PNNL-36588

5G Energy FRAME Report on 5G for Grid Use Case

Year 3 Final Report

August 2024

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Prepared for the U.S. Department of Energy
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Pacific Northwest National Laboratory
Richland, Washington 99354

Abstract

This report provides an extensive overview of the interrelationships among energy, communication, and computing—especially in the context of decarbonization goals, challenges, and opportunities. Technical examples enabled by 5G technologies and their performance are presented, discussed, based on the experiment performed at Pacific Northwest National Laboratory.

This is the first use case focused on using 5G for the U.S. power grid and will be referred to as the 5G for Grid Use Case from here on. Specifically, this use case looks at the workflow, which integrates the performance data of a real-world 5G communication testbed and a grid transmission and distribution co-simulation platform. The cross-domain information flow and logic design are illustrated with a combination of power grid contingencies and events.

Lastly, a summary of the project achievement and outcome is provided, along with a technology roadmap envisioned by the project team.

Executive Summary

A Pacific Northwest National Laboratory (PNNL) research team for the 5G Energy Fabricated Resource and Asset Manager (FRAME) project, funded by the Department of Energy (DOE) Office of Science (SC) Advanced Scientific Computing Research (ASCR) program, has been working on bridging the gap between energy stakeholders and computing/machine learning (ML) resources, especially through the 5G-enabled computing continuum, to enhance energy infrastructure asset management through cohesive data integration and intelligent analytics. This report extends the project year two report[1] and work and presents the PNNL 5G-enabled Grid Unified Edge Emulation Platform for Scientific Computing. In the third-year technical work, this platform is adopted for the second artificial intelligence (AI)/ML examples and interfaced with the 5G for Grid Use Case. All the outcomes and technical designs for cross-domain workflow and information flow among the systems of energy, communication, and computing are now being visualized and represented by this project team, with a combination of software and hardware built on top of PNNL's in-house 5G hardware testbeds.

Expanding from this project and its completed scope, the team also identified new research and development (R&D) opportunities in support of grid decarbonization, sustainability, and energy efficiency. The co-design of energy, communication, and computing provides an integrated view of the emerging technology complex, including technologies for decarbonization, sustainability, grid edge, AI/ML, system of systems, and more. Motivated by the evolution of the fifth-generation mobile communication technology (5G) in this decade and the burst of data services and large language models (LLMs), such new technologies are seen as the revolutionary tides for the whole society with uprising renewable energy resources and ever-growing energy services on the customer side energy services. To address many of the challenges and technology gaps, a co-design concept has gained attention from scientists and researchers across a breadth of scientific and engineering domains.

Furthermore, the research team also explores a future vision of integrating microelectronics and power electronics, so that leveraging the concept of co-design of energy, communication, and computing may be exercised and carried out to maximize the potential of such integrated end-use products of microelectronics and power electronics (e.g., electric vehicles, robotics, grid edge devices) for full decarbonization, better sustainability, and a true continuum of energy, communication, and computing services.

[1] Fan X., D. Wang, C. Qin, K. Guddanti, V. Tiruchirappalli Narayana Kumar, Y. Chen, and J.P. Ogle, et al. 2023. *5G Energy FRAME: The Design and Implementation of Data, Model, and Use Case - Year 2 Report*. PNNL-34658. Richland, WA: Pacific Northwest National Laboratory.

Acknowledgments

From 2021 to 2024, this project was funded by DOE SC through ASCR.

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Finally, the project team would like to recognize our collaborators from the academia and industry communities. We would like to thank Dr. Mauricio Subieta from Nokia, Dr. Liang Du from Temple University, Dr. Walid Saad from Virginia Tech, Dr. Yuzhang Lin from New York University, Dr. Dongliang Duan from University of Wyoming, Dr. Payman Dehghanian from the George Washington University, and Dr. Johan Enslin from Clemson University for their technical discussions and advice to the project team.

Acronyms and Abbreviations

3GPP	the 3rd Generation Partnership Project
AEO	annual energy look
AI	artificial intelligence
ASCR	Advanced Scientific Computing Research
BNN	binary neural networks
CNN	convolutional neural network
CPU	central processing unit
DER	distributed energy resource
DOE	U.S. Department of Energy
DRAM	dynamic random access memory
Energy FRAME	5G Fabricated Resource and Asset Management Encompassment
GFM	grid-forming
GPU	graphical processing unit
HPC	high-performance computing
IBR	inverter-based resource
IoT	Internet of Things
LAN	local area network
LLM	large language models
LTE	long-term evolution
MAPT	microelectronics and advanced packaging technologies
ML	machine learning
MW	megawatt
NC	neuromorphic computing
NSA	non-standalone
PNNL	Pacific Northwest National Laboratory
POW	Point-On-Wave
PV	photovoltaic
R&D	research and development
RedCap	reduced capability
SA	standalone
SC	DOE Office of Science
SSPS	solid state power substation
STTP	Streaming Telemetry Transport Protocol
T&D	transmission and distribution
UE	user equipment
VM	virtual machine

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1.0 Introduction

This report summarizes the three-year work of the PNNL 5G Energy FRAME project, funded by the DOE SC ASCR program, and lays out the roadmap for future opportunities and technology applications. In this section, we provide an extended overview on the interrelationships among energy, communication, and computing, especially in the context of decarbonization goals, challenges, and opportunities.

1.1 Co-Design of Energy, Communication, Computing

Energy, communication, and computing resources are foundational to modern society and economic development. The significant growth of data centers around the world demonstrates the growth of pervasive computing needs, such as e-commerce and ChatGPT-4 enabled learning and working customization. However, this growth also places additional stress on the electricity grid, which is undergoing fossil fuel generation retirement and renewable energy integration. Traditional long-term load forecasts, such as those used by grid stakeholders like Dominion Energy and PJM, did not account for the unprecedented growth in electricity demand from large-scale computing centers, indicated by one recent report [1] by Piedmont Journalism Foundation. Figure 1-1 shows the significant change to the load forecast for the PJM footprint in the coming 15 years, mainly due to the cluster of data centers making Virginia the world's largest market for cloud computing infrastructure.

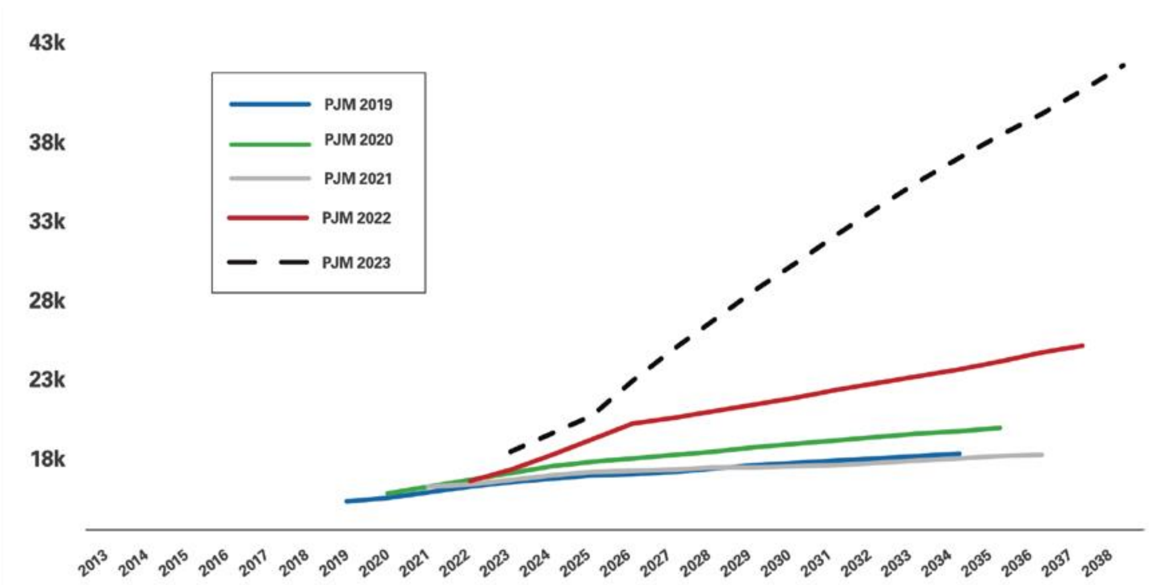

Figure 1-1: The 15-year electric load early forecast of PJM; the dashed line shows significant growth of load considering the predicted growth of data centers. The y-axis represents peak load (MW) (i.e., 43k means 43,000 megawatts of power) [1].

However, the required change of electric grid by data center growth is only one kind of many challenges faced by electric grid operators. The accelerated decarbonization process following many states' renewable portfolio standards urges the evolution of grid transmission network and revolution of the grid generation portfolio, compounded by the uprising of electric vehicles, port electrification, and increased energy prosumers (producer and consumer) with distributed energy resources (DERs). Those new trends in energy service require new technologies to support an uninterrupted transition of the power grid, among which 5G and emerging 5G reduced capability (RedCap) devices may shine and enable affordable solutions to facilitate distributed asset management, monitoring and control, as well as centralized and edge computing.

A co-design methodology for energy, communication, and computing shown in Figure 1-2 has been proposed by the PNNL research team [2]. Their interdependency and complementary nature call for an architectural study to maintain national and regional situational awareness, maximize the benefits of cross-domain scientific planning, and minimize the burden of smart grid transformation and societal services.

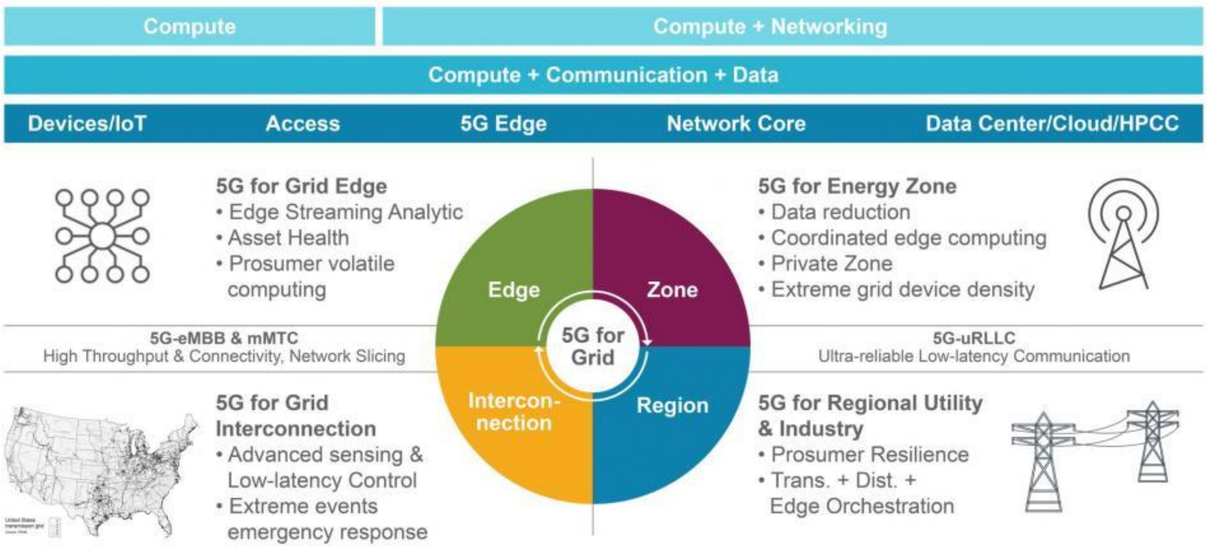

Figure 1-2 An integrated landscape of 5G communication, grid, and computing [2].

