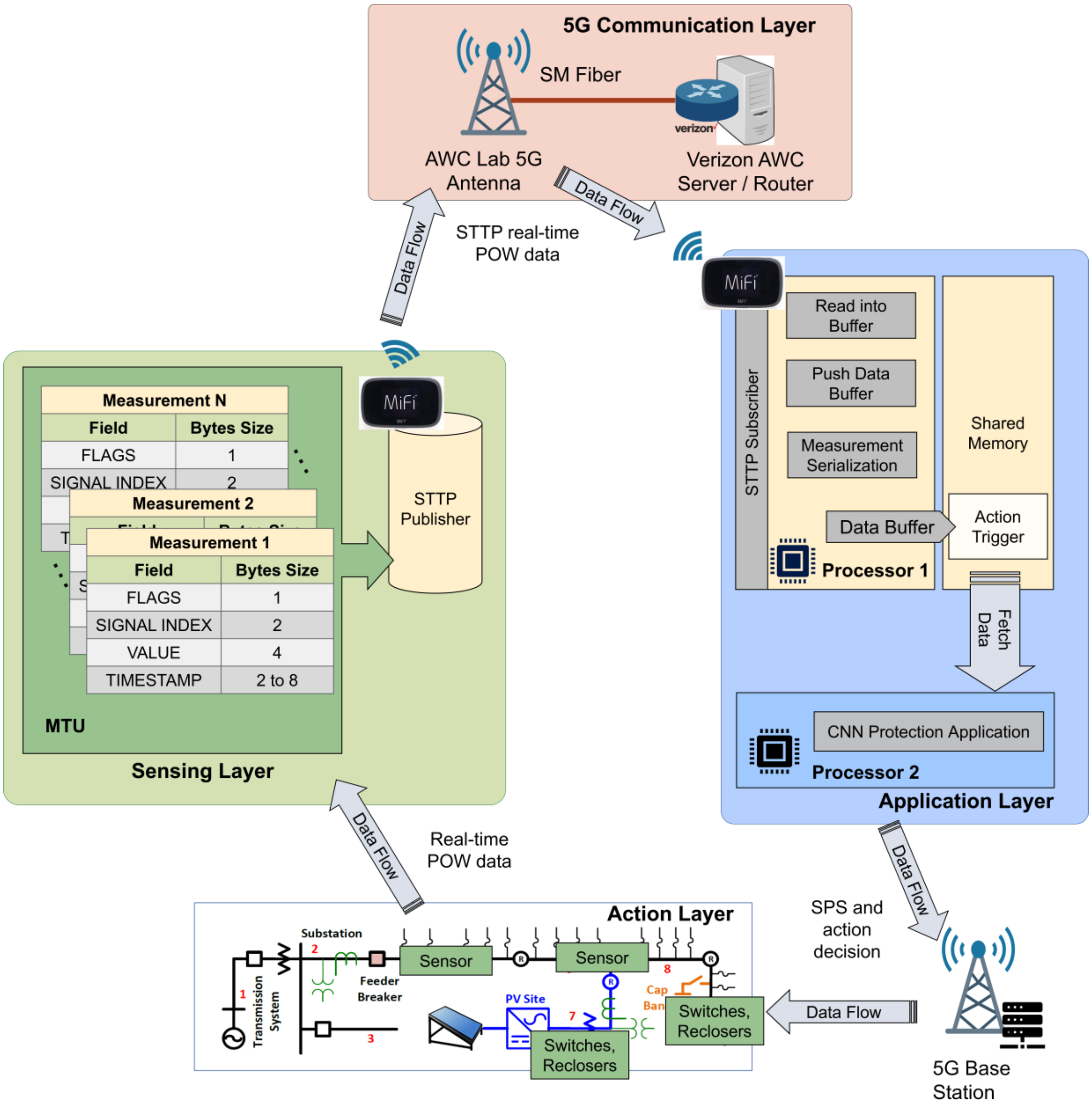


Figure 12 Diagram of 5G-enbled CNN-based learning protection scheme.

