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Technical Characterization and Benefit Evaluation of 5G-Enabled Grid Data Transport and Applications

August 2022

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5G Energy FRAME Year 1 Report

August 2022

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Abstract

This report summarizes the Year 1 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 Program.

5G is a breakthrough technology that enables a fully mobile and connected society, and a 5G-enabled digital continuum will be one of the critical foundations for a clean energy economy and grid modernization. In collaboration with PNNL's Advanced Wireless Communication team and Center for Advanced Technology Evaluation team, the project team has been evaluating the system performance of 5G testbeds in the PNNL 5G Innovation Studio, and has formulated a co-simulation test case of power system transmission, distribution, and communication (T&D&C) networks considering 5G technology and high penetration of distributed energy resources. The methodology developed in the 5G Energy FRAME project can be customized to fit different future grid scenarios to evaluate multiple (dynamic) configurations (computing, sensing, communication, environment) for different stakeholders.

In summary, our main technical highlights in project Year 1 are as follows:

1) Technical characterization of 5G standalone architectures
2) Formulation of co-simulation test case of T&D&C networks embedded with 5G
3) Initial benefit evaluation of 5G communication platform for grid use cases
4) Additional extended discussions on edge computing, artificial intelligence and machine learning, and high-performance computing and cloud computing adoptions.

In addition, a collection of system performance data is shared through the 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
CPU	central processing unit
DER	distributed energy resource
DOE	Department of Energy
EDM	Energy Data Marketplace
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
RTP	Real-time Transport Protocol
SA	standalone
SINR	sign-to-interference-plus-noise ratio
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	ultrareliable low-latency communication
VM	virtual machine
WECC	Western Electricity Coordinating Council

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1.0 Introduction

Based on the 2050 projection of electricity generation from the U.S. Energy Information Administration, total renewable generation will surpass 2.5 trillion kilowatt-hours and account for more than 42% of all generation, with a renewable mix of 47% solar (behind-the-meter and utility scale), 34% wind, 13% hydro, 2% geothermal, and others [1]. High penetration of renewable generation is realized by ubiquitous power electronics in future power systems [2], in which the uncertainty and intermittency may dominate and propagate throughout every layer of grid operations, entailing more frequent interaction among different parts of the power system and henceforth deepening the interdependence between power system and communication networks. More importantly, there is an inevitable yet dramatic paradigm shift of the roles and functions of conventional energy service providers and emerging prosumers countrywide—a prosumer is both an energy producer and energy consumer. Therefore, how to empower the prosumers with the best available energy data and tools to support their asset management and 24/7 operation, as well as boosting the grid resilience with a bottom-up approach, is a critical and urgent engineering and societal challenge.

Moreover, the complexity of power system modeling and simulation has been escalated, mainly due to the significantly increasing amount of high-resolution sensing data (typical continuous point-on-wave data frequency is from 1 kHz to 10 MHz, with an annual data size of 0.5 TB to 5 PB for a single data point), more complex modeling approaches (power electronic proprietary models, artificial intelligent [AI] surrogate models), and the more stochastic nature brought by renewables and energy storage proliferation at both generation and demand sides [3-6]. All these lead to significant communication network capability demands on bandwidth, latency, massive connection, and secure/reliable interoperability. Especially with ubiquitous power electronic equipment that, if not fulfilled, this may jeopardize grid operators' situational awareness and decision making, and even lead to systemwide disturbances [7] or a life-threatening system blackout crisis [8].

Therefore, it has never been so imminent that all energy stakeholders across the nation should collaboratively explore and integrate state-of-the-art communication technology, i.e., 5G in the deployment phase [9] and 6G on the research horizon [10,11]. This is to not only leverage the most advanced communication technologies and break the data silos among energy stakeholders in this energy and society transformation era, but also to enable the unprecedent codesign process of energy, communication, and computing for the envisioned 100% decarbonized economy.

1.1 Electricity Generation Transition with Emerging Communication Technologies

Electricity is essentially a societal service and all interested stakeholders should participate and contribute at their best when the grid faces extreme challenges. The recent Texas rolling blackout due to extreme cold weather and California's rolling blackout due to extreme heatwave urge technology breakthroughs and a comprehensive reevaluation of current regulation and industry practices. Currently, the energy industry is exploring uncharted waters and scrambling for near-term solutions for climate change just to keep the lights on.

The Federal Energy Regulatory Commission Order 2222 opens the new era for energy prosumers with distributed energy resources (DERs), which extend energy generation participation by aggregated format to anyone and any form of energy generation/storage technologies, whether if behind solar photovoltaic, household battery energy systems, or electric vehicles [12]. The recently published National Institute of Standards and Technology's *Framework and Roadmap for Smart Grid Interoperability Standards*, release 4.0 [13], emphasizes a renewed focus on smart grid transformation to support a decarbonized, equitable, secure, and resilient energy future. The standards also state that we must explore and adapt to new technologies inside the energy sector, solve the increasing interoperability challenges with DERs, and analyze the complex dataflows across the multiparty energy ecosystem, as shown in Figure 1.

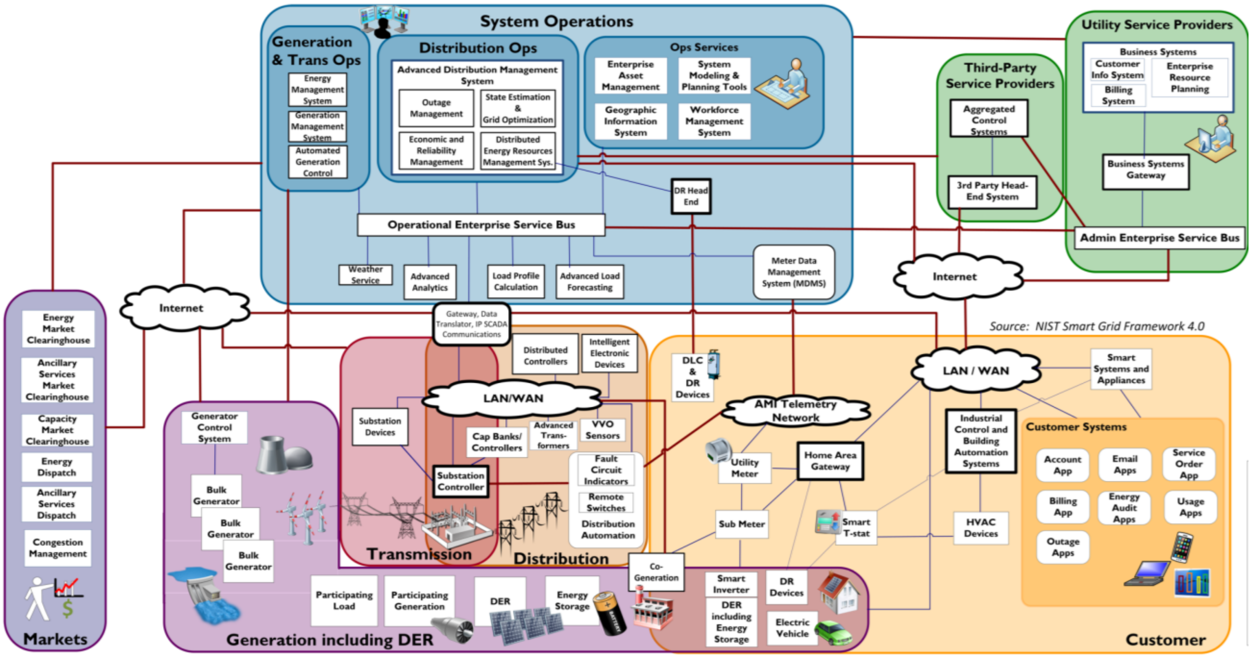
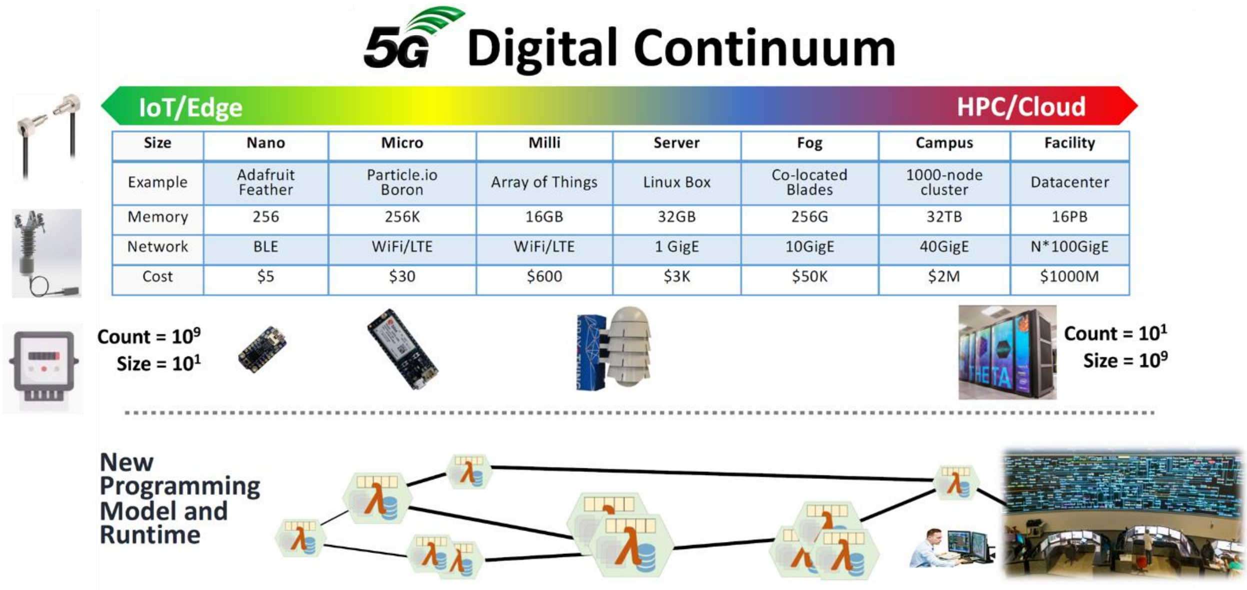


Figure 1. High DER communication pathways scenarios [13].

5G performance is critical to bridge the unparallel volume of data from sensors that are embedded in power system equipment and devices, homes, buildings, factories, communities, and high-density urban areas. These sensors provide power usage and increasingly distributed energy supply data that can be integrated with critical power plant monitoring and control, to collectively provide the best situational awareness to grid operators. One illustration of 5G Digital Continuum [14] from the sensing and computing perspective is given in Figure 2. Through the holistic digital continuum enabled by 5G, diverse data from multiple sources can support more efficient monitoring, control, and coordination of utility and nonutility energy resources for homes, buildings, campuses, transportation, and other participants in a clean energy economy, especially in the Internet of Things (IoT) context [15,16].

5G is expected to provide enhanced mobile broadband (eMBB), ultrareliable low-latency communication (uRLLC), and massive machine-type communication (mMTC). These characteristics are well suited for a clean energy future where many more devices and systems owned by utility and nonutility entities are interconnected to a much more distributed energy grid. Technologies such as massive multiple-input multiple-output (MIMO), mmWave, cognitive radio, network slicing, etc., provide enormous throughput and enable support for diverse service-level requirements. Energy-efficient communication with a high density of connected devices is also crucial for IoT scenarios. In 5G mMTC, one million devices could be connected over 1 km^2 whereas in 4G, only 2,000 devices can be connected [17]. This is made possible by the densely deployed macro-assisted small cells, intelligent interference mitigation techniques, and low-power wide-area network standards such as narrowband IoT (NB IoT) and Long-term Evolution (LTE) machine-type communications.



Size	Nano	Micro	Milli	Server	Fog	Campus	Facility
Example	Adafruit Feather	Particle.io Boron	Array of Things	Linux Box	Co-located Blades	1000-node cluster	Datacenter
Memory	256	256K	16GB	32GB	256G	32TB	16PB
Network	BLE	WiFi/LTE	WiFi/LTE	1 GigE	10GigE	40GigE	N*100GigE
Cost	$5	$30	$600	$3K	$50K	$2M	$1000M

Figure 2. 5G-enabled digital continuum and its extension into grid monitoring and control [14].

Such capabilities enable wide deployment of delay-tolerant power system applications like fine-grained transactive control of DERs. Furthermore, 5G uRLLC is critical for sophisticated wide-area power system protection. High penetration of generation from renewable energy sources, such as wind turbines, increase the current complexity in large-scale power systems. This causes difficulties for traditional protection strategies that only rely on local measurements. Wide-area protection strategies based on measurements from phasor measurement units (PMUs) are a potential solution to the problem [18], requiring millisecond-level latency and ultrahigh reliability.

1.2 Big Data Challenge and Data Gaps in Energy Transition Era

Since the inception of the power grid in the 1870s, operators have been using available measurements from widely deployed sensing instruments and physics-based mathematical models to evaluate operating conditions, provide generation scheduling, and ensure safe and secure grid operations. In the past decade, along with emerging energy generation and storage technologies, the revolutionary impact of energy data has propelled and accelerated to embrace the clean energy economy. But the so-called big data challenges are also evident, such as the fragmented energy data ownership and volatile availability, and lack of standardized dataflow between grid operators, state and national regulators, and the enlightened prosumers drowning in the data boom during this energy transition era.