As part of DOE SC/ASCR funded 5G Energy FRAME project, a group of research work has been done by the PNNL team in conjunction with multiple university partners, including Temple University, University of Massachusetts Lowell, Virginia Tech, New York University, Clemson University, and others[1]. A list of research highlights is given as follows:

- Grid sensor location optimization [3]
- Grid sensor data aggregation and routing [4]
- Grid democratized control [5]
- Grid topology and reliability analysis [6]
- 5G hardware performance baseline study [7]
- Mathematical modeling of linear multiple time-delay systems [8]
- 5G enabled adaptive computing workflow [9]
- A scalable co-simulation platform [10]
- Load and behind-the-meter solar management for grid operators [11, 12, 13]
- 5G-enabled grid edge computing with phasor measurement unit data [14]

[1] https://www.pnnl.gov/projects/5g-energy-frame/collaborations

The abovementioned research work spans over grid sensor, data, infrastructure network modeling, 5G communication hardware and its applications, communication latency study, grid topology and reliability assessment, and scientific computing process designs—including edge computing and high-performance computing (HPC). In this work, the project team explores a bird's-eye view of the system's perspective and is materializing such a concept into the real-world practices of the co-design of energy, communication, and computing.

1.2 Decarbonization Goals, Challenges, and Opportunities

Technologies and innovations are driven by human society for prosperity and well-being. To tackle the global climate crisis witnessed by increasing frequency and magnitude of natural disasters, the United States government and national partners are aiming to keep a 1.5°C limit on warming using a series of new steps to reduce emissions by 50 – 52 percent by 2030[1]. DOE published technical reports, including *On the Path to 100% Clean Electricity* [15] and *Industrial Decarbonization Roadmap* [16], to assess and outline key actions needed for energy transition and economy growth while maintaining or enhancing reliability and affordability. Moreover, recent efforts in the *Puerto Rico Grid Resilience and Transitions to 100% Renewable Energy Study*[2], also presented a comprehensive report[3] on various pathways for Puerto Rico to achieve its renewable energy goals and incorporate stakeholder perspectives while advancing energy resilience for all Puerto Ricans.

In short, there are many challenges and opportunities to fully achieve energy transition and decarbonization, and by the U.S. Department of Energy's Office of Policy, there are ten actions proposed [15] toward 100 percent clean electricity:

1. Maintain the existing clean generation and storage fleet and increase flexibility where appropriate.
2. Rapidly increase deployment of established clean generation and storage technologies.
3. Increase options for clean generation, storage, and carbon management technologies.
4. Plan and deploy enabling infrastructure.
5. Proactively invest in and engage with disadvantaged energy communities to ensure the impacts and benefits of 100 percent clean power are distributed equitably.
6. Augment planning, operations, and market to enable 100 percent clean grids.
7. Ensure system security and resilience as new technologies and threats emerge.
8. Dramatically accelerate electric energy efficiency and demand flexibility.
9. Strengthen domestic manufacturing capabilities and develop resilient and sustainable supply chains.
10. Equitably expand the U.S. clean energy workforce [15].

[1] The White House Briefing page, https://www.whitehouse.gov/briefing-room/statements-releases/2023/04/20/fact-sheet-president-biden-to-catalyze-global-climate-action-through-the-major-economies-forum-on-energy-and-climate/

[2] PR100 official website: https://pr100.gov/

[3] Puerto Rico Grid Resilience and Transitions to 100% Renewable Energy Study (PR100) (Final Report). United States. https://doi.org/10.2172/2335361

Besides the PR100 study, the U.S. Energy Information Administration also provides an annual energy look (AEO) to help understand the energy transition with various technologies and societal scenarios. For example, Figure 1-3 shows that in AEO2023 [17], many of the assumed 2050 scenarios, will double the total installed generating capacity of the 2022 system [18].

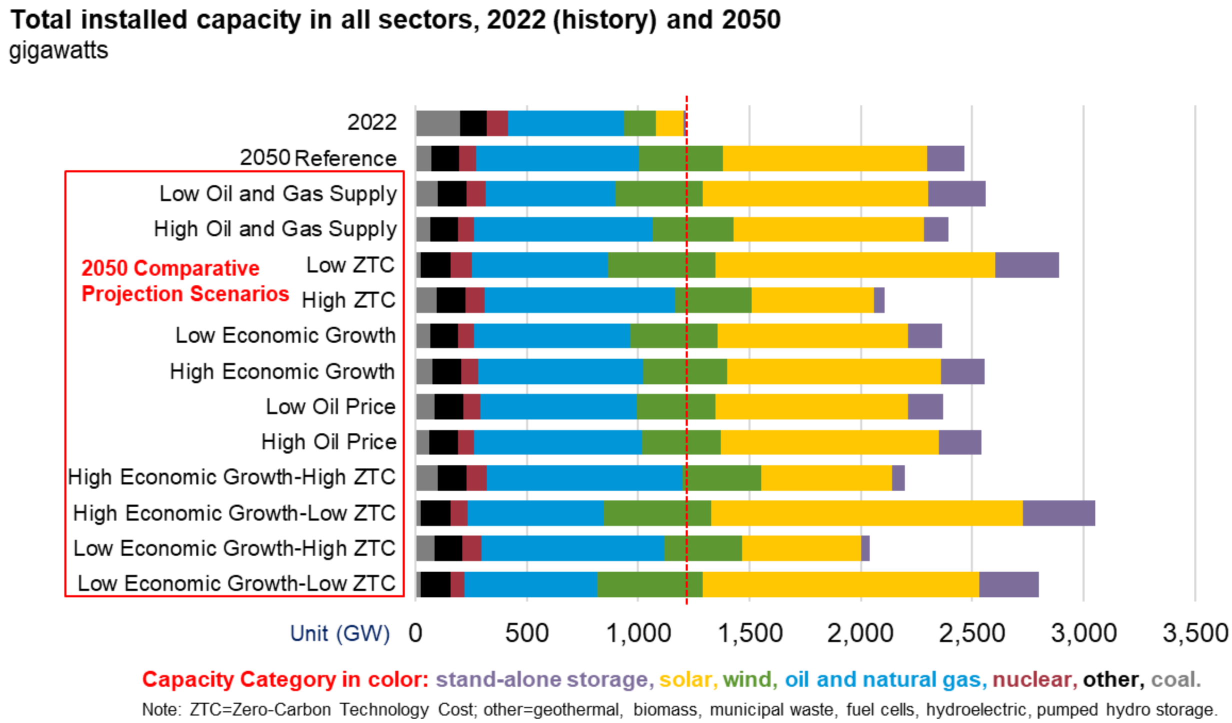

Figure 1-3 U.S. Energy Information Administration shows that the total installed generating capacity more than doubles across most AEO2023 scenarios [17].

1.2.1 Real-World Example of Integrated Energy, Communication, and Computing Service Providers

Emerging business models and services may provide insight on the upcoming industrial and societal adoption of new technologies. Digital Flare Mitigation® projects and Digital Renewable Optimization™ are two energy solutions provided by *Crusoe*[1], which are in addition to the cloud services directly powered by the mentioned two energy solutions. The provided services and solutions map to the above discussion of decarbonization; according to the Economic Development Council of Colorado[2], such cross-domain integrated services were already deployed to Wyoming's Powder River Basin oilfield, Colorado's Denver-Julesburg oilfield, North Dakota and Montana's Bakken oilfield.

In short, considering the remote deployment in many field cases, it would be beneficial to utilize the co-design methodology proposed in this project, to further elevate the business potential and truly enable the fusion of the bits (smallest component of Information in cyber domain) and watts (fundamental unit of energy in physical domain in support of bits).

[1] https://crusoe.ai/energy/index.html
[2] https://edcconline.org/crusoe-energy-locally-based-energy-and-technology-innovator-founded-by-two-kent/

1.2.2 The Challenges of Large Language Model and Power-Hungry AI/ML

The rapid evolution of LLM brings the expectation of increased energy demand and highlights how the possible growth of power-hungry AI/ML may be bounded by the corresponding growth of energy supply[1]. As the foundational service to the societal and economic development, energy serves the technology leap and disruptive innovations (e.g., internet, 5G, electric vehicles). Now we are at the edge of new era of AI/ML and some researchers are considering artificial general intelligence[2] (AGI) to be inevitable as electricity becomes the ultimate enabler for every step of AI/ML. More specifically, LLM and the identified scaling law[3] ignited the global competition of large model training and the appetite for energy is reshaping power grid planners' and operators' existing planning procedures.

Data center modeling for electricity consumption is critical to inform and enable all the stakeholders of power-hungry AI/ML growth. It includes modeling of individual server racks and the integrated server racks supporting graphical processing unit (GPU) and other specialized computing clusters, the heating, ventilation, and air conditioning system that cools the building space, the uninterruptible power supply configuration, and the power distribution network within data center. Relevant work includes Open Rack V3 by the OPEN Compute Project[4], and a data center power system stability analysis by electrical impedance modeling method [19, 20, 21].