In the proposed framework shown in Figure 12, the electromagnetic transient (EMT) waveform data, the POW data, was collected using the Alternative Transient Program (ATP), including three-phase voltage and current at a rate of 10000 sample/second [2], which represents the inverter POW measurement at solar panels. The collected measurements were fragmented into smaller datagrams, and stored in a maximum transmission unit (MTU). When the STTP publisher processed adequate MTU fragments, the available measurements published could be subscribed to and stored in STTP buffers. Once a memory buffer is filled, the subscriber will trigger the action layer, and push the data buffer to the application processor via the high-speed 5G communication network traffic. As a result, the learning-based protection algorithm deployed on the application processor will process the measurements, and feed the special protection scheme (SPS) decision and action command to the switches and reclosers. In practice, the well-trained learning-based model can be deployed to the relay and implemented in a real-time automation controller (RTAC), allowing protection devices to trip the PV whenever faults are estimated.

As of writing this report, we have configured the emulation framework and implemented different programming algorithms to reinforce the communication traffic and handle the network congestion. The validation has been completed using local network. The challenges in implementation include limited computation resources (edge computing), reliable data delivery, network protocol selection, data redundancy, and reliability. Considering the limited computational resources on edge, we implemented the algorithm to combine the communication and application layers using multi-threading and multiprocessing with shared memory. For hi-resolution high-speed POW data with 10000 sample/second, an improper implementation on edge can cause data traffic congestion, which further degrades latency and packet loss. Therefore, we implemented multiprocessing for communication and application on a Dell precision laptop to minimize computational resources. Also, the trigger and data exchange channel were designed on a pre-allocated shared memory to allow the communication to ride through each end. By pipelining and simplifying the data serialization, the average data transmission delay was significantly reduced from 4.413 sec to 0.226 ms (Figure 13). Furthermore, the code implementation also introduces additional meta data, including adding the unique identification and publishing-subscribing timestamps, which makes it easier to recover lost or corrupted data, improving the reliability and robustness of grid applications relying on data stream using the UDP protocol. The whole process was tested through VLAN, and the testing via 5G hardware is underway.

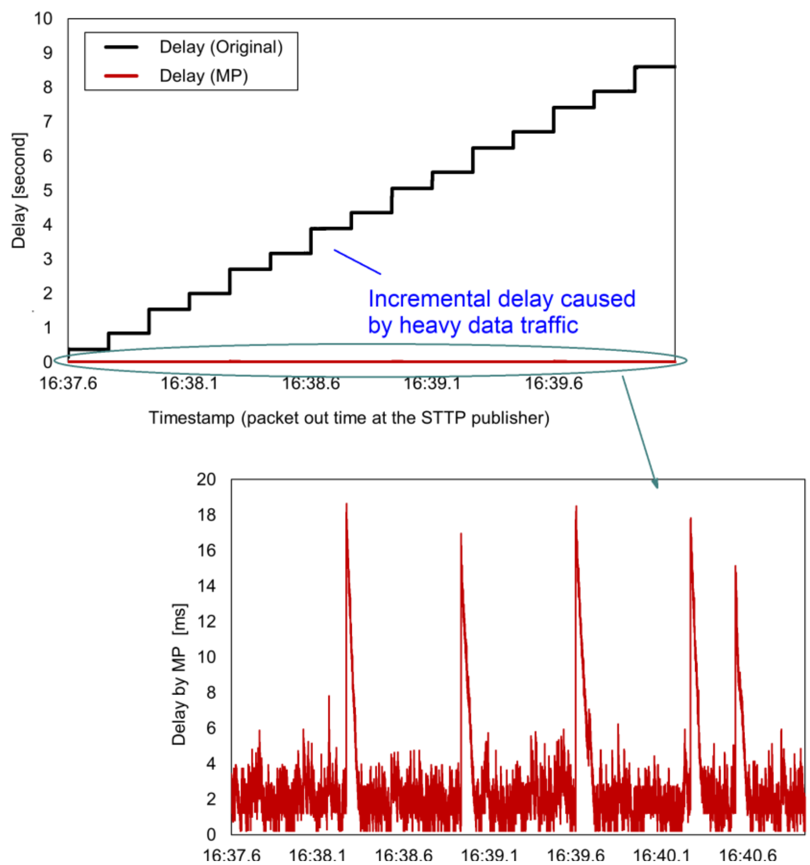


Figure 13 STTP data transmission delay was significantly reduced by mitigative serializing and multi-processing (MP) implementation.