Data silos have been challenging all aspects of scientific exploration and computing, and potentially leading to outdated decision making and nonoptimal solutions, even if it is from a well-curated problem that is solved by world-class supercomputers. In addition, the ever-growing information bubble and data silos lead to biased decision-making processes, conservative generation dispatch, less effective “no-regret” grid investments, and poor performance of grid resources and asset management. The recent Texas rolling blackout crisis urges a better, smarter, and more transparent way for grid operators and customers to understand energy generation and consumption in extreme environments. More importantly, the hidden data and model barriers among different utility departments and operational/information technology engineering groups also exist, and many of the conventional manual processes cannot be sustained with the vast volume of measurement data. Some of the model-based analyses done annually become obsolete due to fast-evolving grid generation mix and operation paradigm shifts.

Pacific Northwest National Laboratory (PNNL) has vast experience in working with utility partners and electricity infrastructure data, including the Eastern Interconnection, Western Interconnection, Texas, and Puerto Rico systems. Moreover, PNNL developed the Energy Grid Data Repository, funded under DR POWER (Data Repository for Power system Open models With Evolving Resources) [19] by the Advanced Research Projects Agency–Energy (ARPA-E). DR POWER is a joint effort by PNNL and the National Rural Electric Cooperative Association, and currently has more than 272,700 curated datasets comprised of more than 1 million downloadable files. In addition, PNNL has supported the Department of Energy (DOE) to develop a suite of prototype buildings covering 75% of the commercial building floor area in the United States; this includes 16 commercial building types in 19 climate locations for recent editions of ANSI/ASHRAE/IES Standard 90.1 and IECC, which results in 3,344 total building models [20,21].

1.3 Urgent Need for Co-design of Energy, Communication, and Computing in Smart Grid

Beside the challenges of energy data silos [4], another identified gap is measurement-based solutions, including modeling, algorithms, and methods such as Artificial Intelligence/Machine Learning (AI/ML). Additionally, tools and distributed controllers, need to be tested and made available to interested energy stakeholders [5,6]. Figure 3 shows various levels of potential computing/learning applications in the 5G fabricated sensing and control infrastructure. Those levels are edge, edge-based energy zone, region, and interconnection. Different energy stakeholders may have different capabilities and needs regarding energy service, communication and sensing service, and computing service. There are emerging needs for effective orchestration of energy domain computation at different levels, for which distributed computing/learning, cloud-based computing, and large-scale high-performance computing (HPC) resources should be identified and scheduled.

Furthermore, a traditional computing methodology would not be able to meet real-time operation requirements, in particular when collective efforts are needed to handle extreme weather events, but the current disaggregated yet siloed mechanisms fail. PNNL has completed extensive research to embrace these challenges, applying HPC techniques to real-world power system applications in the Western Interconnection, Eastern Interconnection, Texas, and Puerto Rico, such as state estimation [22], contingency analysis [23,24], dynamic simulation [25,26], dynamic security assessment [27], and real-time path rating [28] on cluster supercomputers. The team also used cloud computing to do research in an adaptive remedial action scheme parameter setting [29,30], and distributing HPC applications and power system commercial tools in the cloud.

Currently, a 5G communication fabric with the cloud provides the possibility of balancing data, model, and computing allocation and scheduling; as shown in Figure 3. And it serves as the foundation of codesign methodology for Energy, Communication, and Computing [31]. The cloud-edge computing techniques would be critical for online learning and control applications, and an HPC simulation platform that supports massive parallel simulation is a must for multi-agent reinforcement learning. All these computing capabilities will be significantly enhanced by 5G in terms of data collection at different layers and distributing simulation outcomes (commands and controls) to the corresponding recipients at different layers. A much more locally variable supply and demand profile is driving the need for greater and broader visibility throughout the grid, but in particular at the grid edge; and correspondingly, new distributed control methods are needed to respond to local conditions in a timely manner.

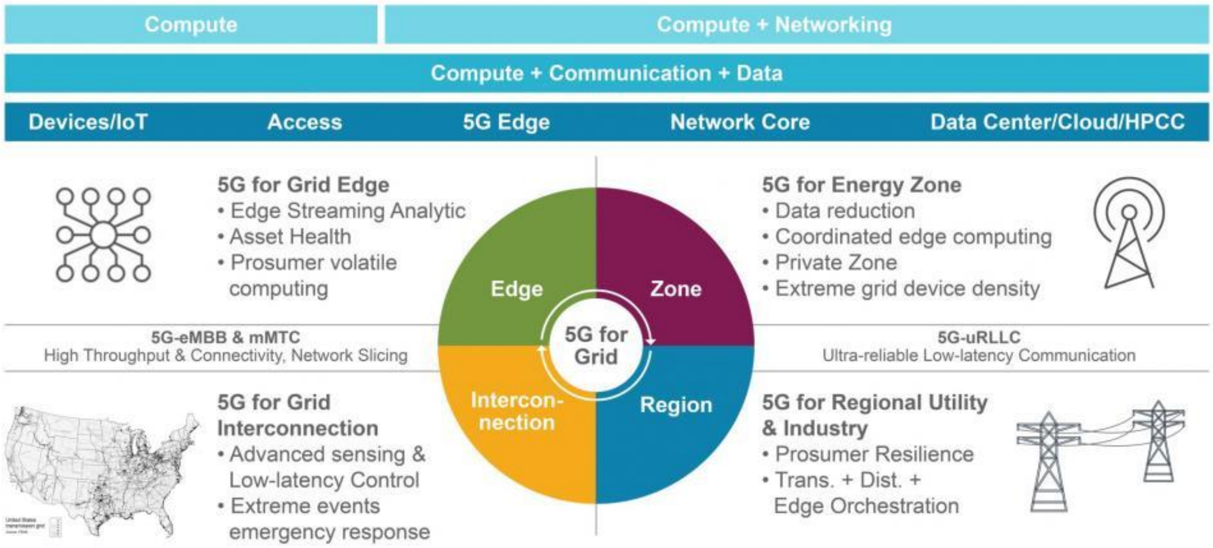


Figure 3. Integrated landscape of 5G communication, grid, and computing [31].

2.0 5G-Enabled Grid Data Transport and Applications

This project explores and develops a holistic 5G Fabricated Resource and Asset Management Encompassment for energy infrastructure (Energy FRAME) [32], which spans fast-evolving energy generation, transmission, and distribution, as well as the emerging prosumers who both produce and consume energy as more citizens generate their own power from DERs.

With 5G Energy FRAME, we provide participating stakeholders with shared access to the growing number of grid sensors and a diverse set of data for local visibility of extended grid state. With these capabilities, new sensors, analytics, and controls can plug into Energy FRAME without point-to-point integrations. New analytics can use authorized available data and publish new insights, enabling enriched data points, virtual sensors, or data aggregations. Applications can dynamically bind with different sensors as the configuration of the grid changes. This flexibility combines with a distributed network architecture and data-driven analytics to infer data when needed, and results in a highly scalable and resilient sensing data service layer. The function of the energy zone is to provide a reasonable yet efficient computing response by leveraging the 5G infrastructure for high throughput, low latency, and a substantial amount of data.

Figure 4 illustrates the proposed 5G Energy FRAME methodology, which embraces 5G technologies to break data silos, bridge computing resources, and enhance energy infrastructure asset management through cohesive data integration and intelligent analytics.

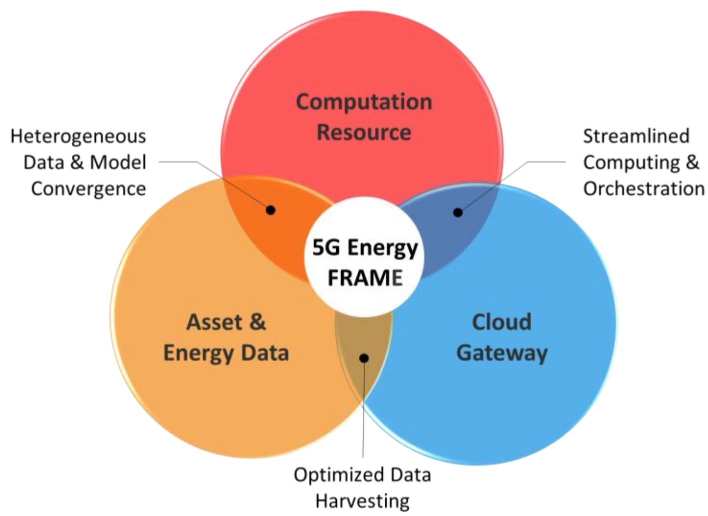


Figure 4. Overview of integrated objectives in 5G Energy FRAME project [32].

Therefore, we examined the technical characterization and benefit evaluation of the 5G communication platform, collected system performance data, and identified applicable grid monitoring and control use cases in the first phase of this project. This report documents the Year 1 work of the project team, in collaboration with PNNL Advanced Wireless Communication (AWC) team [33] and the PNNL CENter for Advanced Technology Evaluation (CENATE) team [34].

It should be noted that this project aims to explore the technology feasibility and address challenges (data silos among energy stakeholders, fragmented communication structures, and inadequate computing resource/analytics) that are not caused by energy policy. It is envisioned that the proposed methodology and platform can adapt with potential policy variations, as the transformational change of the energy industry and the role of consumers is inevitable.

3.0 Technical Characterization of 5G Communication Platform

The high throughput and lower latency of 5G can enable unique streaming analytics and data fusion functions at the level of edge, zone, and cloud computing, and permit an open/private edge-based energy zone enabled by 5G to cater to varying needs from different groups of stakeholders while supporting high connection density. 5G with integrated computing also balances computational burden at edge devices while minimizing the overflow of data. Further, advanced capabilities such as adaptive control logics and customized AI/ML models on edge devices can be reconfigured or upgraded whenever new features have been identified or new data has been incorporated for continuous training.

A clean energy economy brings an evolving energy infrastructure with emerging affordable technologies being adopted. Under the proliferation of DERs and innovative demand-side management, both the grid operators and prosumers need a simple yet effective framework during the transition from traditional centralized computing/learning systems toward large-scale distributed infrastructure, which can collaboratively perform complex computing/learning. Therefore, it is important to provide a baseline of system performances and characteristics of 5G communication platforms and solutions. In this case, the jitter, latency, security configurations, and available compute capabilities will differ greatly based on a user's physical location. In a mobile service provider's network, higher density urban locations will have more computing capabilities with lower latency, whereas rural areas will have limited edge compute capabilities deployed nearby, thus increasing the latency. The specific technical implementation and solutions from different vendors could also vary, such as the non-standalone (NSA) and standalone (SA) architectures for 5G; those could further impact the integrated solution for power utility customers as well as the underlying energy management system functions when 5G is incorporated.

5G NSA was developed to allow 4G network owners to deploy 5G radios with the 4G infrastructure and provide the bandwidth that 5G can offer. 5G NSA's primary feature is increasing the bandwidth of the wireless link. 5G SA utilizes a complete 5G infrastructure and can be used to increase bandwidth and reduce latency, network slicing, etc. The enhancement that 5G SA provides beyond increased bandwidth will be critical to solving challenges, i.e., performing automation in a distributed application such as coordinating DERs during grid emergencies.

Network slicing is a feature of a 5G SA system, and allows multiple virtual networks to be defined while sharing the same physical infrastructure. Figure 5 provides an example of multiple applications using the same infrastructure while operating on different network slices. Through software-defined networking techniques, each of these virtual networks, or slices, can be configured to support their own service requirements. These requirements can provide applications with separate logical networks that can have different levels of priority access, different security profiles, and different definitions for quality-of-service requirements. Network slicing can be used to ensure availability and latency for critical communications [36].

Traditionally electric utility systems have relied on private single-purpose networks to ensure the necessary operational performance for grid communications. This approach is challenged given the diversity and scale of the nonutility generation interconnections of DERs. An appropriately configured 5G network slice holds promise to provide the performance assurance of a single-purpose dedicated network, but now can also fulfill the future distributed grid scale and meet multiple different energy zone needs [37]. Some of these operational needs will require low-latency communications at the grid edge that are difficult to achieve in today's 4G deployed systems. Configuring a slice that uses 5G uRLLC holds promise to meet the increasingly dynamic distributed grid [38].

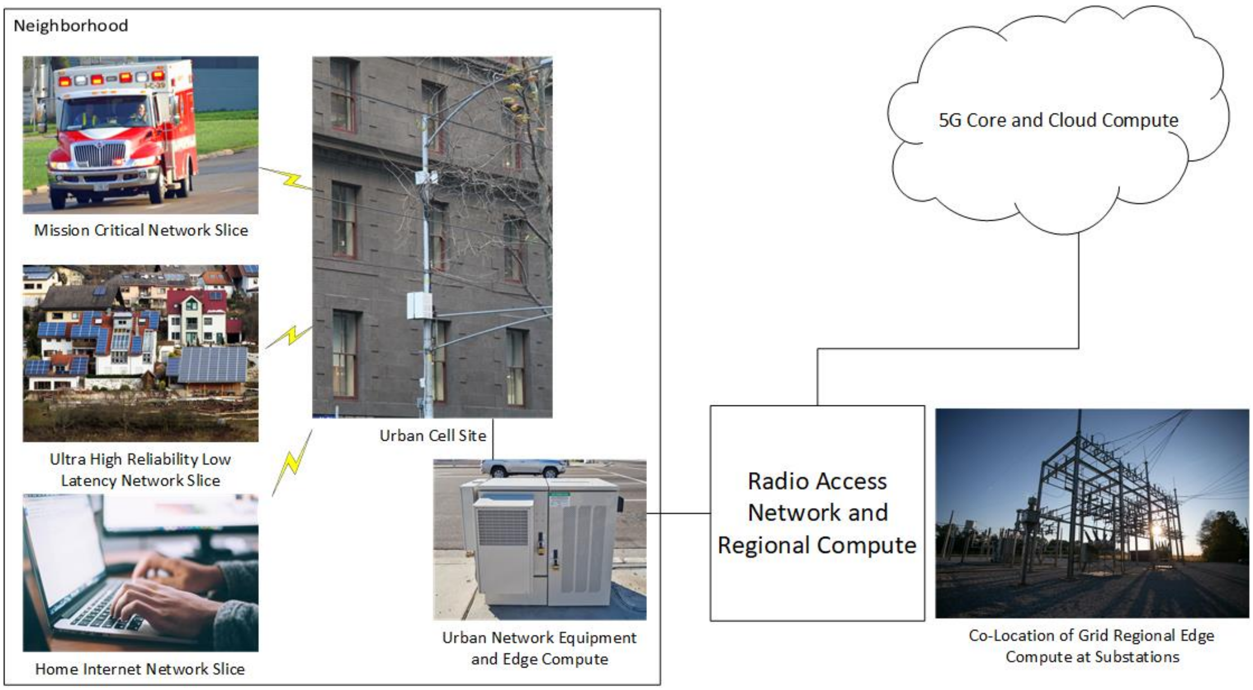


Figure 5. Example of multiple network slices with different priorities and requirements.