In addition, new applications of LLMs and their inference processes may grow exponentially for customers, industrial sectors, governments, and institutions. Open-source LLMs (i.e., LLM360[5]) promote more research and business adoption, and also a wide-spread interest of end-use applications and edge deployment. For example, one recent paper from Apple is online, showing ideas about running LLMs on an iPhone with flash memory in addition to dynamic random access memory (DRAM) and CPU/GPU caches and registers [22]. As a result, such experiments and demonstrations show the feasibility of on-device delivery of LLMs and will further ignite wide-spread adoption of LLMs, especially larger and better LLMs. Therefore, an unprecedented burst and/or ever-growing energy demand will arise. It should be noted that even within a single device, as illustrated in Figure 1-4, the communication bandwidth among flash memory and DRAM, GPU/GPU could vary significantly, which limits the LLM model inference efficiency and efficacy. To enable and explore edge deployment and inference of LLM models, multiple devices can be connected to leverage the aggregated DRAM for distributed LLM model inference, with the assumption that high-bandwidth inter-device communication connections must be established to maintain optimal performance.

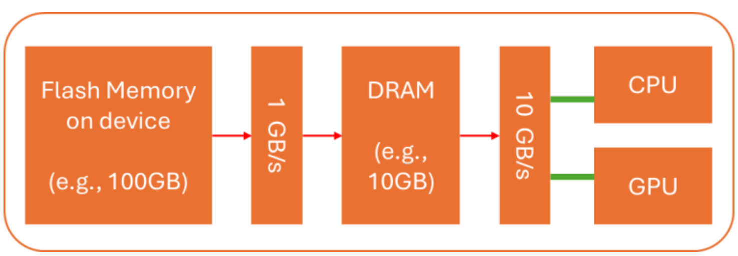

Figure 1-4 An illustration of different bandwidths among flash memory, DRAM, and CPU/GPU cashes and registers within a single device.

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[1] https://spectrum.ieee.org/ai-energy-consumption
[2] https://openai.com/index/planning-for-agi-and-beyond/
[3] Kaplan, Jared, et al. "Scaling Laws for Neural Language Models." ArXiv abs/2001.08361 (2020).
[4] https://www.opencompute.org/documents/open-rack-base-specification-version-3-pdf
[5] https://github.com/LLM360

1.2.3 The Opportunities in Energy-Efficient Applications

Energy efficiency is one of the key metrics to quantify technology maturity, especially for field implementation and wide adoption by the industry. This subsection explores three different pathways in support of energy efficient applications. TinyML, neuromorphic computing (NC), and binary neural networks (BNN) are high-potential samples of energy-efficient applications that may shed light on a future with higher computing needs and reduced energy consumption. The energy sustainability becomes critically important, considering the ever-growing computing needs from consumers, industrial sectors, and societal and economic developments.

TinyML[1] is a worldwide community for low power ML and AI at the edge, supported by tinyML Foundation. One important feature of TinyML is its widely adopted concept of deploying ML on embedded devices, such as automotive microcontrollers units[2] and many related AI/ML applications presented in a recent literature survey [23], through which numerous industrial and customer side applications may be tested, re-designed, and applied in the field to deliver benefits of low-latency and less reliance on network/cloud connectivity. A summary is provided in the *2024 State of Edge AI Report*[3] on how tinyML is well positioned for edge AI applications.

NC is the use of electronic circuits to mimic neuro-biological architectures present in the human brain, where the information is processed and stored locally for usage and is the main carrier for signal transmission [24]. The technology concept was introduced in the late 1980s and has been gaining more attention in the past decades, with its low power and high energy efficiency nature. To continuously advance the field of NC and accelerate scientific discovery, several active research topics[4] identified by DOE SC/ASCR are:

1. Neuroscience algorithms and translation to neuromorphic analog circuits
2. Technologies and prototyping of neuromorphic analog primitives
3. Scalable integration of NC modeling

From the power grid applications perspective, there are potential benefits of leveraging emerging NC technologies with available hardware and simulation capabilities. Doing so can address R&D topics enumerated in a recent literature survey [25], which includes: a) accelerated grid optimization by modeling complex interactions between grid components, such as generators, transformers, and transmission lines and equipment; b) performing grid edge based fault detection and diagnosis by analyzing large volumes of sensor data in real data, and apply spiking neural networks for detecting equipment failures or grid disturbances; c) demand forecasting by RNNs and spiking neural networks to capture temporal dependencies and nonlinear patterns in electricity consumption data; d) renewable energy integration made possible by better forecasting of weather changes and energy production, and thus better grid stability and reliability; e) smart grid control by NC's real-time processing capabilities and its adaptive learning—one particular example will be energy storage optimization that will soon be ubiquitous and tapped into all day-to-day operations at all levels; f) cybersecurity applications due to NC's fast response and low latency processing capabilities.

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[1] https://www.tinyml.org/

[2] Jongmin Lee, "Empowering the Edge: Practical Applications of Embedded Machine Learning on MCUs", May 25, 2023. https://forums.tinyml.org/t/tinyml-talks-on-may-25-2023-empowering-the-edge-practical-applications-of-embedded-machine-learning-on-mcus-by-jongmin-lee-from-nxp/1172

[3] https://www.wevolver.com/article/2024-state-of-edge-ai-report

[4] 2024 Neuromorphic Computing for Science Workshop, access online: https://web.cvent.com/event/8b49ef3c-5bec-4054-a0bf-773fc129fd96/summary

BNNs [26] binarize the floating-point inputs and weights of deep neural networks into binary values: +1 and -1, corresponding naturally to 1 and 0 in digital logic. BNNs utilize a single bit to represent each neuron, thereby significantly reduce computational complexity and memory requirements. BNNs exhibit appealing features, which are extremely hardware friendly.

1. Execution Efficiency: Costly floating-point dot-product operations are replaced with lightweight bit-wise exclusive-nor and population-count operations, boosting execution efficiency by over 10× [27].
2. Memory Efficiency: By representing both inputs and weights as bits, BNNs theoretically decrease capacity and bandwidth demands by up to 32× across the entire memory hierarchy [28].
3. Low Latency: Leveraging computational and memory benefits, BNNs significantly reduce single-image inference latency by up to 58× on CPUs [29] and over 1000× on GPUs [27] and other systems [30], enabling real-time predictions for latency-critical applications.
4. Power Efficiency: Simplified hardware and reduced memory requirements enable BNNs to operate efficiently on energy-constrained edge devices [31].
5. Robustness: The discrete nature of BNNs confers superior stability and resilience against adversarial attacks [32,33].

Although binarization diminishes model capacity and discretizes the parameter space, which leads to accuracy loss, recent work incorporating enhancing model capacity [34] has greatly enhanced the accuracy of BNNs.

BNNs demonstrate immense potential in resource-constrained, volatile, and latency-critical applications, where certain level of accuracy suffices and real-time performance is paramount. BNNs are pivotal for future HPC, cloud computing, and edge computing applications.

1.2.4 5G Reduced Capability Overview

5G RedCap NR (5G new radio) had been started for standardization by the Third Generation Partnership Project (3GPP) in Release 17 and continues to evolve with Release 18 and Release 19. Figure 1-5 shows the ongoing 3GPP activities, in which 5G RedCap standardization was developed and promoted to the whole industrial sector for user equipment (UE) development and commercialization.

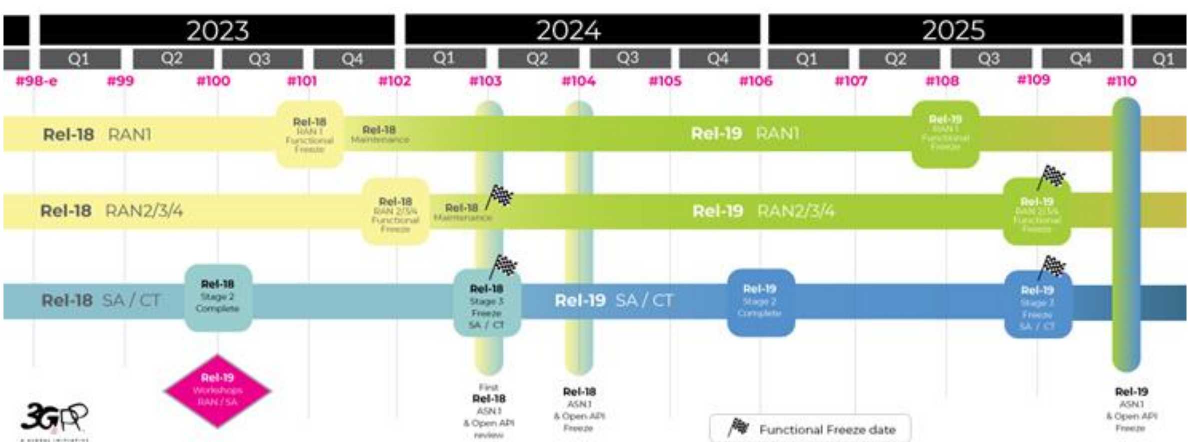

Figure 1-5 Ongoing activities led by 3GPP and their timelines.

In short, 5G RedCap aims to reduce device complexity and provide power saving features, therefore, such end-use device could support Internet of Things (IoT) applications with low-cost, low-energy consumptions for extended battery life, reasonable data rate and latency, and proper reliability. For example, various scenarios of IoT device requirements are illustrated and compared in Figure 1-6, in which 5G RedCap has been identified to appropriate solution for mid-range IoT, including industrial wireless sensors (e.g., Smart Grid), video monitoring, and wearables such as smart watches and medical monitoring devices [35]. Nokia also piloted the field demonstration[1] in U.A.E.