4.0 5G-for-Grid Use Case Design

The main purpose of the first 5G-for-Grid Use Case is to demonstrate the flexibility and capability of the 5G-enabled co-simulation platform, and also to show future potential benefits of ultra-low latency applications, such as 5G for T&D system monitoring and control [17]. It is important to understand the electricity infrastructure transitioning process with exploding renewable integration, especially in the form of inverter-based resources (IBRs). Significant events, such as the Southern California 8/16/2016 event [24] and the Odessa Disturbance [25], are good examples of urgent need of better grid monitoring and control functions.

PNNL research team has been developing various T&D co-simulation examples. One of such examples is [26], which can accommodate 10,000+ inverters, including small-scale and plant-level IBRs with various mixes of Grid-Forming (GFM) and Grid-Following (GFL) inverters on both transmission and distribution systems, up to 100% IBR penetration level.

Now with the 5G communication testbed [16, 17] and two emulated AI/ML examples for grid data anomaly detection and PV plant fault protection, it is complementary to visualize a comprehensive workflow including heterogeneous computation and software for such T&D&C co-simulation. The proposed workflow can be applicable to future real-world demonstration due to the seamless translation of grid analytics enabled by 5G testbed (deployed either in-door or mobile in open field). Figure 14 shows the concept of the first 5G-enabled power grid transmission, distribution, and communication co-simulation use case.

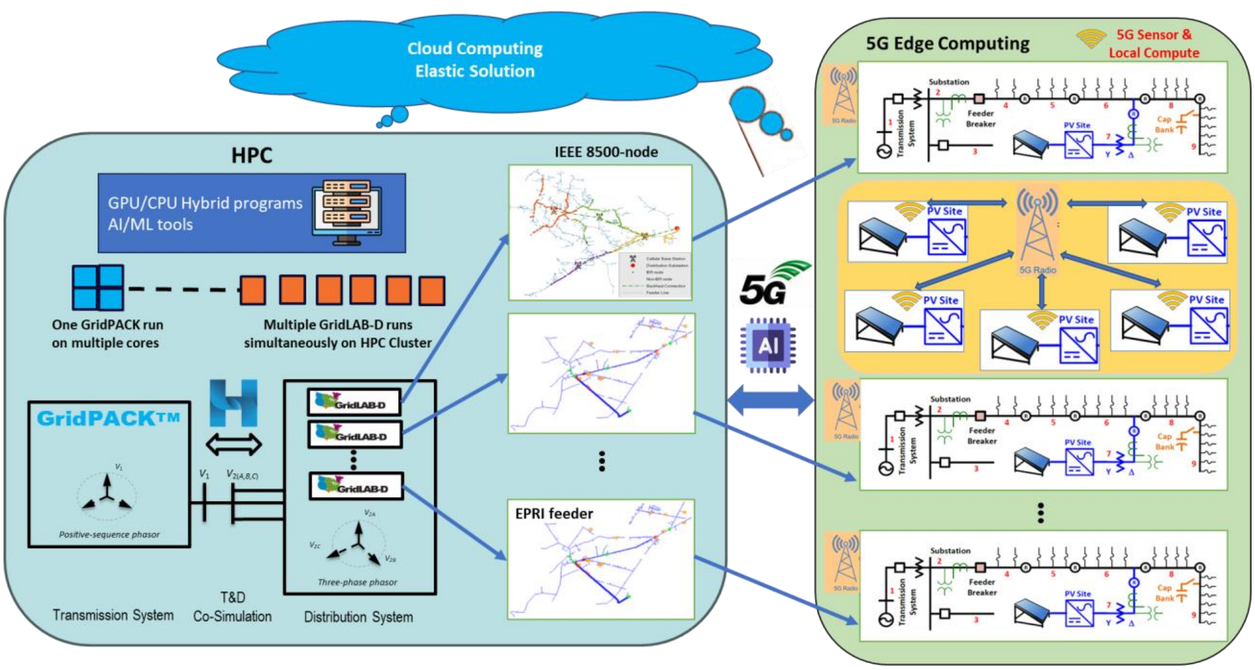
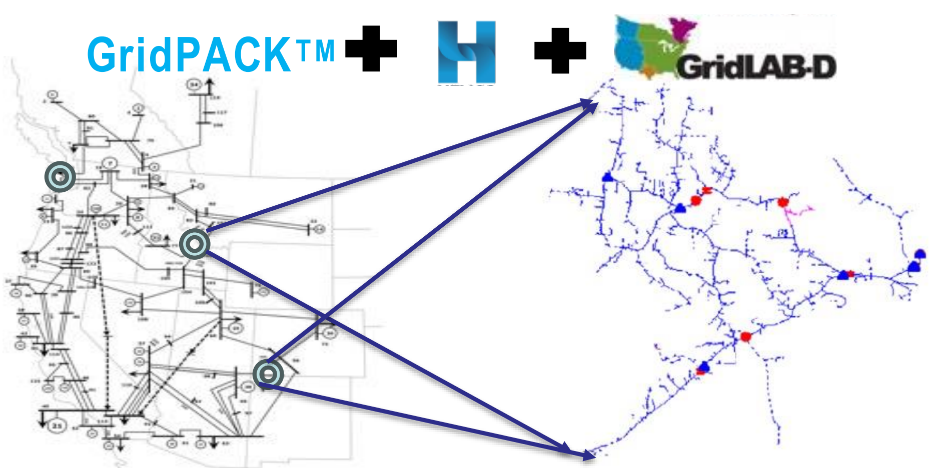