In this section, we provide a comprehensive technical characterization of 5G SA architecture based on PNNL's AWC platform. To be more specific, an end-to-end 5G-enabled data transport will be formulated to evaluate system performances, and data transport behaviors will be captured and aggregated through statistics and shared through publicly available data repositories. More importantly, we will use the hardware equipment and platform in the PNNL AWC 5G Innovation Studio and translate the promise of these capabilities into practical configurations to support grid-edge and edge-based energy zones. Throughout the project lifecycle, we will design a collection of testing scenarios in the 5G AWC, which may include: 1) a single 5G edge equipment test, 2) multiple 5G edge equipment tests, 3) a single 5G edge-based energy zone test with multiple edge equipment, and 4) integrated grid simulation platform based on the individual scenarios (1, 2, and 3) and interfaced with the cloud-based platform. A fully configurable 5G core network [35] will be employed to support fast implementation, and realistic evaluation and demonstration, of new concepts that may not yet be enabled on commercial 5G network deployments.

3.1 PNNL AWC 5G Innovation Studio

In 2020, PNNL established its first 5G testbed in the 5G Innovation Studio as part of the collaboration between the AWC team and Verizon. This state-of-the-art lab has been established on the PNNL campus in Richland, Washington, to support the Lab's mission to tackle some of the world's greatest science and technology challenges in areas such as national security, energy efficiency, and scientific discovery.

5G is a complex technology designed with many options, and is composed of state-of-the-art wireless waveforms, time synchronization, networking, security, and edge and cloud computing. But the simulations and analyses of 5G deployment need data from real testbeds and networks to build highly accurate models. The 5G Innovation Studio is used to obtain realistic data about the 5G system by utilizing real hardware to setup and configure 5G networks with a hardware-in-the-loop type environment. PNNL can setup and configure a range of 5G networks. This allows application simulators, emulators, and hardware to send data through different 5G networks as needed for the specific research question. The data collected can then be used to build models in larger scale simulations for the specific application.

Based on scientific research and engineering application needs, PNNL has multiple ways to implement a 5G network. PNNL has a collection of 5G equipment including 5G NSA with mmWave, 5G SA architectures, and spectrum analyzers as shown in Figure 6

Figure 6 PNNL AWC 5G Innovation Studio and equipment [33].

. In addition, Figure 7 visualizes the inter-relationship among individual components of the 5G communication platform at PNNL, as well as their potential configuration and extension to more resources and capabilities, i.e., an advanced computing platform either hosted on site or in the cloud environment. Such testbeds and capabilities can further be interfaced with other scientific and engineering domain testbeds, i.e., the Power Electronics Laboratory and Interoperability Laboratory both at PNNL.

Figure 6 PNNL AWC 5G Innovation Studio and equipment [33].

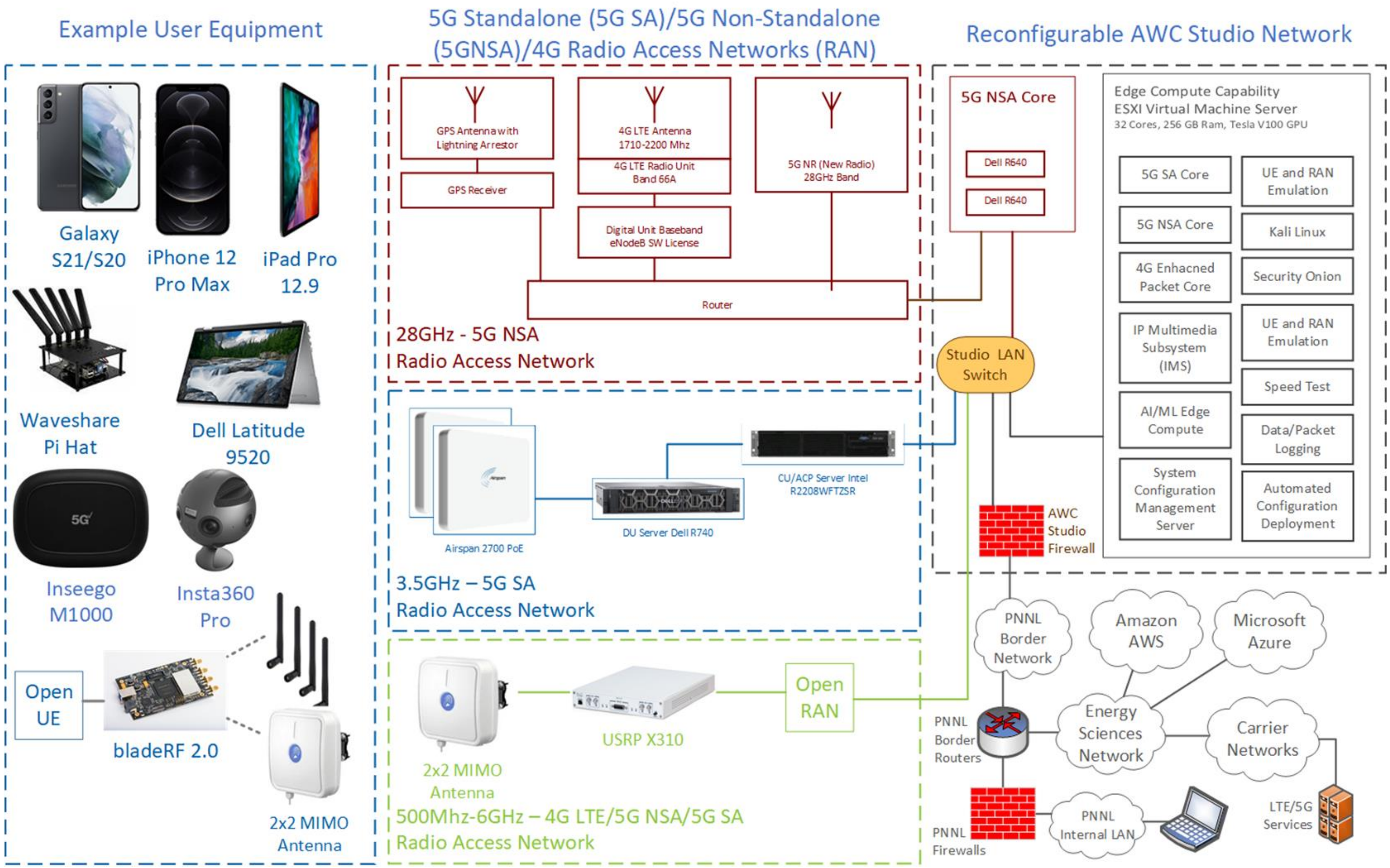


Figure 7. An illustration of PNNL AWC 5G communication platform.

3.2 Testbed Configuration and Simulation Design

A specific configuration has been designed to capture the system performance, enabling end-to-end evaluation. The DER and edge compute are two separate virtual machines (VMs) operating on the same host, which provides common timing to both VMs, and makes it easier to accurately measure time-sensitive properties such as latency. Moreover, each VM is connected to different virtual network adapters with separate virtual local area networks. This ensures that the two machines are configured to communicate through the 5G network. The logical setup of a DER VM connected to an edge compute VM located near the cell tower is shown in Figure 8 and Figure 9. Figure 8 illustrates the setup for Verizon's 5G NSA configuration, which provides a 28 GHz signal for the 5G user plane and an LTE anchor for the control plan. Figure 9 depicts the integrated 5G SA configuration that uses a 3.5 GHz signal for both the user and control planes.

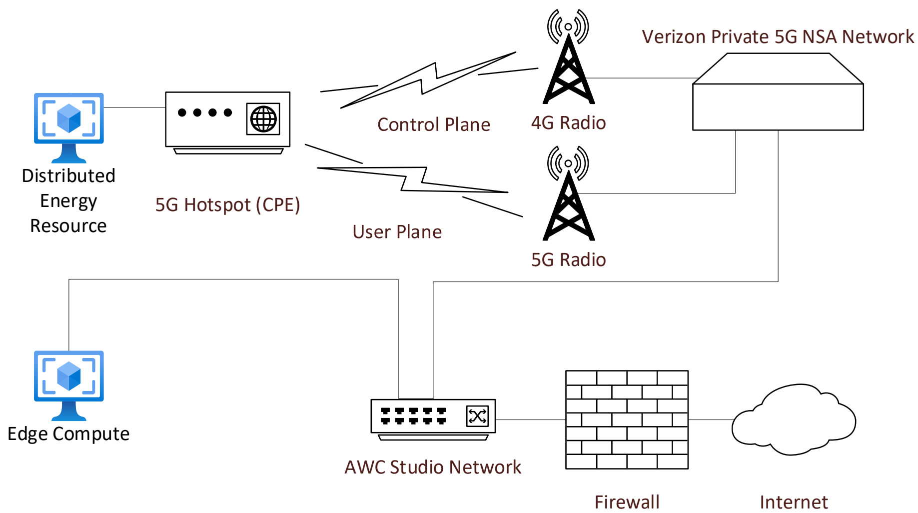


Figure 8. Verizon private 5G NSA network configuration and simulation design.

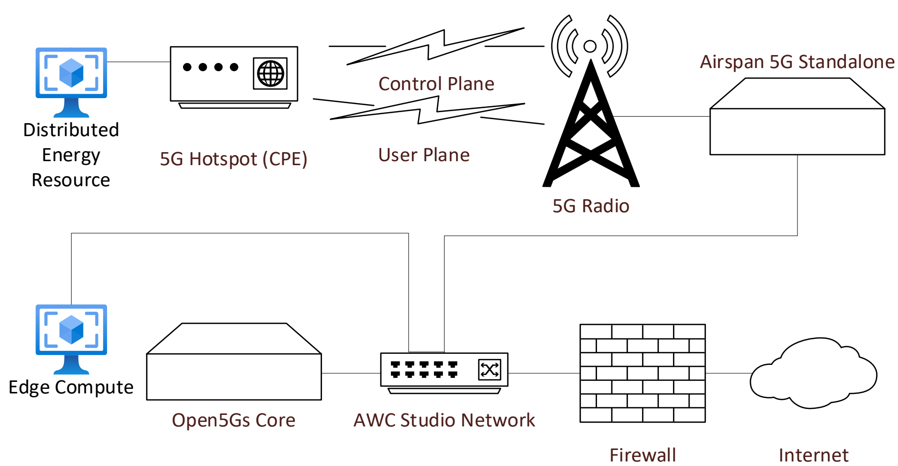


Figure 9. Airspan 5G SA configuration and simulation design.

Multiple tests may be performed using these networks from single data streams across a single hotspot, or through multiple data streams of different types with multiple hotspots. As an example, audio/video streams may be transferred through Real-time Transfer Protocols (RTPs); one example screenshot of the RTP data transfer using Wireshark is shown in Figure 10.

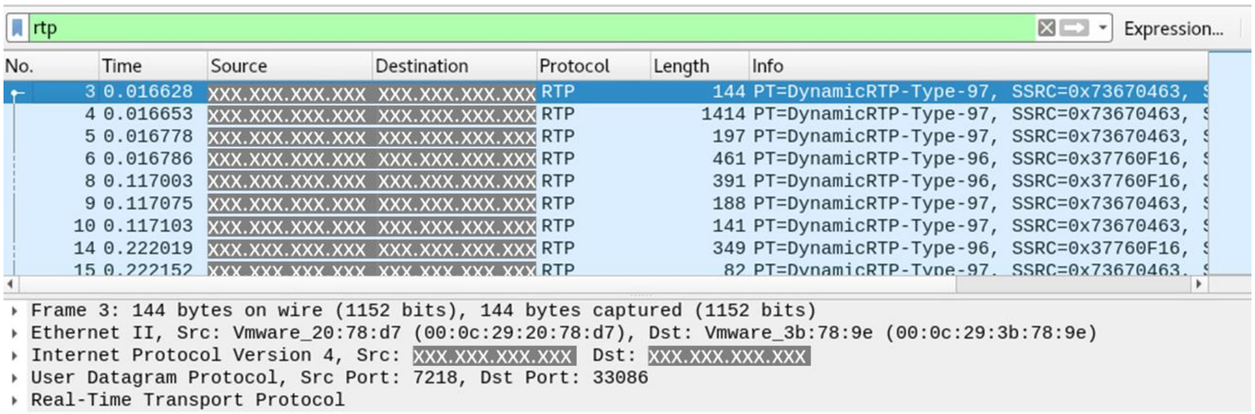


Figure 10 Wireshark packets with time-stamp information for performance evaluation on RTP-based simulations.