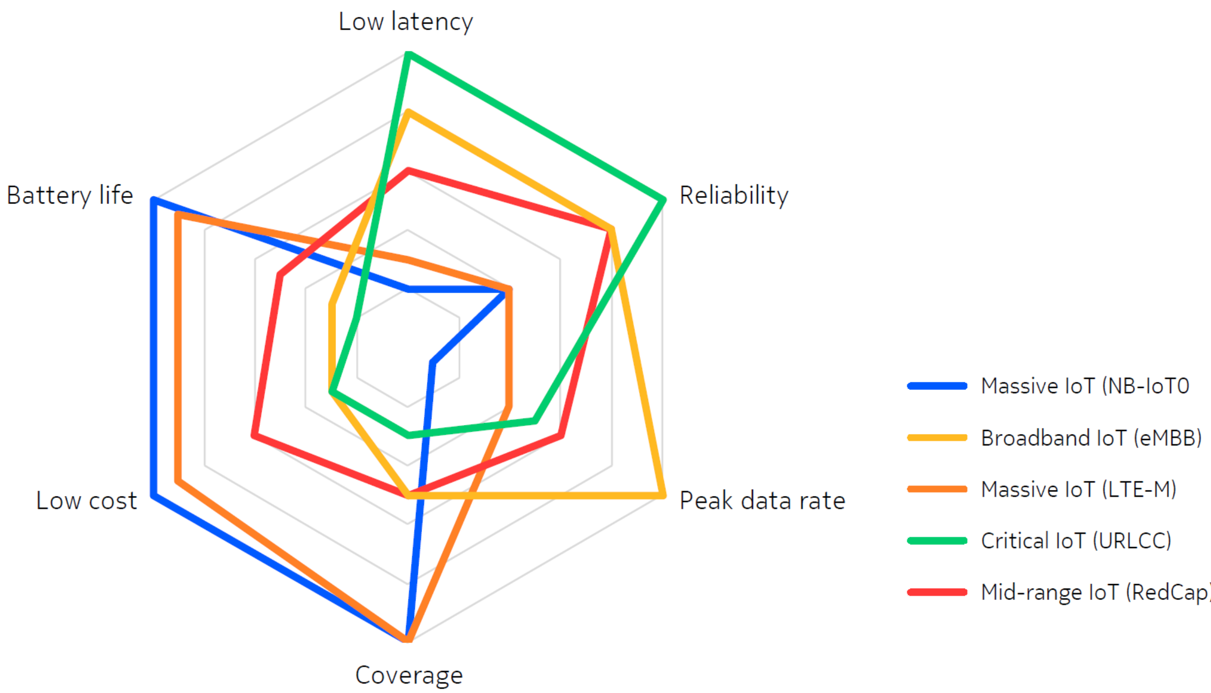

Figure 1-6 An illustration of 5G RedCap equipment capability and a group of IoT use cases mapping to 5G characteristics [35].

Additional technical requirements can be found through the 3GPP website[2] and a summary view provided by Ericsson is referenced in Figure 1-7 [36] to demonstrate the relationship among 4G and 5G systems and specific uplink and downlink performance comparison among different configurations of 5G RedCap UE. One commercialization example is the newly announced MediaTek 5G RedCap solutions, which have 6nm radio frequency system-on-chip technology[3]. Such solution not only shows exciting progress for IoT applications, but also brings an alternative for AI/ML deployment and distributed LLM model inference discussed in previous subsections.

[1] Nokia's 5G RedCap field demonstration at U.A.E. See: https://finance.yahoo.com/news/nokia-nok-solution-expedites-5g-163800564.html?
[2] https://www.3gpp.org/
[3] https://electronics360.globalspec.com/article/20447/mediatek-introduces-5g-redcap-chipset

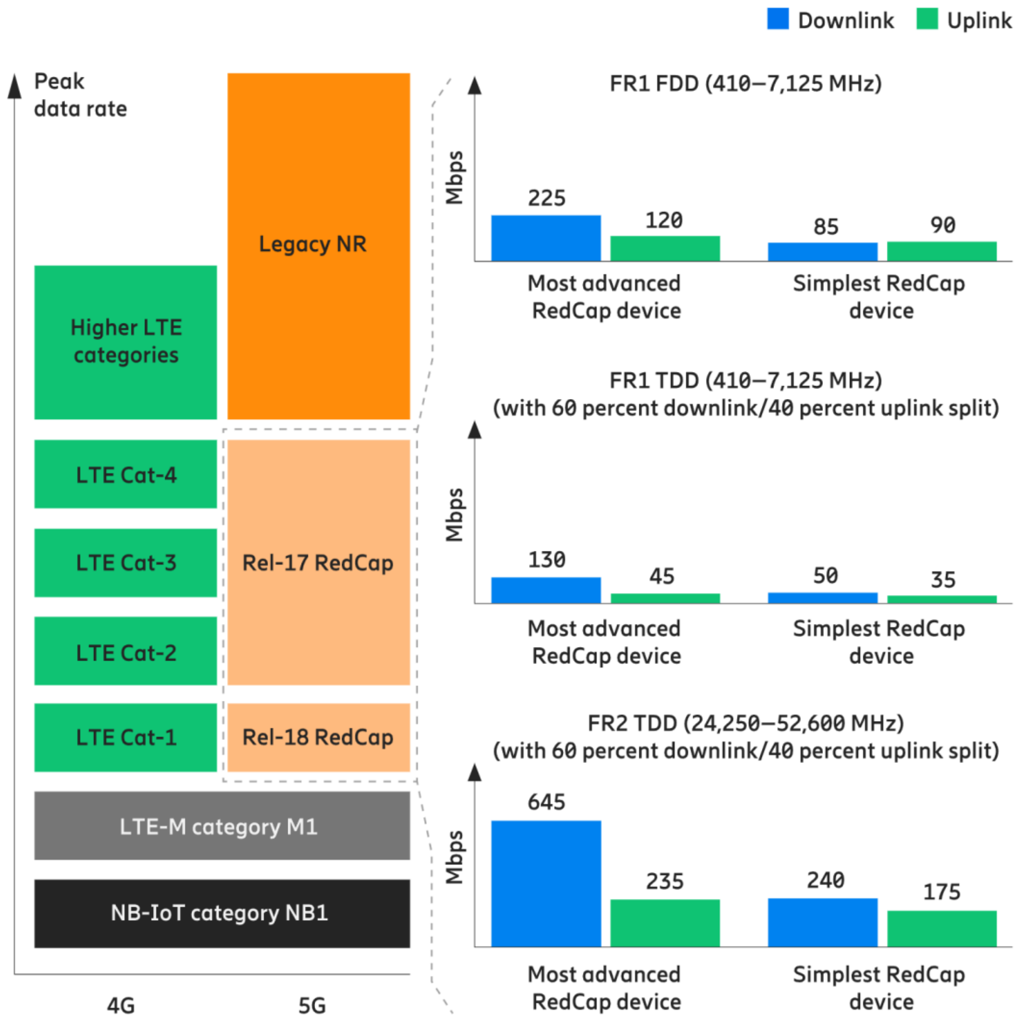

Figure 1-7 5G RedCap performance data from Ericsson [36].

1.2.5 GSMA Open Gateway

Software and application programming interface (API) become more important in complex system management along with the growing demand of interoperability among millions of end-use equipment and hardware infrastructure. Furthermore, system of systems is a critical concept for infrastructure and function modeling—especially from the co-design perspective of energy, communication, and computing. Currently, one industrial frontier has been explored by the Global System for Mobile Communications Associations (GSMA) and its pioneer work, the GSMA Open Gateway[1], representing universal mobile network open APIs for developers. And based on the CAMARA open-source project within Linux Foundation, GSMA open gateway API definitions and reference implementations are free to use (Apache2.0 license).

Similarly to the vision proposed by the 5G Energy FRAME team, such API-based methodologies and mobile network operators' participation will provide the world's largest

[1] https://www.gsma.com/solutions-and-impact/gsma-open-gateway/

connectivity platform so that new services by developers and cloud providers could be rolled out quickly and seamlessly.

1.2.6 Converged Accelerators and Their Applications

To continue to enable customer and bring computing capabilities to the edge, NVIDIA announced their solutions, the NVIDIA *Converged Accelerators*[1], which combines the powerful performance of NVIDIA GPUs with smart network interface cards (SmartNICs) and data processing units. With such solution, the data can be directly shared and accessed through the same GPU memory and high-bandwidth input/output (I/O) operations, to reduce processing latency by skipping the host PCIe system. The converged accelerator also supports 5G virtual radio access networks (vRANs), and currently is being tested by the PNNL Advanced Wireless Communication team, in addition to the in-house 5G non-standalone (NSA) and standalone (SA) testbeds.

In the context of 5G Energy FRAME, this is a new alternative to deliver network connectivity and edge computing capabilities in support of smart grid monitoring and control. It pushes the boundary of distributed system management with a brand new way to receive, store, and process data, showing the powerful impact of engineering co-design to deliver a commercial product considering energy, communication, and computing.

1.2.7 Revisit Co-Design Concept

In this subsection, we extended the co-design concept and discussed the necessities, challenges, and opportunities of decarbonization. The intention is to illustrate the intertwined relationships among newest technology innovations across energy, communication, and computing domains. The speed of evolution within each domain may need to calibrate with the other domain, otherwise they could formulate bottleneck and constraint large volume adoption and fast deployment. It should be noted that the co-design concept does not guarantee to provide a perfect solution, but it is to cultivate the systematic thinking and architectural design, so that the competing priorities across different domains could be abstracted, negotiated, and optimized with stakeholders' inputs.

1.3 Report Structures

This report contains four sections. Section 1 (this section) provides an overview of the co-design concept, and a series of technology innovations and industrial applications that impact decarbonization goals. Section 2 presents the completed simulation and testing for the 5G enabled power distribution protection using AI/ML, based on the designed 5G-enabled Grid Unified Edge Emulation Platform. Section 3 elevates the work in Section 2 and introduces the 5G for Grid Use Case, with details for the technology concept and implementation of the integrated workflow and information flow among the systems of communication, grid transmission, and grid distribution. The simulation results and data will be discussed, along with the summarized findings from this use case. Lastly, Section 4 reviews the whole project achievement and outcome, including the technology roadmap based on the co-design concept.

[1] https://www.nvidia.com/en-us/data-center/products/converged-accelerator/

2.0 5G Enabled Power Distribution Protection using AI/ML

In this section, we will discuss the enabling effects of 5G for the application of AI/ML in power distribution protection and will provide a detailed introduction of a specific example.

Traditionally, power system protection relies on local measurements, such as undervoltage, overcurrent, or distance/impedance protection relays. However, with the increasing penetration of distributed photovoltaic (PV)s and the IEEE Std. 1547, PV inverters can potentially support fault ride-through and improve the transmission system reliability. This presents challenges to traditional protection schemes. The researchers at PNNL explored and presented the new methods of fault detection, including distance-based schemes, focused directional relays, and learning-based schemes [37]. Among them, the data-driven, learning-based protection schemes utilizes convolutional neural networks (CNN) to identify and classify zonal faults.

These schemes could benefit from access to measurements from remote locations in addition to the local measurements, achieving higher accuracy and robustness in the evolving distribution system. However, such implementation relies on a reliable and low-latency communication system to ensure effective data exchange for online detection. The ultra reliable low-latency communication capability of 5G makes more sophisticated protection schemes and algorithms that make use of various measurements from remote locations more promising than ever. Therefore, this 5G-enabled ML-based power system protection application will be shown in our use case 2.

As illustrated in Figure 2-1, communication delay is only one component of the end-to-end delay one must consider when designing and testing a protection or control system.