Figure 14 A detailed 5G-enabled power grid transmission, distribution, and communication co-simulation use case.

Due to the rapid renewable integration, IBRs are widespread in the power system, requiring a transmission and distribution (T&D) co-simulation platform for in-depth analysis. This platform includes three open-source tools: GridPACK^{TM} (HPC transmission system simulator) [27], GridLAB-D [28] (distribution system simulator), and HELICS (co-simulation framework) [29] . It accommodates diverse IBR GFM/GFL configurations, up to 100% penetration, and assesses contingencies occurring in both transmission and distribution systems. For information exchange, at the GridPACK end, the interface load is represented by current injection, receiving the P, Q at the substation from GridLAB-D. GridLAB-D receives the positive-sequence voltage magnitude and angle from GridPACK. HELICS synchronizes the time of GridPACK with the individual time of multiple GridLAB-D federates and controls data exchange between GridPACK and GridLAB-D federates.

In this use case, GridPACK conducts dynamic simulations for one transmission system, such as miniWECC [30], on an HPC cluster with multiple cores. Concurrently, multiple instances of GridLAB-D run dynamic simulations for distribution systems like EPRI feeder, IEEE 34-node feeder or IEEE 8500-node feeder [31]. Users can customize the number and type of feeders and the ratio of GFL and GFM inverters based on their needs. Each feeder includes solar farms (PV sites in Figure 12) with 5G Edge computing capability. AI/ML fault detection codes based on 5G edge computing are deployed at each PV site. When a fault is detected, the AI/ML code triggers actions, and updated information is sent to the HPC cluster to initiate a T&D co-simulation with the new fault condition. After completing the co-simulation, results, including feeder conditions, are analyzed and provided to the 5G environment for monitoring and control.

Figure 15 illustrates a T&D simulation featuring a miniWECC system at the transmission side, with illustration of two loads replaced by the IEEE 8500-node feeder, including 550 IBRs at each feeder [26].



Transmission system (miniWECC)

Distribution system (IEEE 8500-bus feeder)

Figure 15 An Example of T&D co-simulation (the miniWECC transmission & nineteen IEEE 8500-node feeders)

By tripping one feeder at the distribution side (as shown in Figure 16), the T&D co-simulation platform clearly displays the observable P and Q outputs on the feeder side, as well as the Voltage magnitude at the interface buses and frequencies for the synchronous generators. Notably, there is one synchronous generator close to the fault location that has a large frequency oscillation, which shows that the fault at the distribution side could potentially make synchronous generators unstable. This kind of detail won't be observed in aggregated models, highlighting the advantage of this detailed co-simulation over traditional aggregated models.