3.3 Performance Data of 5G Communication Platform

In this section, the corresponding performance data of a 5G communication platform is introduced and discussed, along with initial performance testing using audio/video streams, ping and iperf3 for User Datagram Protocol (UDP) and Transmission Control Protocol (TCP), and a speed test server. The following datasets are also available through the following publicly available repositories: *https://www.pnnl.gov/projects/5g-energy-frame/publications*

The initial data was collected with the Airspan 5G SA configuration as illustrated in Figure 9. An internal LibreSpeed test server [39] and iperf3 [40] with ping running concurrently were used to test and capture the testbed performance, including bandwidth, latency, and jitter. Also shown in Figure 9, the DER VM acted as the client to connect to both the LibreSpeed test server and the iperf3 server that operated on the edge compute VM.

Figure 11 shows upload and download data rates that were achieved from the 5G connected DER VM. The maximum data rate is 464.03 Mbps and the minimum is 148.69 Mbps, with an overall average data rate of 306.01 Mbps for downloading. Similarly with respect to the uploading, the maximum data rate is 62.54Mbps and the minimum is 37.97Mbps, with the average data rate of 52.43 Mbps.

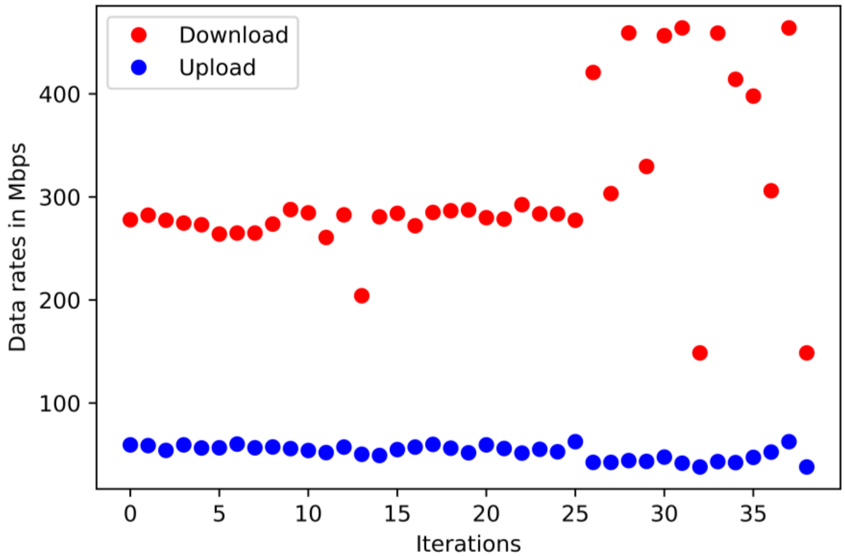


Figure 11. Performance of download and upload data rates, using DER VM as Client and internal LibreSpeed speed test server.

Figure 12 shows the roundtrip latency, and jitter with latency of packets when using LibreSpeed test server. The latency was between 15 and 37 milliseconds, with the jitter on the roundtrip packets between 2.5 and 18.31 milliseconds.

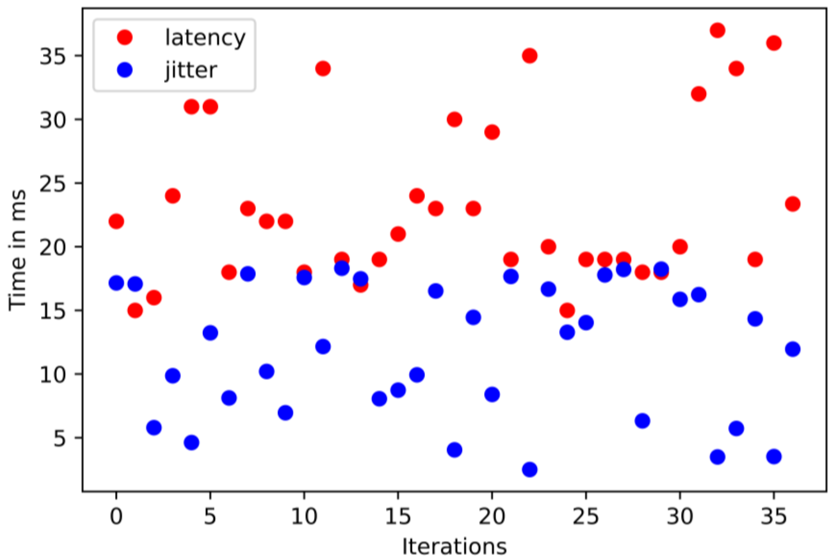


Figure 12. Performance of roundtrip latency and jitter, using DER VM as Client and internal LibreSpeed speed test server.

The performance data was collected using iperf3 and ping concurrently to measure the bandwidth, jitter of UDP packets, and roundtrip latency of the connection while under load. Download data rates were generated with iperf3, where the sender is the edge compute VM and receiver is the DER VM. Figure 13 and Figure 14 show the sender data rate compared to the data rate received.

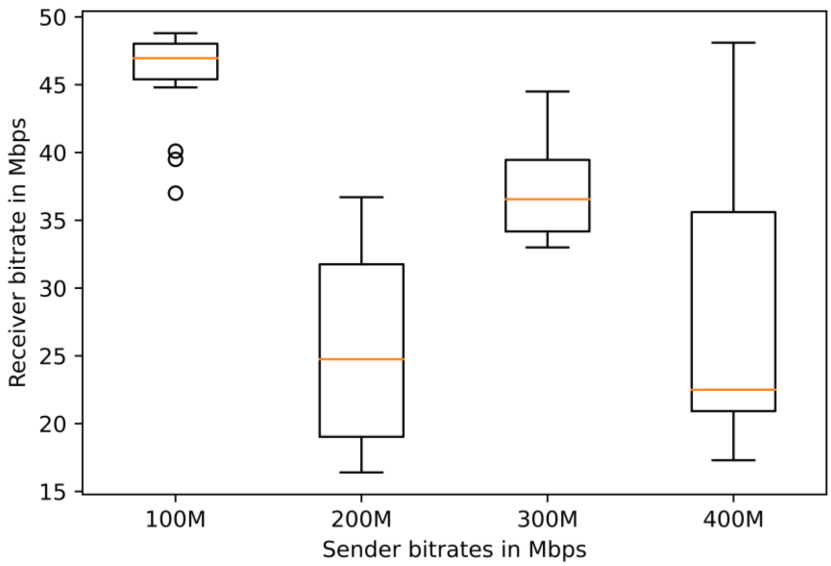


Figure 13. Performance of UDP Receiver (Edge Compute VM as iperf Server) vs. Sender (DER VM as Client) data rate using iperf.

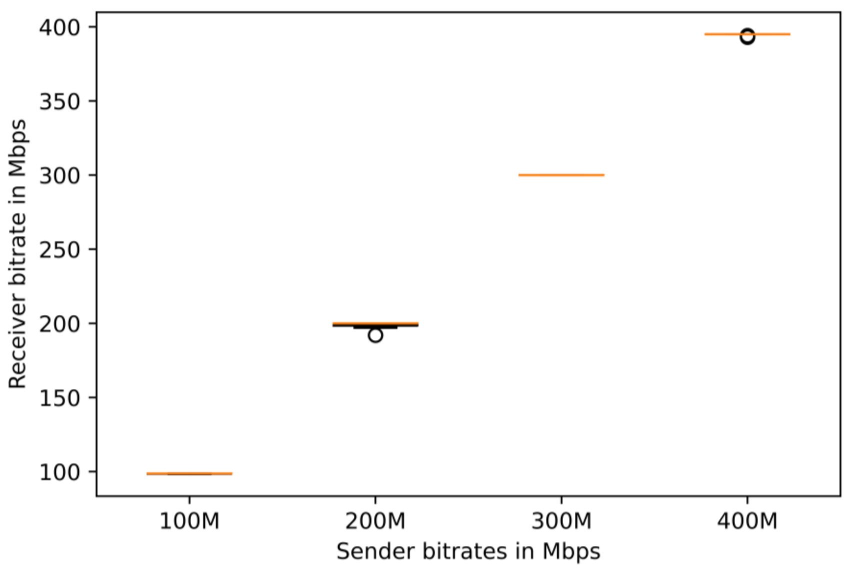


Figure 14. Performance of UDP Receiver (DER VM as iperf Server) vs. Sender (Edge Compute VM as Client) data rate using iperf.

Moreover, latency was measured using ping running concurrently with the UDP packet flow to measure the latency while the system is under load, and the results are shown in Figure 15 and Figure 16. Jitter was measured as the variance in arrival of the UDP packets sent by iperf3, the results of which are displayed in Figure 17 and Figure 18.

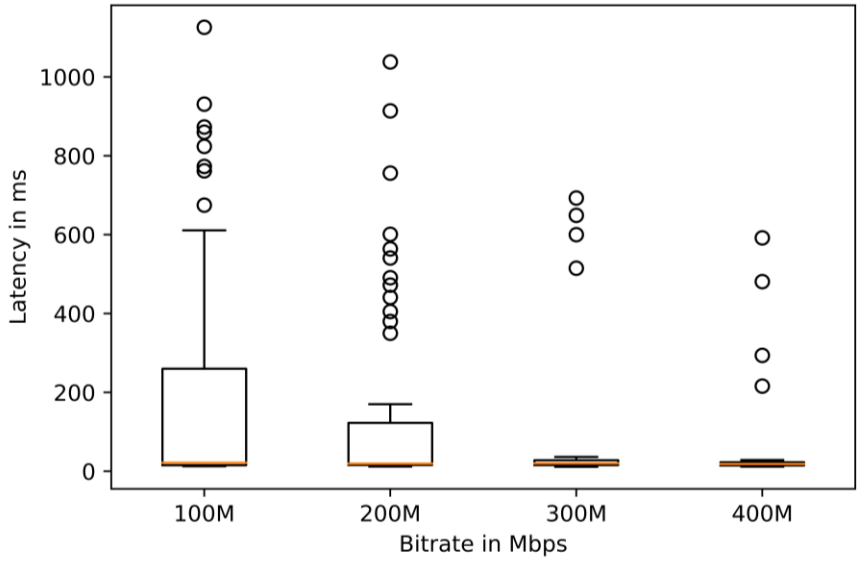


Figure 15. Performance of ping roundtrip latency with iperf UDP generating data on DER VM as Client and Edge Compute VM as iperf Server (upload).

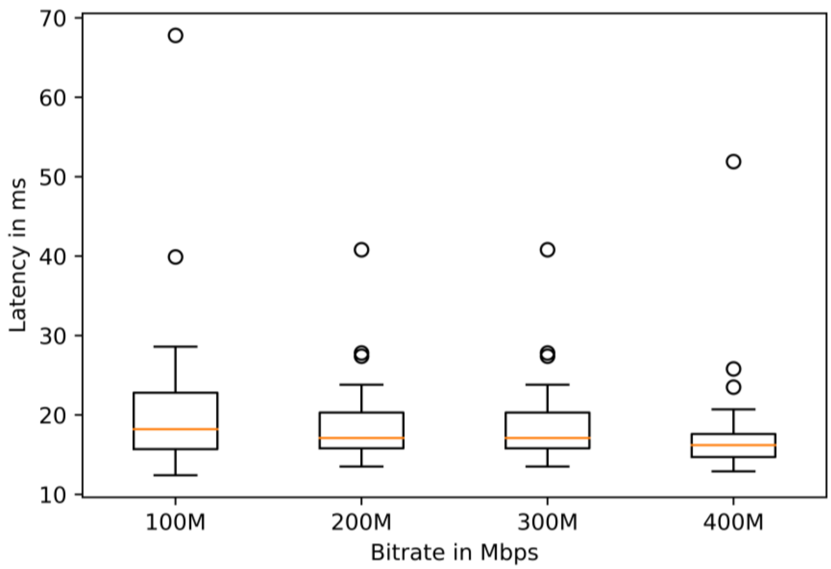


Figure 16. Performance of ping roundtrip latency with iperf UDP generating data on Edge Compute VM as Client and DER VM as iperf Server (download).

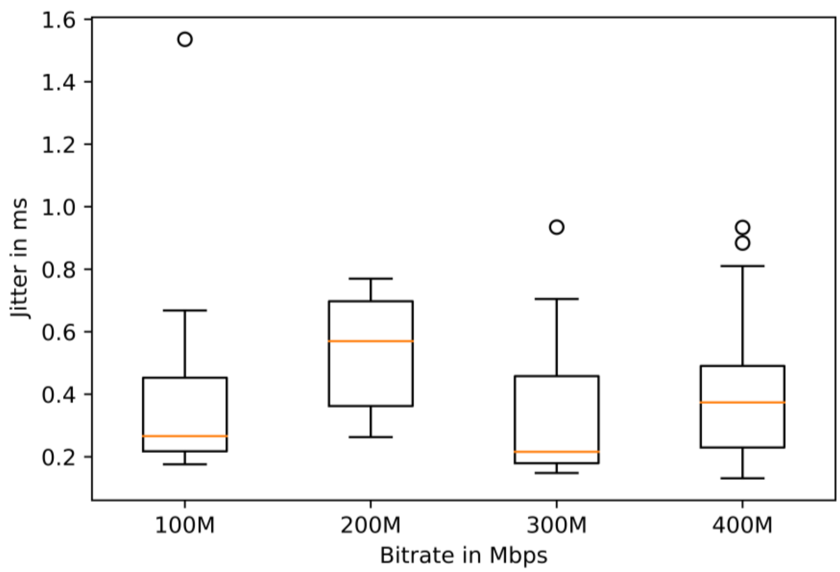


Figure 17. Performance of jitter using UDP with iperf UDP generating data on DER VM as Client and Edge Compute VM as iperf Server (upload).