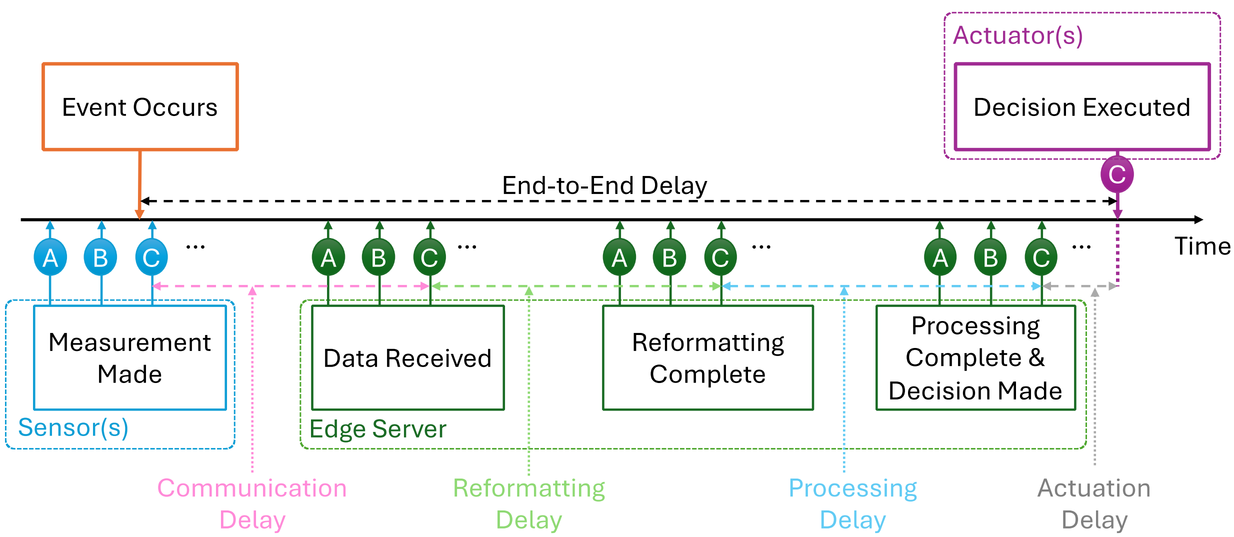

Figure 2-1 An illustration of power grid event monitoring and control/actuation process considering various types of latency/delay.

2.1 PNNL 5G-Enabled Grid Unified Edge Emulation Platform for Scientific Computing

Leveraging PNNL's 5G hardware testbed, the project team implemented the 5G-enabled grid protection framework and tested the system performance from the grid data and AI/ML applications perspectives.

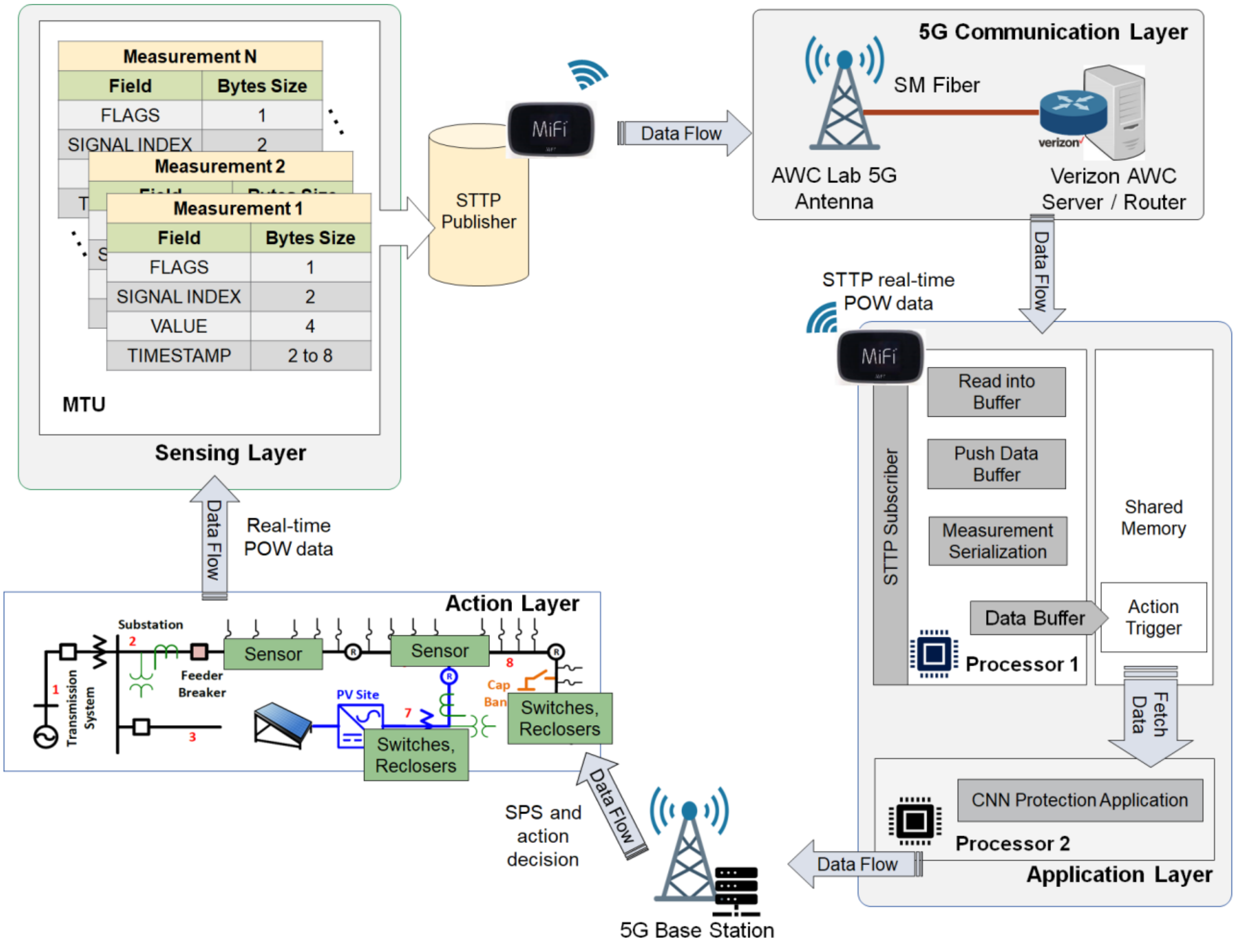

Figure 2-2. The data flow in the designed 5G-enabled grid protection framework.

Figure 2-2 illustrates a closed-loop, learning-based grid edge protection framework, which utilizes a 5G communication network. This framework[1] is designed to be applicable to general types of grid protection schemes. Streamed time-series measurements, such as Point-On-Wave (POW) data or synchrophasors from the power grid, are transported from the sensing layer to the application layer via the Streaming Telemetry Transport Protocol (STTP) publish-subscribe architecture or other similar protocols. The subscribed signal-level data at edge-computing resources is decoded and serialized into data buffers for a learning-based protection application. The data buffer size is fixed to match the input vector format of the trained deep learning model.

[1] *5G-enabled Grid Unified Edge Emulation Platform for Scientific Computing*, PNNL Software Copyright, 32945-E.

The fine-tuned protection model used at the application layer executes the identification and classification, returning the action decision back to the action layer for intelligent electronic device (IED) operations.

2.2 The Hardware-Based Implementation and Performance Assessment

Here we provide a detailed description of the use case implementation with PNNL in-house hardware testbed and demonstrate the feasibility and applicability of the proposed platform.

2.2.1 Communication Protocol for Point on Wave Data

Grid Protection Alliance promotes streaming POW data using the STTP – IEEE 2664-2024 [38, 39]. STTP is specifically designed using publish-subscribe architecture, which allows real-time scalable data to be directed and dynamically subscribed by the application layer using 5G efficient and secure communication networks. The low latency and telemetry functionality is well suited for a 5G-enabled grid edge protection scheme with low latency and reliable data handling. Figure 2-3 retrieved from Grid Protection Alliance NASPI presentation shows the protocol data structure, and the payload compression design is shown in Figure 2-4.

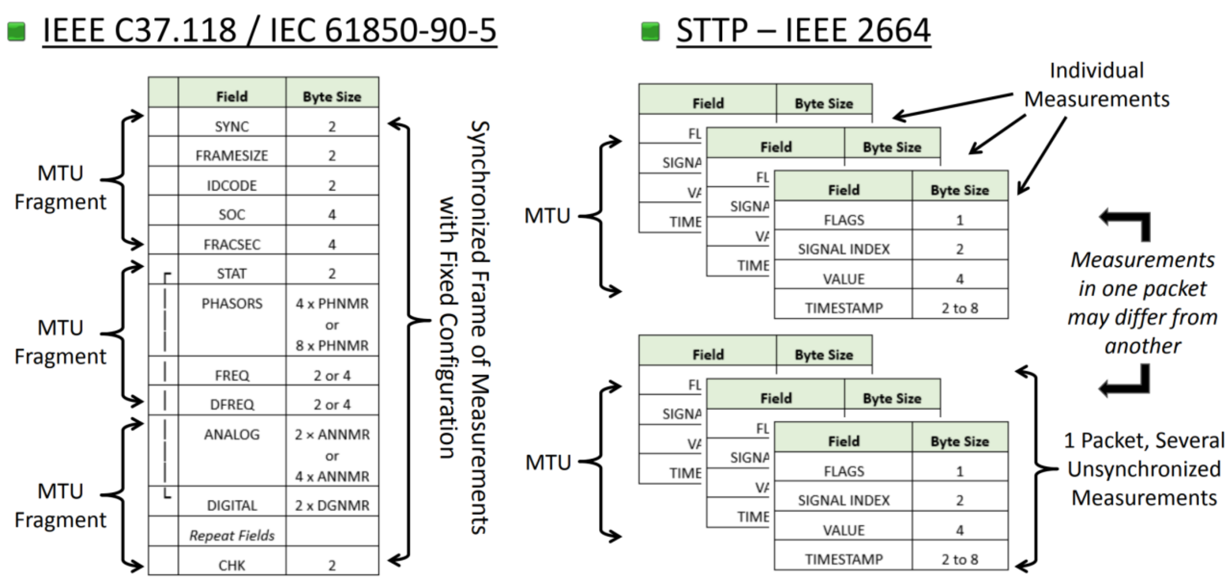

Figure 2-3 A comparison of two grid data transport protocols [38].