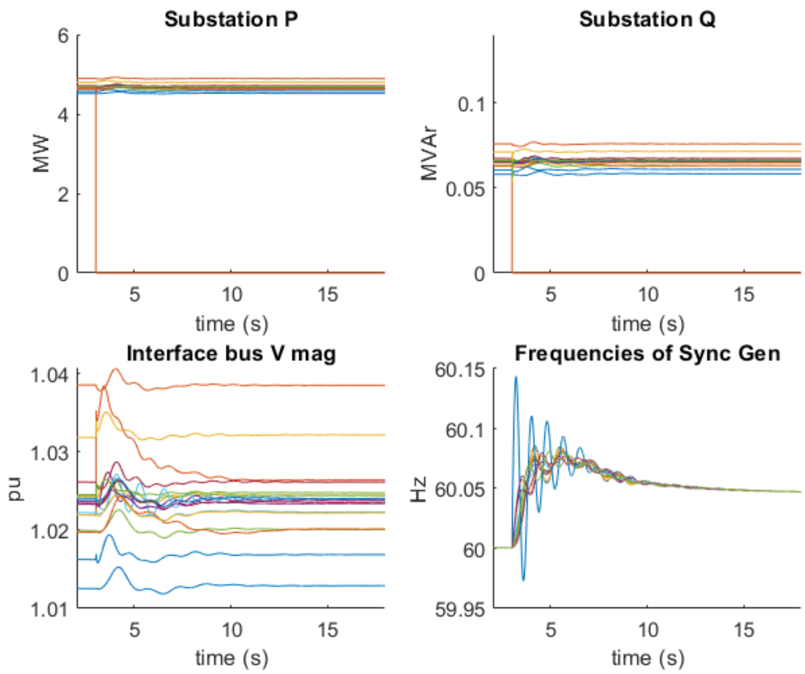


Figure 16 T&D co-simulation results: P, Q outputs at substation sides, voltage magnitude at the interface buses, as well as frequencies of synchronous generators at the transmission side.

Given the T&D co-simulation's capability to simulate faults at the distribution side [31], integrating the 5G-based AI/ML code is straightforward. Upon AI/ML tool detecting faults, the tool's outputs, encompassing new conditions at the distribution-side at one or more distribution systems, can be communicated via 5G or other communication protocols to the T&D co-simulation platform. This introduces new faults with updated distribution system configurations. The overall T&D co-simulation results are also be shared with the AI/ML tool and relevant devices at the distribution system, updating grid conditions and model parameters. The introduction of this 5G-based AI/ML code enriches the T&D&C co-simulation's efficacy for conducting comprehensive studies.

Harnessing HPC capabilities allows for a parallel model encompassing one transmission system and multiple distribution systems, ensuring efficient integration and scalability even with numerous distributions. The synergy of HPC clusters and 5G edge computing empowers efficient machine learning retraining, incremental learning, or continuous learning based on real-time grid conditions and training data. This enables fine-tuned adaptive model parameters, enhancing the precision and reliability of grid management. Moreover, the T&D co-simulation framework's applicability can be extended to other applications on the same or different HPC clusters. Cloud interaction further unlocks potent and flexible functionalities. This workflow's feasibility has been shown in [17].

5.0 Conclusions and Next Steps

The 5G Energy FRAME project dives into the 5G-enabled applications for power grid monitoring and control. Two AI/ML examples utilizing PNNL's 5G testbed are provided with design, implementation, and results, along with the newest in-house testing data for 5G equipment performance. Last but not least, the design of 5G-for-Grid Use case is discussed and illustrated, with preliminary results from a group of power grid simulators.

5.1 Year 2 Progress Summary

This subsection provides a summary of project year-2 work.

5.1.1 5G Data Summary

Grid data is a general definition of any related information applicable to power grid representation, in the context of sensing, monitoring, operations, and control. In particular, power grid measurements and components of mathematical models provide a vivid data-model-convergence example to represent the largest cyber-physical system (CPS) in our world. From either the communication domain perspective or the computing domain perspective, the transmitted and processed data may be packaged, compressed, encrypted, buffered, time aligned, stored in memory, distributed, and delivered for next step applications, regardless of whether it is a streaming timestamped measurement, or a sub-block of grid model admittance matrix.