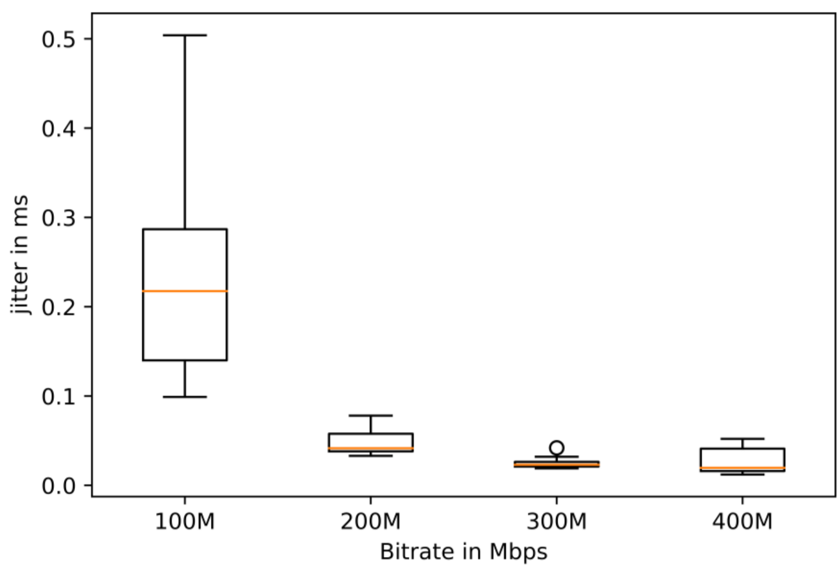


Figure 18. Performance of jitter using UDP with iperf UDP generating data on Edge Compute VM as Client and DER VM as iperf Server (download).

TCP type packets were sent by iperf3 with ping running concurrently to measure the effects of the TCP's window size over 5G, and to capture the bandwidth and latency of the system under load. Download data rates are generated with iperf3 in TCP mode with the sender being the edge compute VM and the receiver the DER VM.

The send vs. receive data rate corresponding to upload and download are shown in Figure 19 and

Figure 20. In addition, the latency data encountered by *ping* while TCP data were being sent is shown in Figure 21 and Figure 22.

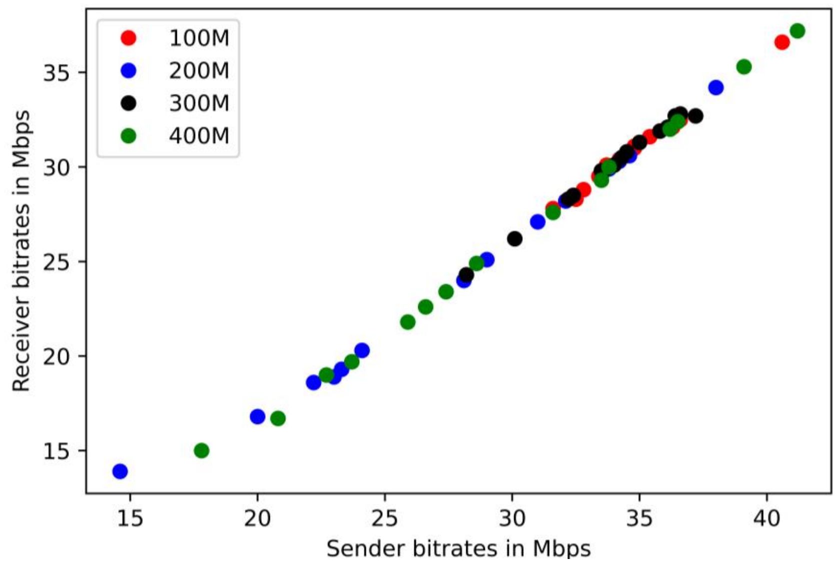


Figure 19. Performance of TCP Receiver (Edge Compute VM as iperf Server) vs. Sender (DER VM as Client) data rate using iperf.

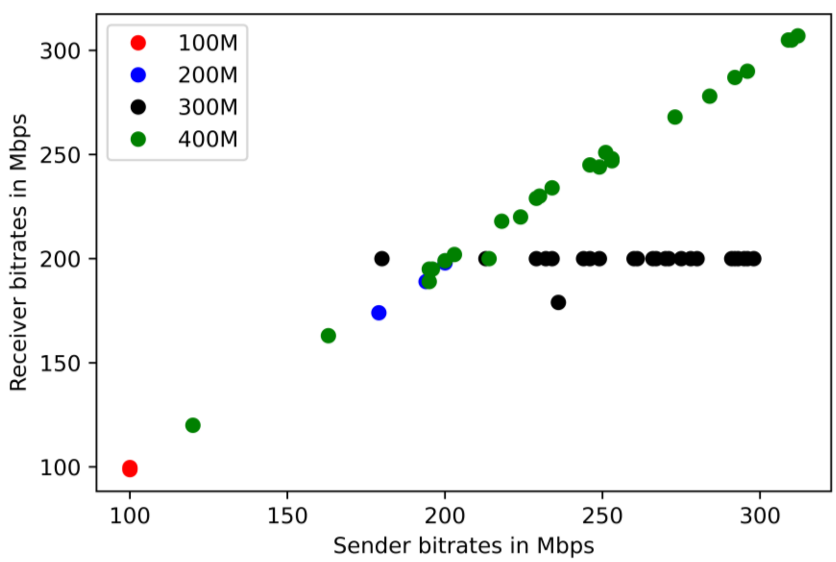


Figure 20. Performance of TCP Receiver (DER VM as iperf Server) vs. Sender (Edge Compute VM as Client) data rate using iperf.

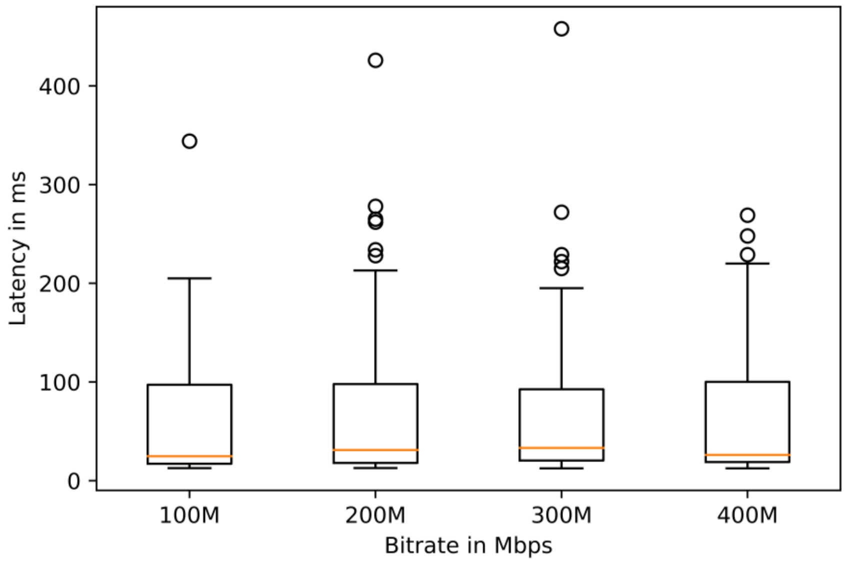


Figure 21. Performance of ping roundtrip latency with iperf TCP generating data on DER VM as Client and Edge Compute VM as iperf Server (upload).

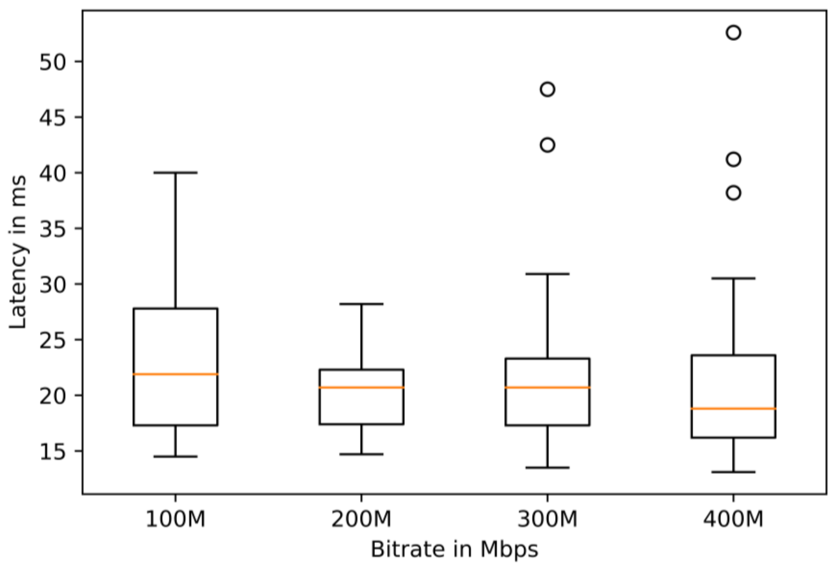


Figure 22. Performance of ping roundtrip latency with iperf TCP generating data on Edge Compute VM as Client and DER VM as iperf Server (download).

In summary, the data described in this section is the initial performance data that was collected using the Airspan 5G SA system. In the next phase, the project team will continue to test the base capabilities of the network, including:

- Comparing data with additional data collected using the Verizon private 5G NSA system
- Increasing the number of concurrent data flows across a single device
- Concurrently measuring upload and download data
- Increasing the number of devices that are connected and formulating various scenarios.

Furthermore, when both 5G SA and NSA performance data have been collected and analyzed, they should be comparable to deploying a local 5G network with edge compute capabilities at a given location. Power grid use cases and applications could be imposed and implemented in such a testbed. We plan to add latency to the control and data plane of the Airspan 5G network to emulate scenarios where parts of the 5G network core are located in different geographic locations.

Finally, latency will also be introduced to the edge computing servers to emulate scenarios where the edge compute is located on the 5G base station in a neighborhood cell tower, or at a regional location such as a power system substation, or in a more distributed manner depending on a given use case. It will be important to capture the data before introducing data from the power system simulation tools in order to provide an in-depth understanding of the network's capabilities, and also to develop a full suite of testing procedures that verify the network's functionality.

3.4 Go Beyond 5G Wireless Communication: The Frontier of Edge Computing for Enterprise Use Cases

5G's low latency is possible due to the distribution of HPC throughout the network. The User Plane Function (UPF) allows user data from a device to be routed to another device, local computing, or through the backbone network and internet. By deploying the UPF at the network's edge (i.e., at the cell site), data from a 5G device can be routed to adjacent compute servers within milliseconds. With the latest software and hardware, it is possible to send 5G radio frequency data directly to a local computing resource, i.e., graphical processing unit (GPU). In this case, the latency will be minimized by performing all the processing of the 5G stack and deploying the UPF inside the same GPU, making the user data available to other analytical functions without leaving the GPU.

In this case, the GPUs become an integral part of the cellular service infrastructure and provide for processing user data without incurring the latency necessary to transfer data between the GPU and any interfaced central processing unit (CPU). Understanding the limitations and security of these systems will be critical for low-latency applications, such as the fault protection function and grid emergency response, by coordinating battery energy storage systems and other DERs. For example, the converged accelerators concept proposed by NVIDIA has been implemented in their products, A100X and A30X, which enables a unified platform of networking and computing, and further can be customized to deliver such combined capabilities in edge computing, telecommunications, and various enterprise business use cases [41].

With these emerging hardware and software capabilities, low latency may be assured and bring benefits to power grid applications, in particular for the future power-electronics-dominated grid when there are more interactions between power system transmission and distribution networks. Communication technology could provide benefits by controlling different locations and equipment with customized parameters for power generation [42], though it is anticipated to be enormously complex considering the evolving landscape of synchronous generators, and grid-forming (GFM) and grid-following (GFL) inverters in transmission and distribution (T&D) networks. But there is potential to employ an advanced and new coordination and control scheme, through the integrated computing and communication capabilities, to maximize benefits during the grid evolution stage [43]. Additional examples and applications include monitoring system conditions in real-time, facilitating frequency control, and enabling seamless communications among multiple neighboring areas for local and wide-area situational awareness.

With GPUs being a part of the cellular service infrastructure, more powerful functions will be unleashed with excellent performance in both computing and AI/ML. Processing locally on GPUs can help preprocess and filter data for different applications at different locations (i.e., cloud, upper level, or local), with reduced data size and minimized risk. Potential power system examples and applications include behind-the-meter load estimation, energy usage forecasting, bad data detection, and model/parameter validation and verification. Using advanced AI/ML algorithms, such as deep learning, incremental learning, and federated learning, more functionalities can be explored such as processing local image/video in real time to capture/predict the changes/trends for decision making, continuously upgrading the AI/ML model with new data while preserving knowledge previously learned, and enhancing system prediction collaboratively while maintaining data privacy at the edge, which is a must-have function for power utility companies.

3.5 Go Beyond 5G Wireless Communication: A PNNL Reinforcement Learning Example for More Efficient 5G Network by Federated Learning Workflow

PNNL CENATE researchers [34] have been working on both ns-3 [44] physics-based simulations, and neural-network-based approaches, for automatic topology creation of 5G networks and adaptive power reduction using signal strength optimization. Specifically, the ns-3 model provides flexibility to test federated learning models and algorithms, and can be used to model 5G network behaviors. In their study, network tuning focuses on transmission power of User Equipment (UE) and Next-Generation Enhanced Node B (GnB), as well as the power used by the PUSSH and PUSCH channels. Another tuning candidate is the beamforming type, which includes choosing between five available types in ns-3 and the corresponding burst periodicity. The burst periodicity is the frequency at which signals are being sent out of the antenna. This value is also used to pair UEs to GnBs. Lastly, topology parameters are vital for lowering interference at the GnB level. If the UEs are well-balanced between the available GnBs that can lower potential interference. Spreading the UEs evenly across the GnBs is not an option since it would waste potential resources that could be used by other users of the network.