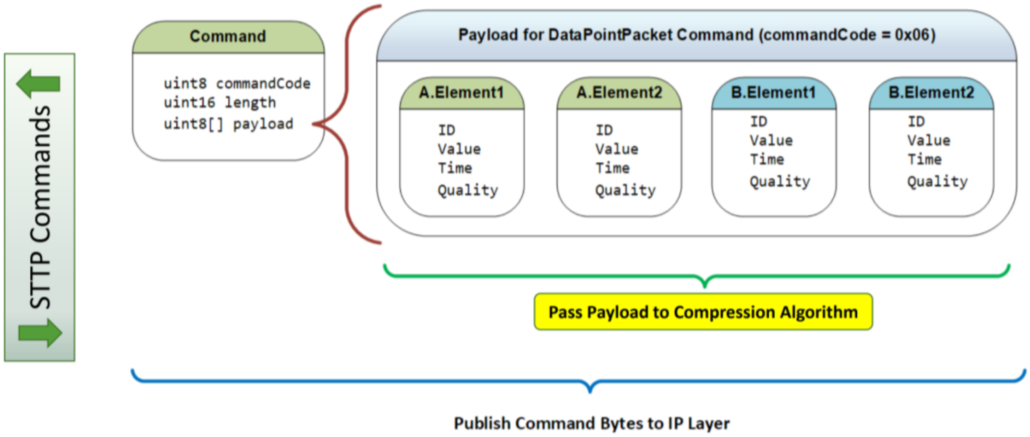

Figure 2-4 Data compression design as part of the STTP protocol [38].

The takeaway advantages of using STTP in the designed framework are highlighted below:

- High fidelity and high volume streaming communication protocol
- Intrinsically reduces losses and latency compared to user datagram protocol and the transmission control protocol
- Reduce bandwidth utilization by data compression
- Standard for STTP
- Enhance security with authentication and encryption options

2.2.2 CNN Model as Grid Edge Computing Example

Within our experimental configuration, we utilized the open-source tool OpenPDC[1] as our main signal generator to formulate POW signals embedded with faults. The POW data is constructed in the shape of (6, 10^4) per second. A single data packet includes six channels of values – 3 phase voltage and current magnitude. The measuring rate is 10,000 samples per second. The continuous streaming data are transported using IEEE 2664 Streaming Telemetry Transport Protocol [2].

By configuring a virtual device and csvAdapter within OpenPDC's input layer, we were able to simulate crucial sensor measurements, such as three-phase voltages and currents. An illustrative depiction of the output from the virtual device showcases the three-phase signals and is presented in Figure 2-5. Operating within a virtual machine (VM) environment, the integration of OpenPDC afforded us precise control over the signals, making sure there is both accuracy and repeatability in our experimental scenarios. This setup allowed us to manipulate the signals effectively, tailoring them to mimic various fault conditions with precision and consistency.

[1] openPDC, Grid Protection Alliance. Accessed: https://gridprotectionalliance.org/phasor-PDC.html
[2] Streaming Telemetry Transport Protocol. Access: https://github.com/sttp

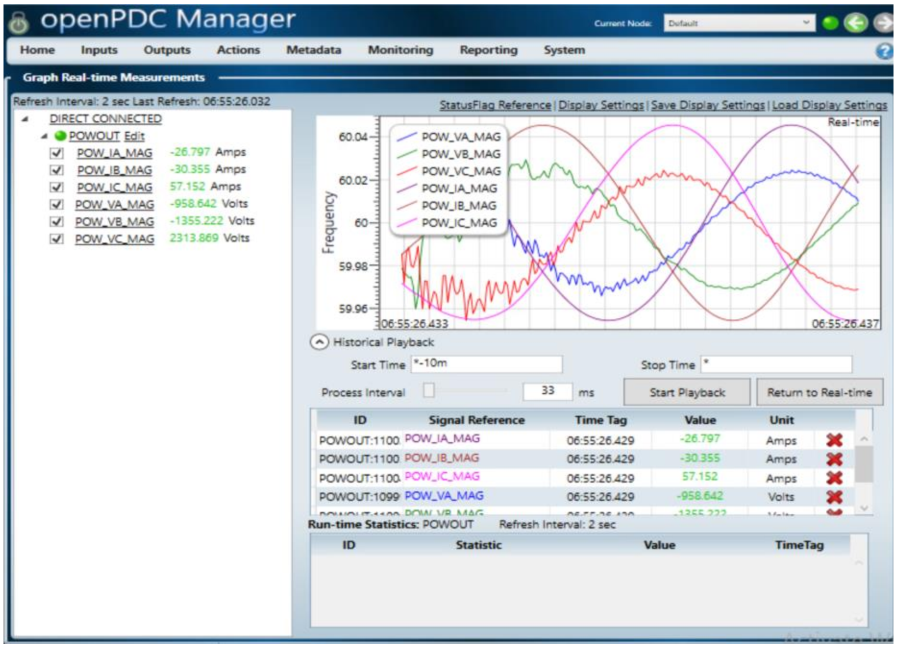

Figure 2-5 Generate 10k sample/second POW streaming signals using OpenPDC.

Simultaneously, another VM was configured specifically to execute a convolutional neural network (CNN) based protection model designed to identify faults within the generated signals. The signal source and ML-protection VMs are connected through a switch that can change the network to be either 5G or local area network (LAN). This VM served as the computational backbone for our fault detection system, leveraging the power of ML to analyze and classify the incoming data streams in real-time. By segregating this task into a separate virtual environment, we could effectively manage computational resources and optimize the performance of the CNN model. Effective CNN training requires an electromagnetic transient model of the distribution system, which can be updated post-installation using real-time data. When applicable, the trained CNN model could be deployed and integrated into a real-time automation controller and can also be used in tandem with protective relays. Figure 2-6 illustrates the logs of this CNN protection model that processed streaming POW data.

```
Received 6,169 bytes of metadata in 0.065 seconds. Decompressing...
Decompressed 52,577 bytes of metadata in 0.001 seconds. Parsing...
Parsed 103 metadata records in 0.012 seconds
    Discovered:
        1 DeviceDetail records
        101 MeasurementDetail records
        0 PhasorDetail records
        1 SchemaVersion records
Metadata schema version: 14
Received signal index cache with 6 mappings
Receiving measurements...
Received success code in response to server command: 2
Client subscribed as compact with 6 signals.
Z61 2024-03-06 07:19:38.797349
Z61 2024-03-06 07:19:54.263412
Z61 2024-03-06 07:20:01.769403
Z19 2024-03-06 07:20:03.449699
```

Figure 2-6: The CNN protection model processed the streaming signals by subscribing the POW data from OpenPDC and providing the fault information.

The above results demonstrate the availability of implementing the learning-based protection with a 5G network. To further assess the performance of the 5G-enabled learning protection scheme, we evaluated the delay in terms of communication, reformatting, and processing. The definitions of these three delays are shown as below:

- **Communication Delay**: the elapsed time from a packet (samples of three-phase voltage and current at one time instant) is sent out at the sensor (STTP publisher) to the time it is received at the edge server (the STTP subscriber)
- **Reformatting Delay**: the elapsed time of transforming the data format from Python list to Numpy.ndarray (Numpy.ndarray is the required input format of the CNN model)
- **Processing Delay**: the elapsed time of the CNN model executing the detection/zone identification

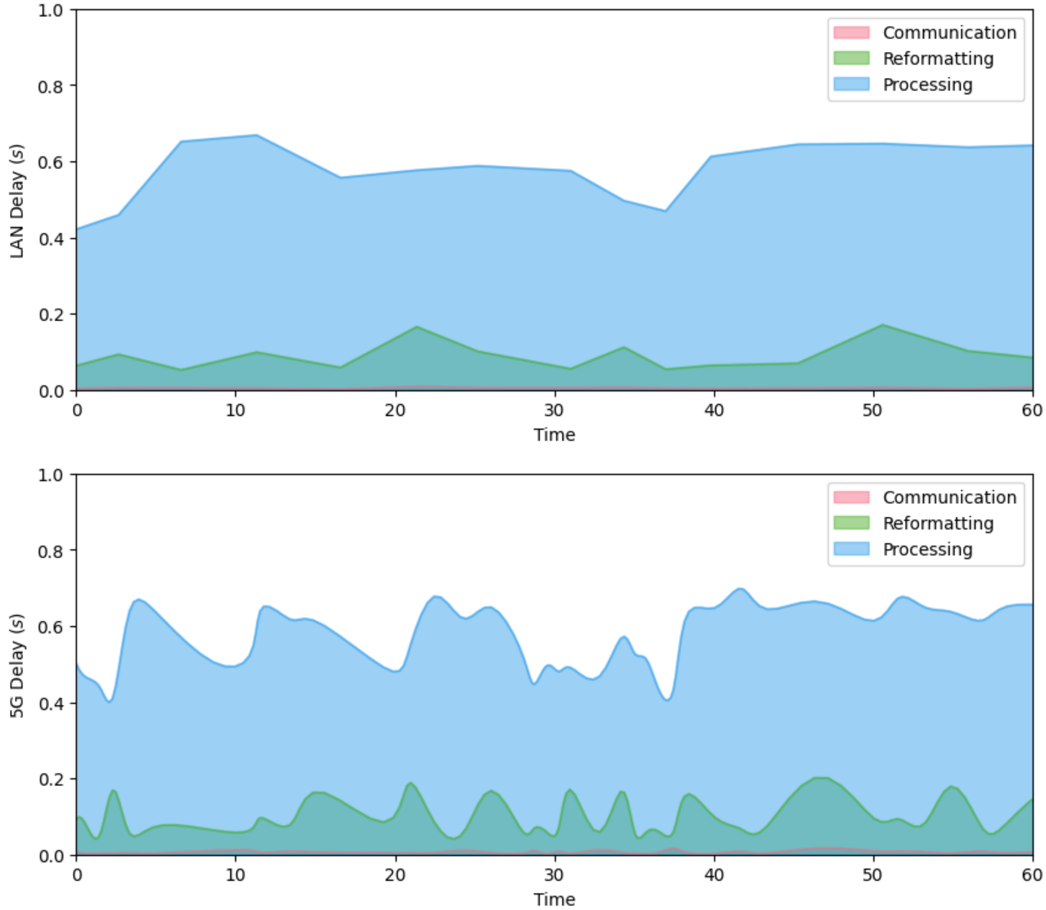

Figure 2-7: System performance illustration for the online grid edge computing with CNN model in LAN and 5G network configurations, respectively. The horizontal axis is the system operation timestamp at real-time and the vertical axis is the stacked delay, consisting of communication, reformatting, and processing delays.