One of the challenges is the streamlined data sharing mechanism, through a multitude of data generation processes and data ownership, following the specific regulations and compliances across the power industry. The combination of 5G and Cloud service may fulfill the technical needs of grid data sharing, and it is a reason for optimism for enabling access to both 5G services and Cloud services in a more affordable way for end users.

5.1.2 5G-enabled AI/ML Examples

Through the close collaboration with PNNL's AWC team [19], two AI/ML examples utilizing PNNL's 5G testbed are provided with design, implementation, and results, in Section 3.0. The main objective is to demonstrate the capability of 5G testbed and serve as the prelude of the first 5G-for-Grid Use case, and also to explore the benefits of 5G-enabled Grid Unified Edge Emulation Platform for Scientific Computing.

5.1.3 5G-for-Grid Use Case

Complex scientific computing process, i.e., developing and using the cross-domain co-simulation tool for national grid studies, requires deep expertise in tool automation and scientific domain knowledge. And the benefits of having a workflow to enable such computing process, is long-lasting and allow further customized configurations from different groups of users to be supported.

The first 5G-for-Grid Use case developed in this project, aims to demonstrate how to develop an adaptive/expandable workflow that can coordinate distributed computational and data infrastructures to provide robust and efficient computational supports, which can be adopted for other scientific/industrial applications. To be more specific, PNNL has developed the GridPACK

HPC library for power grid simulation on cluster machines [27]. For example, GridPACK has achieved the fastest time for dynamic simulation reported in the literature: with 16 cores, it can solve Western Electricity Coordinating Council 20-second dynamic simulation in 19.5 seconds. A GridPACK task manager has been developed to dynamically allocate computational loads to each computing core based on its availability, which has been tested with Siemens' Power System Simulator for Engineering (PSS/E) to run dynamic security assessment in parallel at the task level without modifying its core engine [33]. Two-layer task management has been evaluated with the applications of dynamic security assessment under uncertainty [34].

The dynamic balancing scheme has obtained a near-linear speed up for in-house massive contingency analysis with 10,000 cores [34], the best performance reported in the literature. This dynamic load balancing scheme would be extremely useful in computing load assignment in this workflow management effort for obtaining optimal computational performance. We will also leverage the team's experience in designing and implementing DOE Grid Optimization (GO) Competition Platform [35] and Washington State University–PNNL Advanced Grid Institute (AGI) GridSandbox project [36] to provide a user-friendly experience for participating stakeholders.

By designing and implementing the streamlined computing and orchestration workflow, we can foster a balanced and sustainable computing ecosystem, and empower potential energy stakeholders with better resource and asset management by optimized 5G integration.

5.2 Next Steps

The project is entering the third project year, and this subsection describes the next steps of the project team, with a focus on the 5G-enabled workflow from the computing perspective.

5.2.1 The 5G-enabled Workflow Outlook for Grid Transmission, Distribution, and Communication Co-simulation

The workflow will offer users an open-access environment that provides remote access to data, models, software, and even algorithms, hosted by various computing platforms, including edge, local HPC, or cloud servers. Edge-based computing equipment will be collaboratively coordinated to fulfill the need for heterogeneous modeling, computing, and control while ensuring consistent performance characteristics in distributed energy infrastructure. Supercomputer facilities can support efficient ML model retraining/update for the edge computing equipment; for example, based on the most recent training data in Section 3.2, the self-evolutionary grid edge ML models can be refreshed/upgraded with the new model parameters generated from HPC or Cloud compute. We will leverage PNNL Research Computing and existing supercomputer resources (Cascade and Constance) to provide computation and data storage support for large-scale co-simulation of transmission and distribution networks, process the massive amount of grid data, and provide rapid prediction of grid behavior and real-time visualization of key grid features for decision making.

The first 5G-for-Grid use case can demonstrate the unique capability of the developed scalable T&D co-simulation platform for large-scale simulations with detailed IBR behaviors at both transmission and distribution sides, which is unavailable using the traditional aggregated IBR models. With this proposed workflow and 5G-enabled platform, different control strategies with different types of IBR models can be evaluated at different penetration levels of IBR in the power grid. The platform will help researchers better study the impact of new technologies, i.e., IBR and 5G, and understand how those technologies will affect the grid's reliability, efficiency, and security.