In ns-3, the 5G-LENA New Radio core module can simulate a 5G SA network, where the 5G NSA network is usually overlaid on top of the 4G LTE network architecture. Importantly, additional capabilities should be formulated or explored to connect the ns-3 simulated nodes to external hardware or VMs, thereby allowing more flexible, sophisticated, customized, extended network structures/configurations to be evaluated [45,46,47].

This work simulates a simple federated learning setup, and by using ns-3 alongside the Direct Code Execution Module, it allows interactive clients and the New Radio core module. In preliminary experimentation, eight clients are divided between two servers. Each of these clients trains a local model using a random assortment of pictures and sends the model weights to a centralized server. Once the central server receives the weights, it calculates an average of the weights and returns the average back to the clients. This setup allows us to explore the impact of having two groups executing federated learning workloads on the resulting noise of the network. This work also found that federated learning style workloads, many-to-one and one-to-many nodes, produce higher signal-to-interference-plus-noise ratio (SINR) compared to traditional one-to-one network communications. This result is observable even between a one-client-to-one-server setup and a two-clients-to-one-server setup. The latter has a measurably lower SINR compared to the initial setup, indicating that more noise was present in the network compared to the initial setup.

Some highlights of CENATE results are given in Figure 23. The team found that, compared to a commonly used heuristic, using a dynamic approach (reinforcement learning) can lower the average SINR by 12.5%. This means that adaptive UE connections can lower signal noise, thus reducing the need to resend data in the network. By dynamically adapting the parameters of the network, bottlenecks were reduced as observed during a linear regression run.

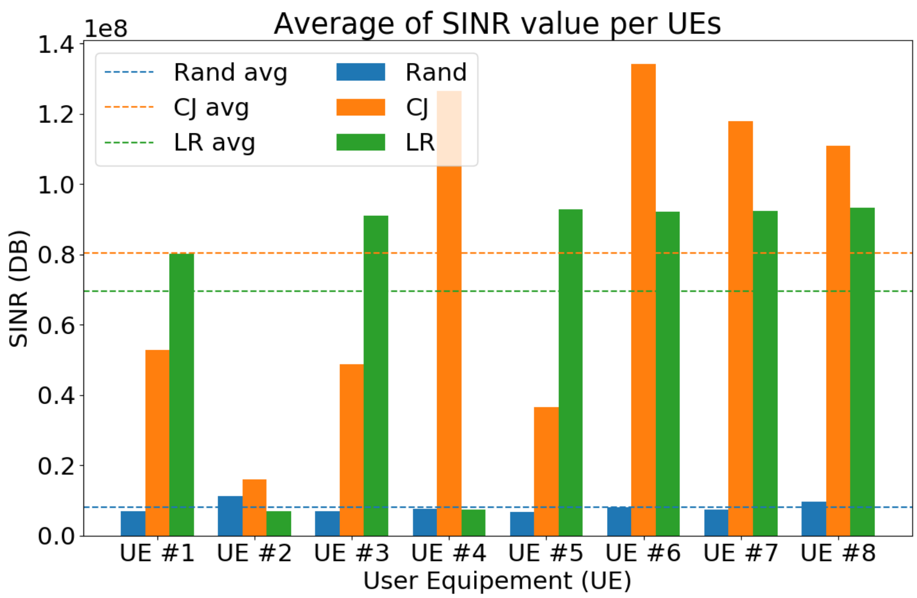


Figure 23. PNNL CENATE results.

In this scenario, a bottleneck happens when the SINR of a UE is significantly lower relative to the other UEs. For example, UEs #2 and #4 are considered bottlenecks for the linear regression run. Also, there is a 10X increase in the resulting SINR compared to random, which shows that their model learns from the changes in SINR when the network's parameters are updated. In the future, the team plans to explore applications of ML-based tuning on spectrum-sensing tasks in a 5G network. Spectrum-sensing can be considered a mathematically intractable optimization problem [48], so ML may be well-suited for approximating a solution. This also interests power utility companies, emerging grid service aggregators, and energy prosumers, as the available communication technology and energy management service may all relate to spectrum management to some extent (i.e., Citizens Broadband Radio Service spectrum in the 3.5 GHz band).

In summary, this federated learning example for a more efficient 5G network demonstrates the benefits of software-based simulation and potential with a hardware-enabled platform; in addition, the developed capability complements the codesign of energy, wireless communication, and computing domains. Considering the growing trend of high-impact, low-probability events such as hurricanes, post-event infrastructure restoration will not only benefit from a codesign framework, but also lead to enhanced survivability and broader societal impacts.

4.0 Benefit Evaluation of 5G Communication Platform for Grid Applications and Use Cases

Operations for the future high DER and storage grid architecture will include centralized, distributed, and decentralized control modalities that dynamically shift across that continuum depending on the state of the grid. The physics-informed data structure can be enhanced to support a more dynamic architecture model spanning the control methodologies. Considering the complex nature of power system T&D network models, it is critical to explore a generic way to interface and represent transmission, distribution, and communication (T&D&C) networks, so new technology like 5G could be effectively assessed and its potential quantified regarding various grid applications and use cases.

Therefore, the coordination of T&D&C systems [45] should respect the physical properties and operational constraints of individual networks; more importantly, the developed methodology will also help identify the convergence of common characteristics among different types of models, as well as key attributes for cross-domain and integrated interdependency analysis. In this project, we will adopt a high DER penetration scenario for integrated T&D&C networks to explore and demonstrate the benefits of 5G technologies for grid use cases.

4.1 Base Network Model for Transmission and Distribution Use Case

The simulated T&D&C networks consist of one transmission network *T* and multiple replicas of the testing distribution network *D*. The *T* network is a modified miniature Western Electricity Coordinating Council (miniWECC) model including 41 synchronous generators and 21 load buses [49]; an illustrative diagram is shown in Figure 24. More specifically, load buses #24 and #69 are the original miniWECC buses, then the other 19 are newly added interconnection buses for test feeders. Table 1 lists the load bus information, including interconnection bus numbers, and the corresponding miniWECC bus numbers and names.

Each load bus is connected to one *D* network, which is the modified IEEE 8500-node test feeder [50]. Within each *D* network, there are 550 embedded, including 275 GFM and 275 GFL inverters shown in Figure 25. Overall, the integrated system contains 100,000+ nodes and 10,000+ inverter-based resources (IBRs).

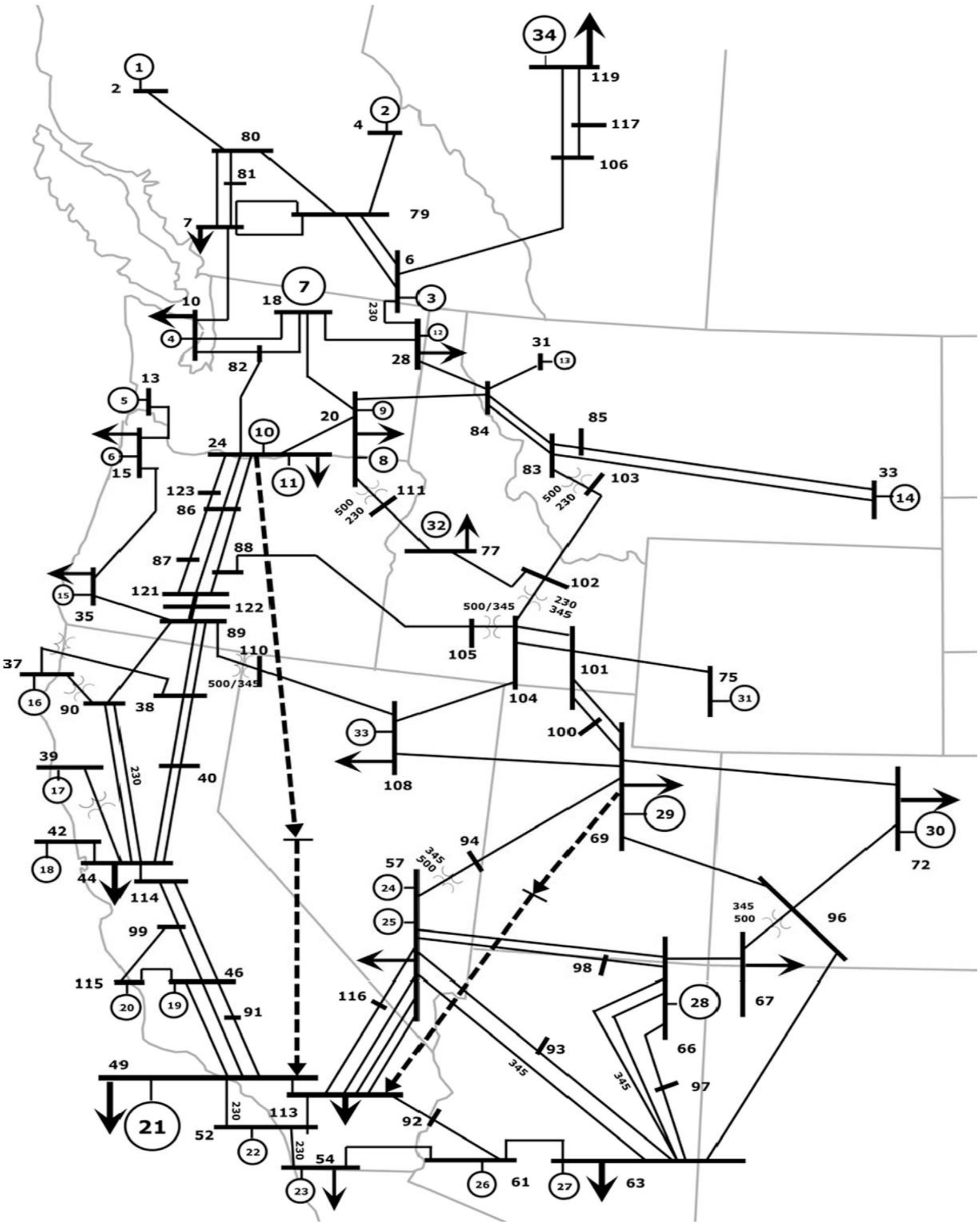


Figure 24. miniWECC test case [49].

Table 1. miniWECC Load bus numbers and names.

Added Load Bus #	miniWECC Bus #	miniWECC Bus Name
24	24	JDAY-24
69	69	Slc
1008	8	BCH-8
1011	11	SEA-LOAD
1016	16	ORE-16
1021	21	ORE-21
1026	26	ORE-26
1029	29	BDY-GEN
1036	36	ORE-36
1043	43	SFO-LOAD
1050	50	SC-LOAD
1055	55	SDG-55
1056	56	LAS-LOAD
1064	64	PHX-LOAD
1070	70	SLC-LOAD
1073	73	COLO-73
1078	78	IDA-78
1095	95	FC-LOAD
1109	109	NEV-109
1112	112	SC-112
1120	36	ORE-36SE

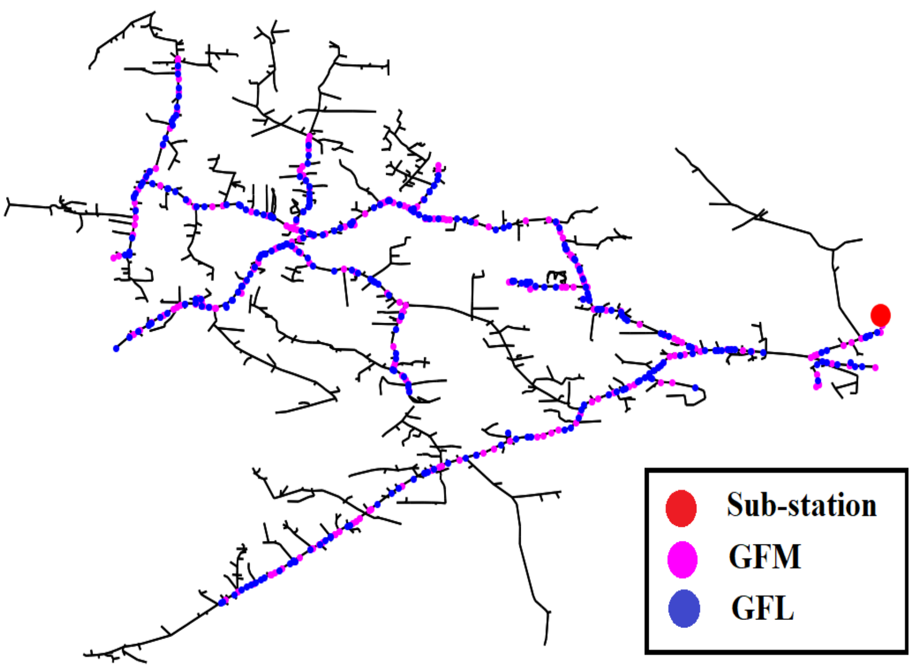


Figure 25. Modified IEEE 8500-node feeder test case [50].

4.2 Preliminary Results of Graph-based T&D Resilience Evaluation

We start out with a streamlined graph-based topology assessment for the integrated power system T&D networks and then extend to T&D&C use cases in the next subsection. An HPC cluster with 40 nodes and a total of 2,400 CPUs is utilized to process this integrated T&D network [51]. In short, the node-ranking results not only verified the applicability of the proposed method, but also revealed the potential of distributed GFM and GFL inverters interacting with the centralized power plants. Two case studies were conducted to demonstrate the effectiveness of the proposed topology assessment method.