The stack plots in Figure 2-7 provide insights into how efficiently the communication, reformatting, and overall CNN processing are being completed; how quickly the data can be transmitted via LAN and 5G network; and how fast the information can be parsed from streams to send to actuators. By examining the cumulative distribution function plots depicted in Figure 2-8, it is evident that the communication delay between the wireless 5G network and LAN wire connections were remarkably similar, with an average delay about 6 ms.

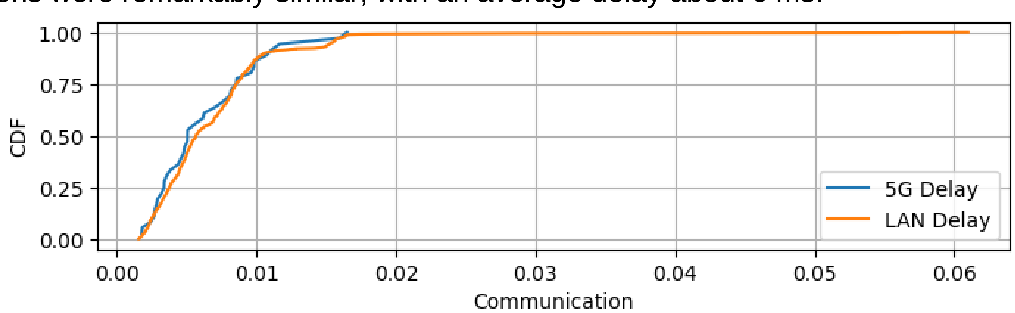

Figure 2-8: System performance assessment by cumulative distribution function. Horizontal axis is the delay for the online grid edge computing with CNN protection model in

seconds; vertical axis is cumulative distribution of communication delay for LAN and 5G.

This similarity underscores the advanced capabilities of 5G technology for enhancing power system protection. Meanwhile, significant delays raised from reformatting and processing tasks are primarily attributable to the unpacking and transformation of large data packages. Despite this challenge, the CNN protection model was successfully constructed using TensorFlow. It is anticipated that processing delays can be mitigated through optimizations in the codebase, leading to improvements in overall efficiency.

In short, the key takeaways from this use case are:

- 5G has the capability to transmit high-bandwidth data with minimal latency.
- 5G can support learning based protection scheme and transfer the streaming sensor data.
- ML model's processing speed depends on devices' computational capability. To deploy the learning-based protection model for real-time applications, it is necessary to assess the processing delay to avoid communication congestions.

2.3 Supporting Grid-Scale Use Case as Next Steps

The in-house hardware, software, and cross-domain modelling capabilities of the PNNL research team well positioned the 5G Energy FRAME project to pursue the 5G for Grid Use Case from the scientific computing perspective. It is also important to understand that such integrated studies may be constructed in a multi-phase, multi-step study process in which upon the completion of the first several steps a large quantity of experiment and simulations can be further designed and delivered based on customized design and specific research preferences.

In a power system real-time control or protection use case, the end-to-end delay denotes the delay from the occurrence of the event to the time when correct decision(s) regarding the event is(are) executed. The end-to-end delay is composed of communication, reformatting, processing, and actuation delays. These delays as observed in the 5G-enabled protection example are illustrated in Figure 2-9.

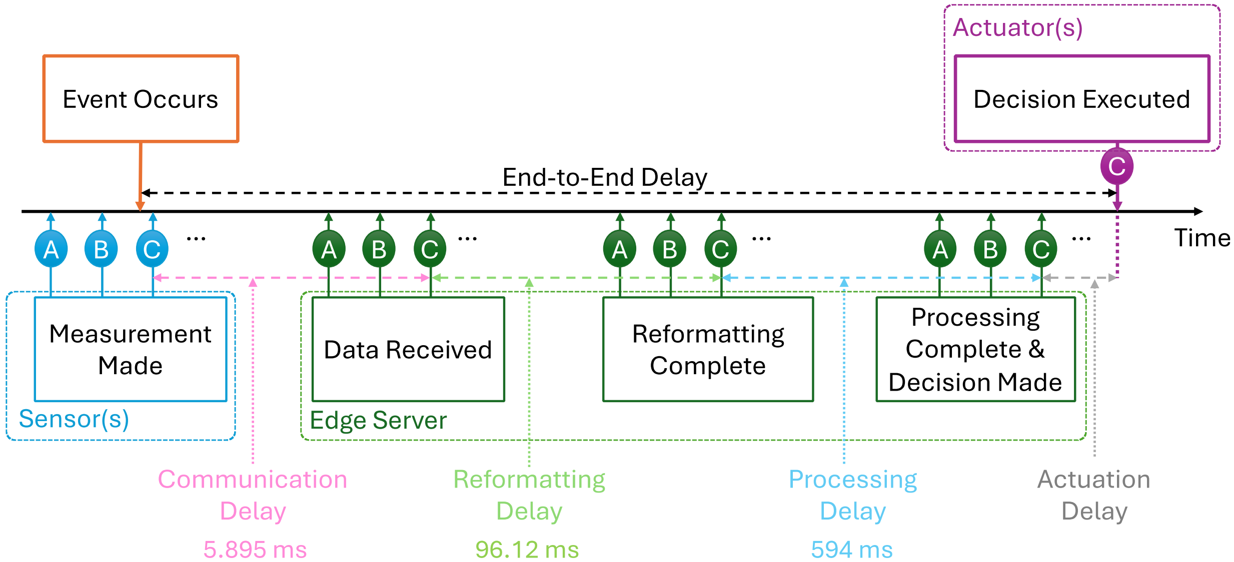

Figure 2-9 End-to-end delay composition with averaged measurements in the 5G-enabled protection example.

Table 2-1: End-to-end delay composition in the 5G-enabled protection example.

Delay Type	**Observed Measurement Statistics**		
	Average	***Min***	***Max***
Analog sensing	Depends on the specific sensor	Depends on the specific sensor	Depends on the specific sensor
Communication	5.895 ms	1.455 ms	16.990 ms
Reformatting	96.120 ms	50.920 ms	203.840 ms
Processing	593.929 ms	418.785 ms	698.547 ms
Actuation	Depends on the specific controller	Depends on the specific controller	Depends on the specific controller
Total (End-to-End)	695.944 ms	471.16 ms	919.377 ms

In the next section, the details of implementing the 5G for Grid Use Case will be given, including the technology concept, the implementation and results, the data availability and sharing, and the summarized findings.

3.0 The First 5G for Grid Use Case

In this section, we introduce a pioneering effort to enhance power system operations by integrating 5G technology into a high-performance, scalable transmission and distribution (T&D) co-simulation platform. The primary goal of this use case is to address the growing complexity of power systems, which demands more efficient and reliable monitoring, control, and protection schemes. The T&D co-simulation approach allows for a holistic evaluation of the interactions between T&D systems, which are increasingly interdependent due to the proliferation of DERs.

One key issue we aim to solve with T&D co-simulation is the need for coordinated control and real-time decision-making across different layers of the power grid. Through co-simulation we can facilitate T&D co-design, enabling more integrated solutions that account for the complexities of the entire grid.

5G technology plays a critical role in this use case by providing the necessary communication infrastructure to support real-time, high-bandwidth data transmission. To study the impact of 5G technology, the T&D co-simulation platform is utilized to demonstrate how 5G technology enables monitoring and control of the grid status and facilitate the adoption of artificial AI/ML techniques. An example outcome of this approach is to study the impact of various communication latencies on the resilience and reliability of the power system followed by faults.

A conceptual design of the 5G-enabled power grid transmission, distribution, and communication co-simulation use case is shown in Figure 3-1. The left block represents the high-performance, scalable T&D co-simulation platform, which will be covered in Section 3.1. The right block contains a finer detail of each distribution network equipped with 5G-enabled, AI/ML based fault detection tools.

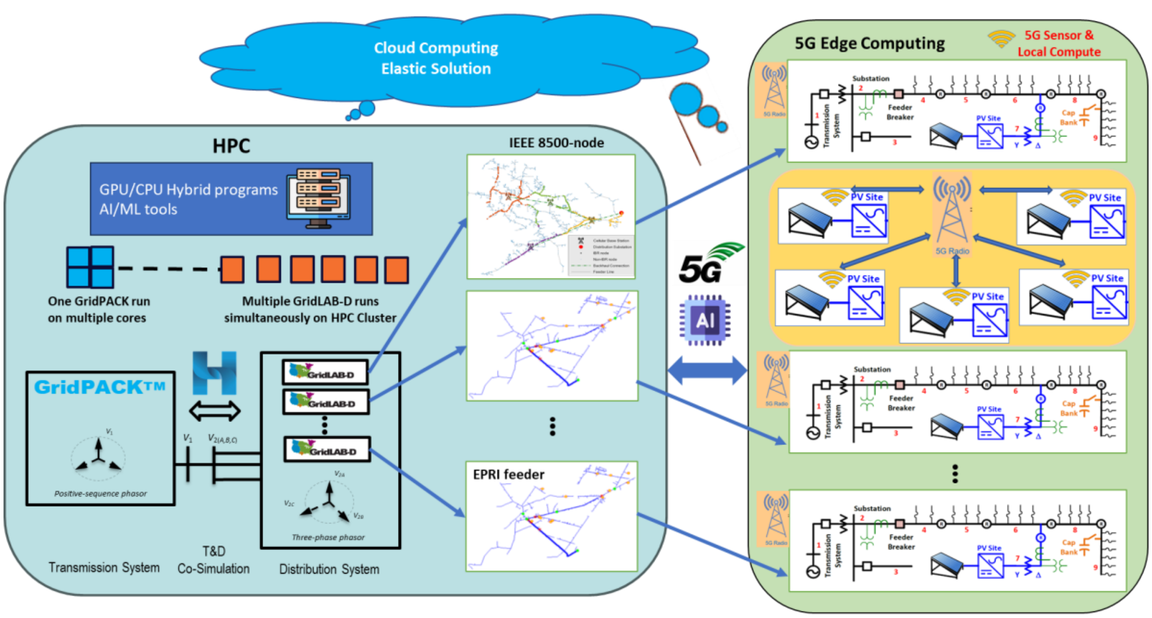

Figure 3-1 A detailed 5G-enabled power grid transmission, distribution, and communication co-simulation use case [40].