5.2.2 Enhancement of Heterogeneous Computing Capabilities in 5G Testbed

Advanced Wireless Communication Team [32] at PNNL has partnered with Nvidia to get access to and build out an instance of the NVidia's Aerial Research Cloud which is a 5G/6G network. This network is a platform to perform research investigating 5G and 6G concepts, especially for use with Mobile Edge Computing. Network has radio units that send raw RF data to an A100 GPU for processing the 5G stack. The A100 GPU that runs the 5G stack has enough resources to also run 3rd party edge computing, such as the analytics for stabilizing the power grid. This provides the lowest latency known for access to 3rd party edge computing from a connected device since the edge computing is built into the cell site and can act as a node in a distributed high-performance computer. The next step will be to incorporate the analytics and compute models for this work into the NVidia network and make modifications to that network to see how low of latency is possible.

5.3 Cross-cutting Research Potential and Impacts

The overall project work and outcome may benefit not only the power grid analytics and electricity infrastructure transitioning to 100% renewable, but also shed light on other scientific domains and a generic modeling practice enabled by 5G capabilities.

5.3.1 Collaboration with Center for Advanced Technology Evaluation (CENATE)

The DOE Office of Science established the Center for Advanced Technology Evaluation (CENATE) [37] at PNNL in 2015, to assess the impacts of emerging computing, memory, and networking technologies on DOE computing missions. As CENATE has evolved over three funding cycles, the emphasis has shifted from examining exclusively technologies aimed at High-Performance Computing (HPC) systems and applications, to exploring computing more broadly, considering technologies such as advanced wireless networking and metrics of interest, including cybersecurity. A key aspect of CENATE's mission is to foster collaborations within the DOE computing portfolio and with industrial and academic technology developers.

Collaboration between CENATE and the 5GEnergyFRAME project developed around a capability to simulate 5G and other wireless networks in order to gain an understanding of how they may be useful in the monitoring and control of complex engineered systems, including the power grid. Using the ns-3 discrete event simulator [38], the collaboration created tools to simulate 5G wireless networks under a variety of configuration and load conditions. The next step will be to refine the simulator to enable the study of larger networked systems and to verify simulated predictions on physical systems, including the AWC 5G innovation studio.

5.3.2 Workshop Planning for Co-design of Power Electronics and Microelectronics

The evolution of both smart phone and electric vehicle in the past two decades, has shown the profound impacts of integrating the power electronics and the microelectronics. As a result, our modern life is being impacted by the screens around us, as well as the algorithms and informative data streams behind those screens. In 2018, one technical report from DOE Office of Science [39] highlighted the co-design benefits centered around microelectronics, several co-design examples are given as follows [39]:

1) Computer & System Architectures – Circuits – Low Voltage Devices and Enabling Materials – Chemistry and Processes

2) Real-Time Control Applications/Algorithms – Real-Time System Software – Distributed Computing and Communication Integrated into Smart Grid System Architectures

3) Smart Grid System Architectures – Circuits – Devices – Chemistries – High Power Electronics Materials

4) Smart Sensors and Experimental Diagnostics – Materials – Devices and Circuits – Component Integration – Algorithms, Programming, and Control

In 2022, PNNL research team published the white paper named 5G Enabled Transformative Co-design and Co-simulation Framework for Grid Decarbonization and Modernization [40], this white paper identified that the complex multi-domain behavior can be analyzed in the co-simulation environment across varying operational and environmental scenarios. Based on a set of configurable objectives across the different domains, simulation-driven multi-factor optimization can lead to an optimal co-design.

More importantly, such co-design concept and the developed 5G enabled T&D&C co-simulation platform can be extended, to further promote and accelerate the application of advanced computing and communication technologies in power systems, considering the increase penetration of DERs and energy storage [41, 42], distributed ledger technology (DLT) [43], migration of Data Centers, Offshore and Onshore wind development, as well as high voltage direct current (HVDC) interregional transmission projects.

Therefore, it is valuable to conduct more workshops centered around the co-design of microelectronics and power electronics, so a better future grid can be visioned, designed, assessed, validated, and coordinated among various stakeholders.

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