In Case 1, we assessed the resilience of the topology under normal operation, when energy flows from generators in the *T* network to loads in the *D* network. We identified the most important nodes in both networks using the cross-closeness centrality and the cross-betweenness metrics; these results are valuable for both planning and operational purposes. For example, new equipment can be planned to reduce the number of nodes with excessively high importance. In normal operation, more resources can be allocated to nodes with high importance to enhance the reliability of the grid. In a restoration effort, the nodes with high importance should be prioritized to help the system recover from a disaster as soon as possible.

The identified top-ranked nodes in the *T* network using the cross-closeness and cross-betweenness centrality are shown in Table 2. Close observations reveal that seven nodes are ranked top ten by both metrics, which indicates the nodes that are the closest to the *D* network are also the most important hubs during the energy exchange between the generators in the *T* network and the nodes in the *D* network. Furthermore, the top-ten ranked nodes by the cross-closeness centrality are all located in the middle of the WECC region; in particular, the node 108 is close to the geographic center of the whole WECC region.

Table 2. Critical nodes in the *T* network for the interdependency between *T* and *D* networks.

Rank	Cross-Closeness Centrality	Cross-Betweenness Centrality
	Node	Node
1	108	69
2	89	89
3	110	108
4	69	24
5	35	110
6	86	35
7	24	44
8	104	57
9	15	96
10	96	63

For the *D* network, because each of the 21 test feeders is directly connected to a load bus of the *T* network through its substation node, which is not only the closest node to the *T* network, but also serves as the root of a test feeder model; all energy exchanges (can be bidirectional) between *T* and *D* networks need to go through it. According to both the cross-closeness and cross-betweenness centrality metrics, it is evident that the substation node and the nodes adjacent to it are the most important nodes in the *D* network.

In Case 2, we investigated the resilience of the system in a black-start restoration scenario. There are eight of the 41 synchronous generators being randomly selected and assumed to be black-start capable: #2, #10, #13, #15, #18, #22, #28, and #33. Then the distribution of node importance was compared in the system under different circumstances: A) solely relying on traditional synchronous generator-based black start; and B) with the help of GFM inverters. In Scenario A, eight generators will start independently and deliver power to the other 33 generators without black-start capability through the *T* network; while in Scenario B, the GFM IBRs in the *D* networks also have black-start capabilities. The eight selected black-start synchronous generators, along with all the GFM nodes, will supply power to the 33 generators.

To account for the differences among different generators and GFM IBRs, the calculated cross-betweenness centralities are weighted by the power capacities (MW) of the source black-start generators/IBRs, respectively. As a result, larger weights are given to generators with higher capacities, whereas IBRs are assumed a uniform capacity of 250 kW. The distribution of the importance of transmission buses are presented in Figure 26. Kernel density is employed to estimate the distribution density of the nonzero normalized betweenness centralities in both scenarios. Comparing these two distributions of grid bus importance, the distribution for Scenario B is much flatter, i.e., has much fewer high-importance buses and more low-importance buses. This suggests that by involving GFM IBRs, there are fewer critical buses in the network for black-start restoration, which makes the system more resilient.

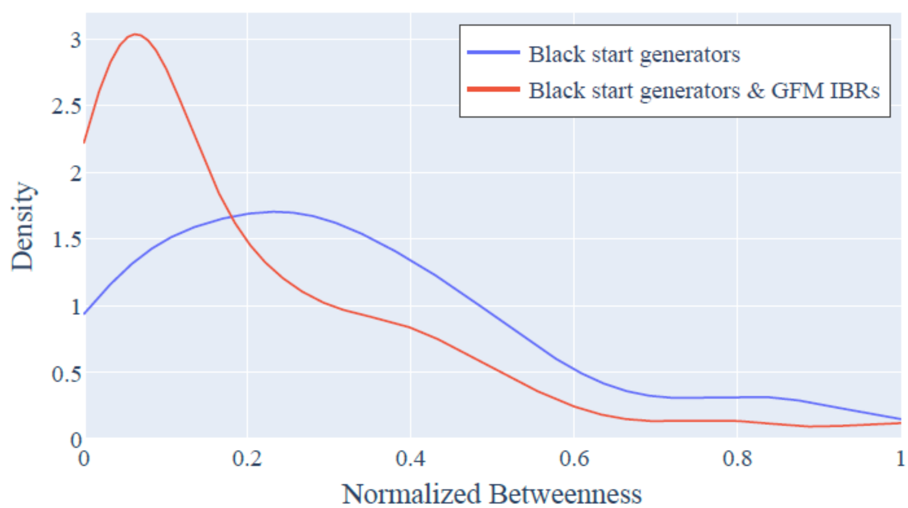


Figure 26. Comparison of the distribution of transmission bus importance during black-start restoration with and without GFM IBRs [51].

4.3 First 5G for T&D&C Grid Use Case at PNNL

To effectively evaluate the benefits introduced by 5G technologies, communication networks should be created to perform use case evaluation regarding 5G. For power grid transmission networks, we leveraged existing methodologies from the team's previous work [46] to create a synthetic communication network model for the Western Interconnection (Figure 27), which includes three Reliability Coordinator control centers:

1) California Independent System Operator (RC West) at Folsom, California
2) Bonneville Power Administration at Vancouver, Washington
3) Southwest Power Pool at Little Rock, Arkansas

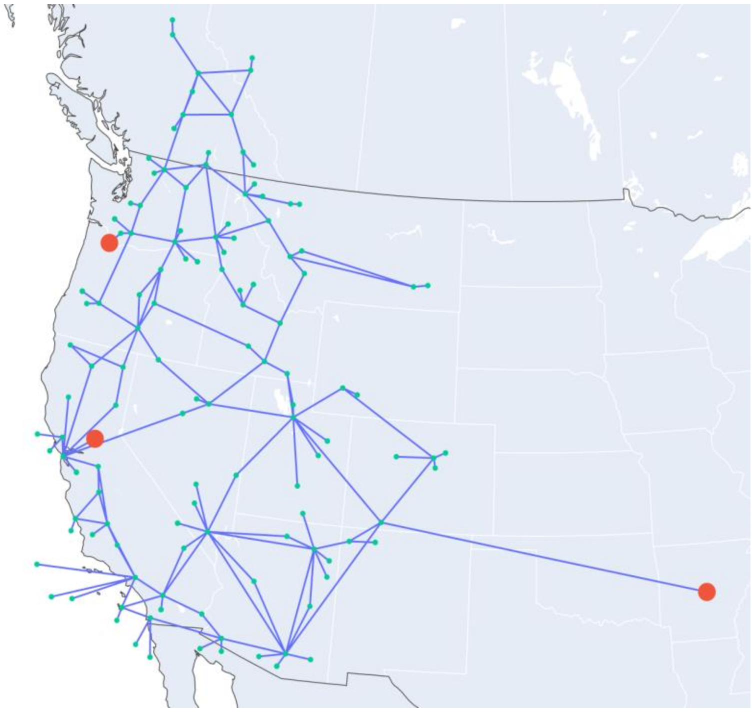


Figure 27. Synthetic communication network for miniWECC transmission network model.

For a distribution network model, a 5G base station deployment may be optimized considering the availability of edge computing resources, accessibility of computing (locally or via low-latency communication) at various locations, and the computing needs of grid monitoring, control, or protection applications. The grid and its customers are expected to benefit from advanced control and coordination, which requires accessible and sufficient computing resources. Centralized and distributed methods have been proposed for different kinds of coordination [52,53]. The performance of distributed control methods may be significantly affected by placement of advanced controllers, which in turn is highly dependent on the accessibility of computing resources. Therefore, this will be an interesting and important co-design problem in the power system planning domain as fine-grained, real-time controls gain wider adoption. As an example, we proposed and implemented a clustering-based method to plan the placement of 5G base stations for power system applications. The 550 inverters were partitioned into different numbers of clusters using the k-means method and calculating the within-cluster sum of squares (WC-SOS), as shown in Figure 28.

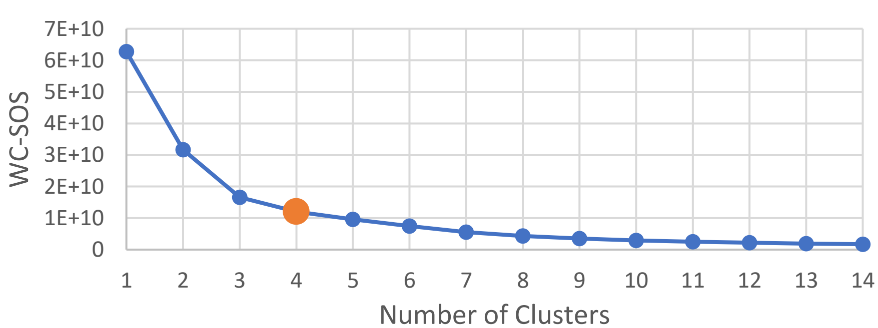


Figure 28. Identifying optimal cluster number for modified IEEE 8500-node feeder model with distributed IBRs.

Using this elbow analytic method, we selected four as the optimal number and grouped inverters into clusters (as shown in different colors in Figure 29). A 5G cellular network base station may be deployed at the centroid of each cluster for optimal coverage. Furthermore, a tree-like backhaul network is assumed to connect base stations to the wired core network originated from the distribution substation. Note that, in practice, the range of a base station depends on the frequency band, terrain, user density, etc. For instance, a 3G/4G/5G macrocell base station can cover up to 150 km in a plain area, whereas the range of a 5G mmWave base station is about 250–300 m [54]. The use case in Figure 29 is an example of a reasonable configuration, and further tuning could be performed based on the specific use case and simulation configurations.

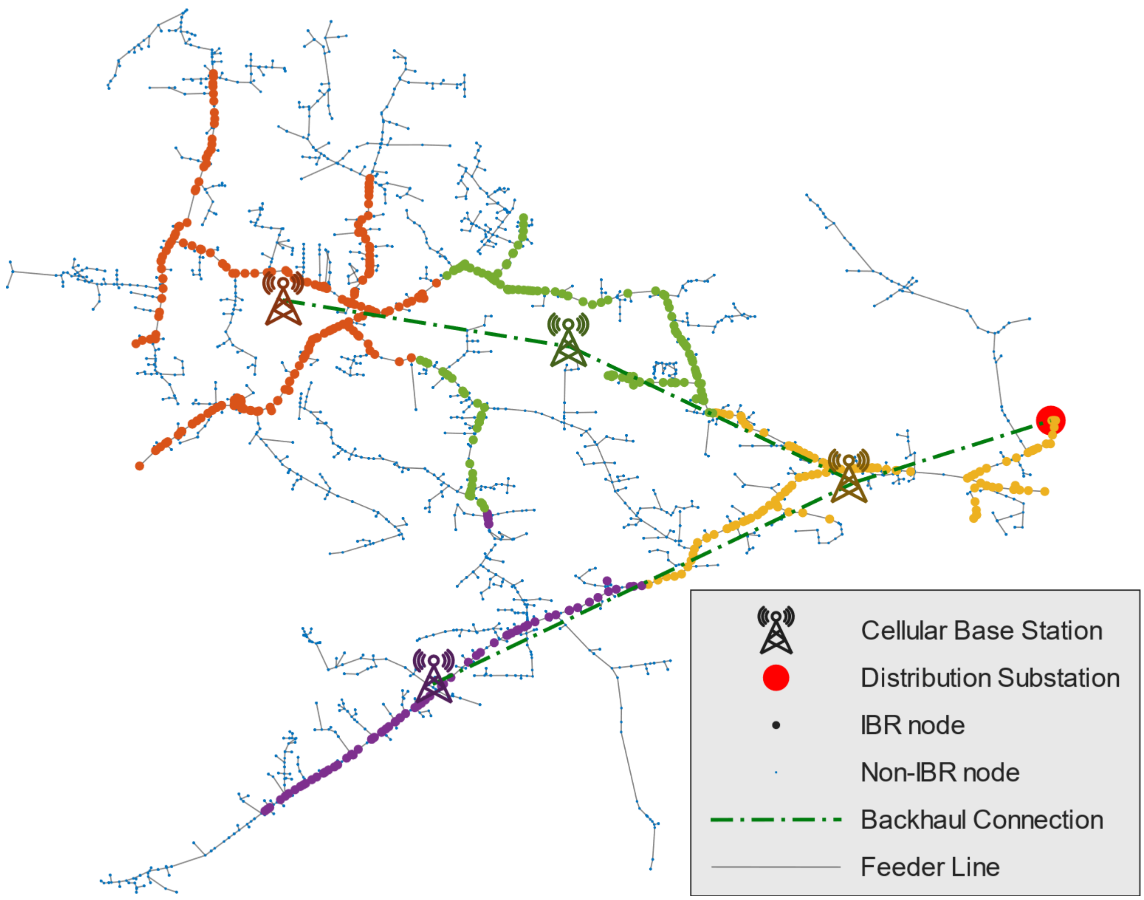


Figure 29. Integrating 5G into the T&D&C grid use case.

With this communication network overlayed on top of the distribution feeder, we can extend the graph theoretic analyses in previous sections with more details at distribution-level applications. This now opens up possibilities for future studies regarding T&D&C network interdependency, along with various higher level applications [55,56]. Furthermore, packet-level dynamic simulations on the communication network can be performed in ns-3 to validate the results of graph theoretic analyses, which is a natural extension of our previous study in this research domain [57].

5.0 Next Steps for 5G Energy FRAME

The 5G Energy FRAME project kicked off in August 2021, by August 2022 the project team has achieved the research goals, and established strong collaboration with PNNL AWC and CENATE team despite the challenges posted by pandemic and in-person laboratory work restrictions. This section provides an summary of Year 1 progress and an overview of year 2 projected research.

5.1 Year 1 Summary and Year 2 Overview

The first 5G grid use case focuses on a 5G-enabled communication network modeling for a T&D use case with high penetration of IBRs. To fulfill the envisioned use case, the miniWECC transmission network was interfaced with multiple modified IEEE 8500-node feeder models, and an innovative graph metric-based method has been applied to generate a corresponding communication network for T&D networks. To be more specific, in our use case a *T* communication network mainly relies on optical fiber and microwave technologies, while in a *D* communication network there are graph-optimized 5G base stations to provide the connectivity and services to those inverters within its radius.

With the completed technology characterization and initial benefit evaluation in Year 1, 5G has shown great potential to support various power system functions, especially to the new distributed control paradigm considering the proliferation of DERs. Therefore in Year 2, the newly generated communication network could be simulated and assessed through both a software-based platform (i.e., ns-3) and the PNNL AWC testbed in the 5G Innovation Studio. More importantly, a full assessment with 5G NSA deployment, as well as 5G SA deployment, may be performed with current AWC testbeds supported by Verizon and Airspan. Lastly, based on the collected communication performance data including bandwidth, latency, and jitter, a multi-objective optimization problem [58] can be formulated and solved considering the accessibility and availability of computing, communication, and grid monitoring/control resources.

Another important research task in Year 2 will be the cloud-based Energy Data Marketplace (EDM) and Energy Learning Warehouse (ELW). As an EDM, this platform aims to break the data silos between different groups of stakeholders, speed up information sharing across multiple domains and large geographical regions, and foster aggregated intelligence filtering capabilities based on distilled data from edge devices and edge-based energy zones. EDM will host all the data, model, and extracted intelligence that are connected to 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, i.e., utilities, prosumers, microgrid and smart building operators, DER aggregators, energy service providers, smart communities, and researchers. Moreover, the proposed ELW platform supports continuous integration and delivery (CI/CD) of edge computing functions and ML models as well as the efficient yet flexible distribution/deployment of retrained edge computing models. ELW is highly interconnected with EDM, and they are complimentary to each other to fully support the self-evolutionary applications at grid edge and edge-based energy zones.

In summary, the cloud-based platform achieves optimal energy data harvesting by serving as both EDM and ELW. As a result, we can provide a transparent and collaborative energy data harvesting platform and enable organic dataflow in the 5G fabricated digital continuum, break the data silos, and enable the smooth information flow and model maintenance.

5.2 Extended Discussion: Grid Data and AI/ML Applications

ML integrates complex models and algorithms with programming machines to predict reliable decisions and functions, provides better understanding of physics and mechanics, and reveals hidden insights by learning from existing relationships and characteristics in the data. A broad range of algorithms under the ML umbrella has been designed and characterized by unsupervised, supervised, and reinforcement learning, which has demonstrated the potentials to solve the multidisciplinary challenges. In general, ML aims to accomplish different types of tasks including classification, clustering, forecasting, and optimization through the data in various scientific and engineering domains. The AI field and related learning approaches have been classified in Figure 30.

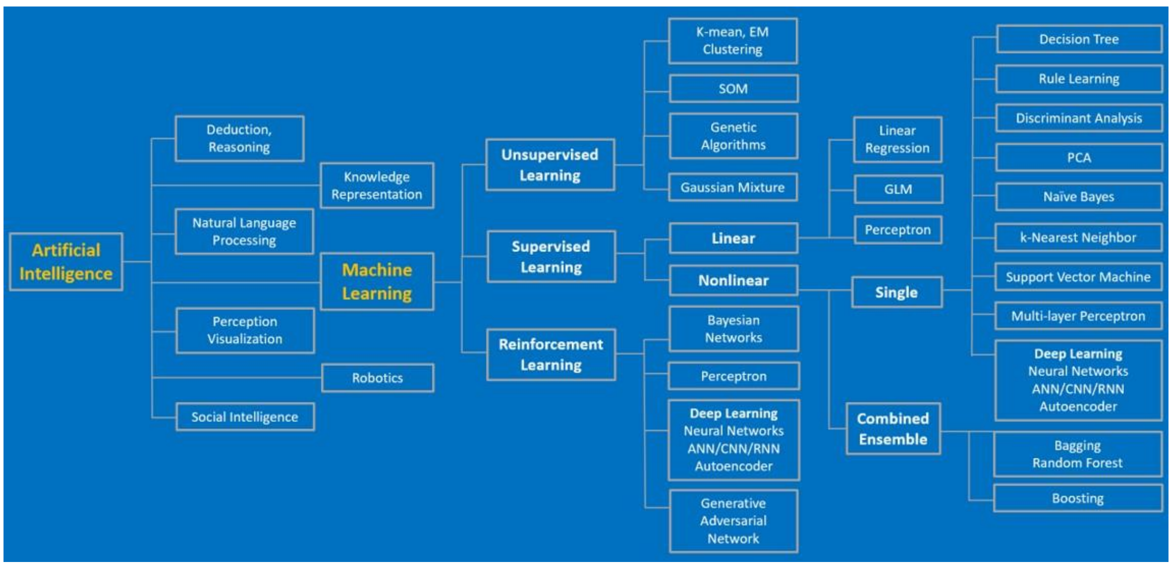


Figure 30. AI field and the categories of ML.

As in the transition of existing power grids to smart, decarbonized, and resilient grids, power system operators and planners start to incorporate all types of data in monitoring, control, and communication. The big data analytic pipeline integrated between multisource high-volume grid data and AI/ML are in urgent need to address the data collection and featuring, dynamics monitoring, anomaly detection, forecasting, impact evaluation, and so on [59–63]. For example, with the datasets from rising deployments of PMUs and severe weather-related outages, PNNL researchers developed and applied several statistical and ML methods to monitor system abnormalities, predict system events, recognize patterns, and characterize the impact of extreme events on the grid [64–68]. These applications are crucial for assuring grid security and reliability.

Under data analytics topics, a fusion platform merges data from diversified sources in terms of information, size, and behavior into a unified representation, by correlating and fusing information to assist the overall understanding of a system or phenomenon. A data fusion framework is shown in Figure 31. The increasing amount of information naturally motivates the integration of data fusion and AI/ML to preserve features and reduce system complexity. Such communication in data model integration require 5G, which is making it possible to build network systems that can be efficiently connected virtually with high throughput and ultralow latency communication services [69].

Together, 5G and AI/ML on-device comprise the essential ingredients for intelligent network edge. AI/ML can be integrated at different levels in 5G, and the intelligent network edge is beneficial for both end users and operators gradually. The data model cycle in the network edge can further enhance data augmentation and deliver new capabilities by learning/extracting big data sources and facilitating functions including network planning, identify dynamics, forecasting, and decision.

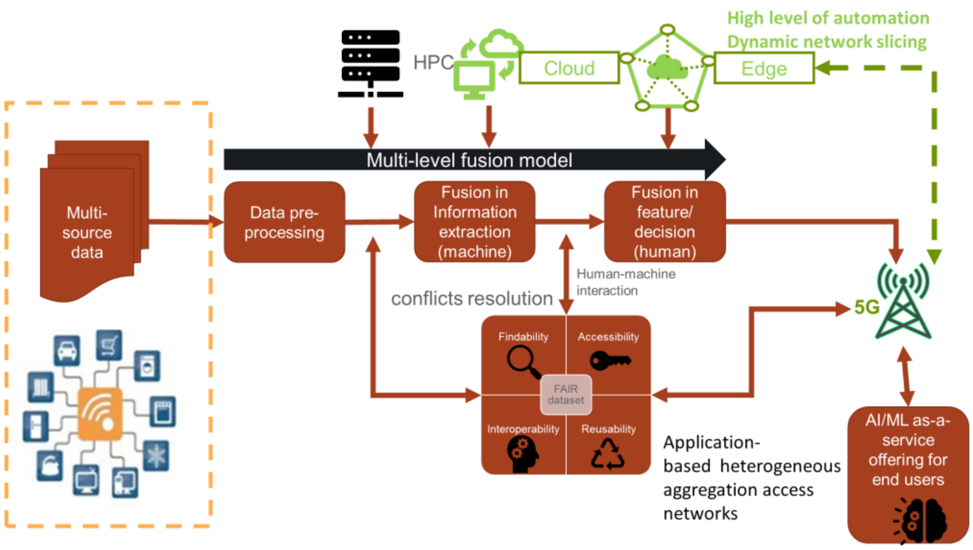


Figure 31. Data fusion framework integrated with various computing sources and 5G.

5.3 Extended Discussion: Cloud and HPC Platform Integration

Evolution of the power grid not only advances by new power generation and energy harvesting technologies and hardware, but also inspires new operational paradigms and business models. To cater to broader needs from various energy market participants and renewable energy development and interconnection, it is important to develop a streamlined computing and orchestration workflow for selecting various computing resources, simulation tools, computing assignment queuing, and data post-processing.

Figure 32 shows a conceptual view of the computing framework that orchestrates edge computing, HPC (including hybrid CPU + GPU), and cloud computing together. Grid operation datasets and streams can be collected by UE or grid sensors, such as smart meters, µPMUs, weather stations, etc., and transmitted to 5G base stations. In the AWC 5G testbed, ESXi VMs play the role of edge servers, gathering all signals transferred from base stations. To narrow the communication scope and better track the data exchange process for performance evaluation, data trace within the 5G Innovation Studio is studied. In the real world, the UE exchanges data with multiple base stations, and one edge server aggregates the data from neighbor base stations.

Compared to UEs, edge servers are not limited by energy capacity and are equipped with more advanced computation and storage capacity. Therefore, edge servers can undertake some lightweight data processing computation tasks, as well as any time-critical control when applicable. Benefiting from adjacent computation and processing, data volume transferring to cloud servers may be reduced.

The cloud platform is in charge of the framework's resource orchestration and task allocation. The intermediate results calculated in the edge server are stored in the database and used as inputs for applications deployed in the cloud. In our first 5G for grid use case, a GridPACK-based co-simulation scheme is powered by HELICS [70,71]. The simulated system consists of one *T* network and multiple replicas of the *D* network in the cloud platform, and edge servers are used to provide the real-time *D* information. Managed by the cloud platform, the edge server will perform data processing and cleaning to get refined data and send it to the corresponding *D* network in the cloud for updated signals and/or topology. The intermediate simulation results in the *D* network are passed to HELICS for coordinating the T&D co-simulation. When the co-simulation finishes, the final simulation results are delivered back to UE ends.

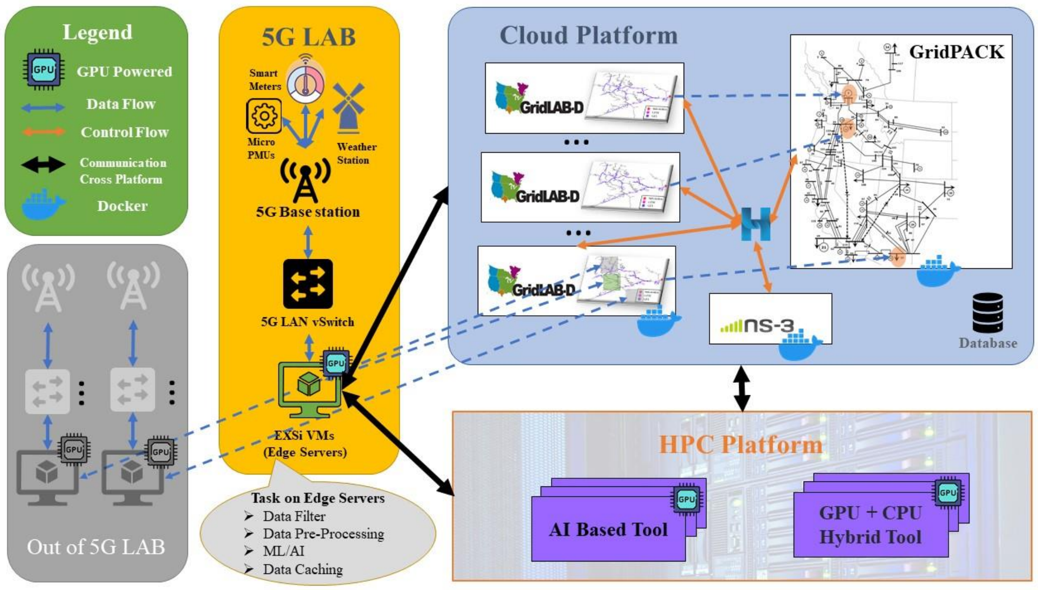


Figure 32. A conceptual view of the computing framework.

Docker containers are used for better delivery and consistency. It is also important to recognize emerging computing platforms, for example the newly commissioned HPC platform JUNCTION at PNNL. It is a reconfigurable system designed to use HPC hardware efficiently. This system includes a standard CPU attached to one or more field programmable gate arrays. Researchers have recognized the significant performance gains that reconfigurable hardware can provide for computationally intensive problems, and such a platform could significantly boost its usage and adoption through the proposed cloud platform. However, there are still many unanswered questions about the applicability of reconfigurable HPC systems. Many of these questions are being explored at CENATE [34]. In our use case, the heterogeneous computation architecture in the interfaced HPC platform provides powerful capabilities and addresses large-scale computation workloads. Computation-intensive applications and tools, such as GridPACK, hybrid HPC tools with a combination of CPU and GPU, and ML tools can be deployed on the conventional and customized HPC platforms. When the simulation and analysis finish, the results are passed to the proper destination and aid users in decision making.

In summary, this conceptual framework shows potential flexibility to coordinate various large-scale power system simulations on heterogeneous computation resources. With the proposed framework, simulations will be dispatched to the most suitable architecture based on the requirements of the computation and communication. Each architecture’s computation capability can be dispatched and used with high efficiency, and the overall performance of simulations can be significantly improved through the proper integration of different architectures and technologies.

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