In the context of our use case, while the simulations provide valuable insights they do not fully capture the complexities of real-world scenarios. The measurement and edge computing devices shown in Figure 3-1are geographically distributed over a wide area. Transmitting and concentrating this data is a nontrivial communications problem. By incorporating 5G into this use case, we account for communication-related challenges and demonstrate the capability of simulating 5G in addressing these issues, ensuring that our simulations are capable of simulating the actual deployment scenarios for transmission, distribution, and communication co-simulation.

3.1 The Introduction of the T&D Co-Simulation Platform

In this case study, the role of 5G technology in grid study is evaluated through the T&D co-simulation platform, which consists of three open-source tools:

- GridPACK™: An HPC-based positive sequence phasor simulation tool used for studying the dynamics of balanced transmission systems.
- GridLAB-D: A three-phase phasor simulation tool that can study the dynamics of unbalanced distribution systems.
- HELICS: A framework that enables co-simulation of different simulation tools.

GridPACK™ is used to simulate the transmission system, taking advantage of the fact that transmission systems are balanced and thus considering only positive-sequence quantities. This simplification is inappropriate for distribution systems, and so GridLAB-D (which handles unbalanced systems) is used for distribution. HELICS is used to integrate the two simulators together. Individual distribution systems are also often decoupled from one another, and so this approach also allows for better parallelization of the distribution simulation. One GridLAB-D instance is used for each distribution system.

Figure 3-2 is an illustration of the T&D co-simulation workflow. The platform is deployed under an HPC environment. GridPACK can be run on multiple cores. The load nodes in the transmission system can be represented by detailed feeder models simulated in GridLAB-D. If more than one load buses are simulated, the platform supports multiple GridLAB-D runs simultaneously. The data exchange in this co-simulation is enabled by HELICS.

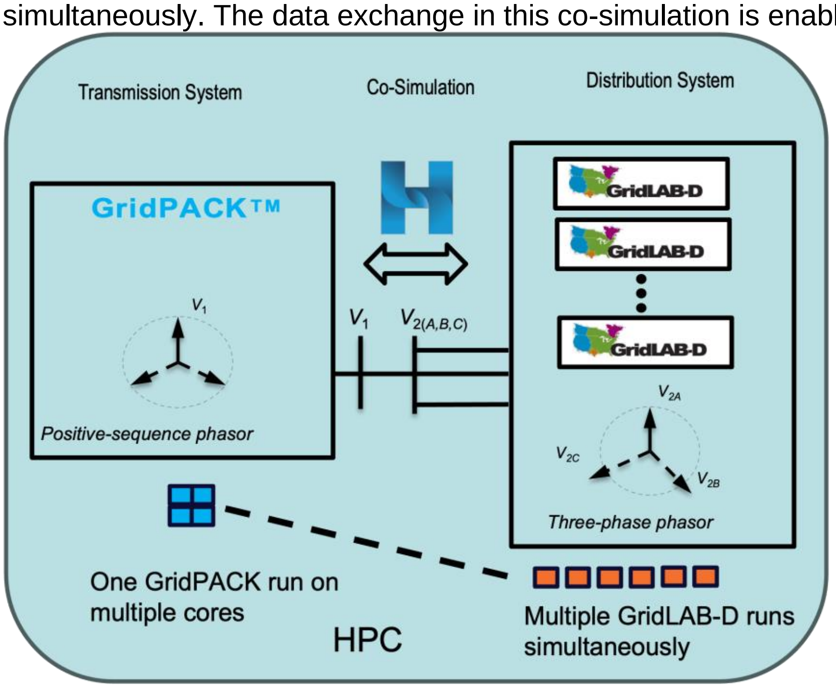

Figure 3-2 An illustration of power grid transmission and distribution co-simulation workflow using GridPACK, GridLAB-D, and HELICS.

An example of the initialization and data exchange between GridPACK and GridLAB-D is shown in Figure 3-3. In this example, the simulation time steps are 1ms, 5ms, and 5ms for GridPACK, HELICS, and GridLAB-D, respectively. The boundary conditions are active and reactive power of feeder-head substation (Substation P, Q) on the GridLAB-D side and voltage magnitude and angle of interface bus Vm, Va on the GridPACK side. These conditions are exchanged based on HELICS's 5ms time step.

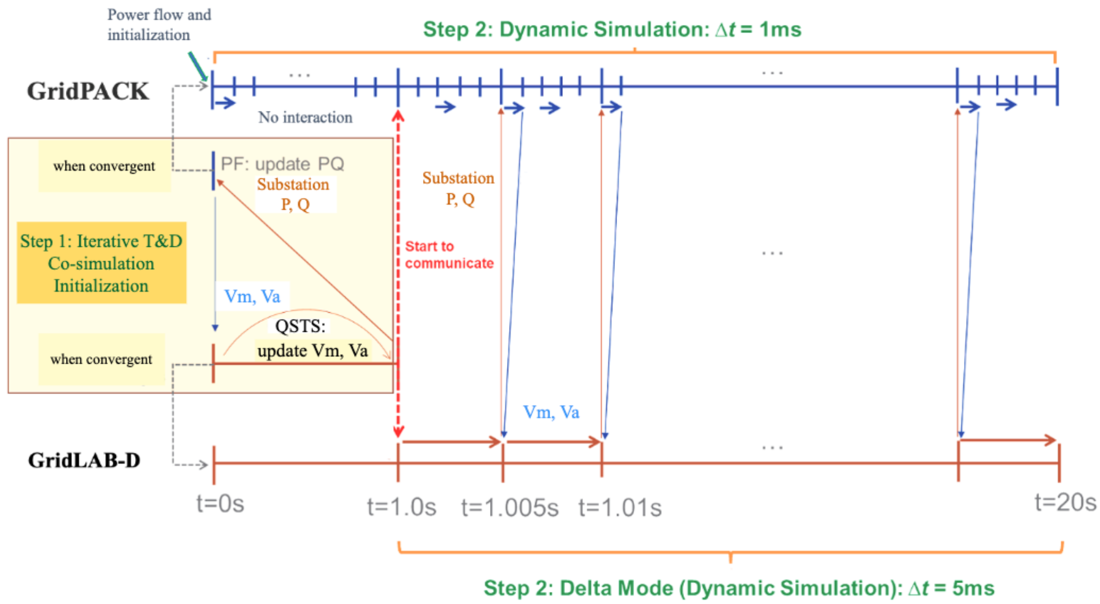

Figure 3-3: The co-simulation mechanism between GridPACK and GridLAB-D enabled by HELICS, where the time steps for GridPACK/HELICS/GridLAB-D are 1ms/5ms/5ms, respectively [41].

This T&D co-simulation platform facilitates dynamic stability studies in large-scale bulk power systems, accommodating inverter-based resource (IBR) penetration levels up to 100 percent. It includes high-fidelity models, such as the Western Electricity Coordinating Council-approved REGFM_A1—a first-generation generic grid-forming (GFM) inverter model integrated into major commercial tools. Additionally, the co-simulation fidelity has been validated against a commercial electromagnetic transient simulation tool to ensure its accuracy [42].

This T&D co-simulation platform can handle:

- IBR penetration levels up to 100 percent.
- Various GFM/ grid-following inverter combinations in the transmission system, distribution system, or both.
- Different quantities of distribution feeders.
- Multiple contingencies in both T&D systems.
- Diverse faults affecting both T&D systems.

More details of this simulation platform can be found at [10, 43].

3.2 The Implementation of Case Set Up and Simulation Results

This T&D co-simulation platform enables us to study the utilization of 5G-enabled AI/ML tools deployed at either the transmission side or distribution side. This report focuses on extending the capabilities of this platform through integration with an AI/ML-based fault detection function within the distribution system. This data-driven approach operates independently of communication systems, addressing challenges associated with future high PV penetration scenarios—a key objective of this co-simulation platform.

The effectiveness of AI/ML-based anomaly detection is evaluated by simulating various IBR fault scenarios within the distribution network. For instance, AI/ML algorithms can effectively detect and isolate a fault, enabling the targeted tripping of a single solar farm in a specific zone. In contrast, systems without AI/ML capabilities may rely on more conservative strategies, resulting in the unnecessary tripping of multiple solar farms and increased energy loss. The benefits of this functionality can be assessed through this T&D co-simulation platform using reasonable simplifications.

The T&D system used in the study consists of the IEEE 39-bus transmission system [44], shown in Figure 3-4, integrated with 16 instances of IEEE 34-node feeders [45], shown in Figure 3-5, which represents the 16 loads in the 39-bus transmission system. The transmission system is simulated in GridPACK™ and each of the 16 feeder models is simulated with its own instance of GridLAB-D. Each feeder is equipped with two 50 kW GFM IBRs, except feeder 10, where two GFM IBRs rated at 300 kW are installed to better illustrate the impact of IBR tripping with larger capacities. The two IBRs are installed at the node 806 and 812 at the IEEE 34-node feeder.

The test study consists of two parts: (1) tripping IBRs at different time steps without any faults, and (2) tripping IBRs at different times following two three-phase faults at different intervals, each lasting 0.1 seconds. The three communication delay values—average, minimum, and maximum—listed in Table 2-1 at the end of Section 2 are considered.

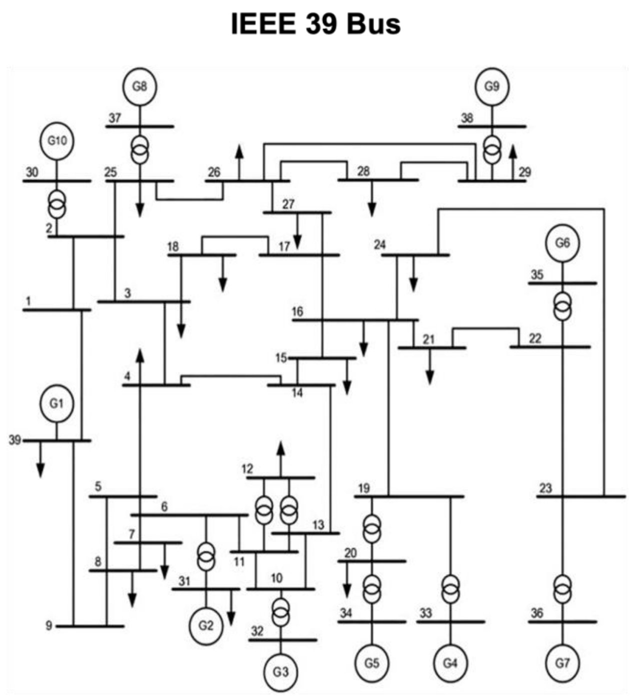

Figure 3-4: The single line diagram of the IEEE 39-bus transmission system [44].

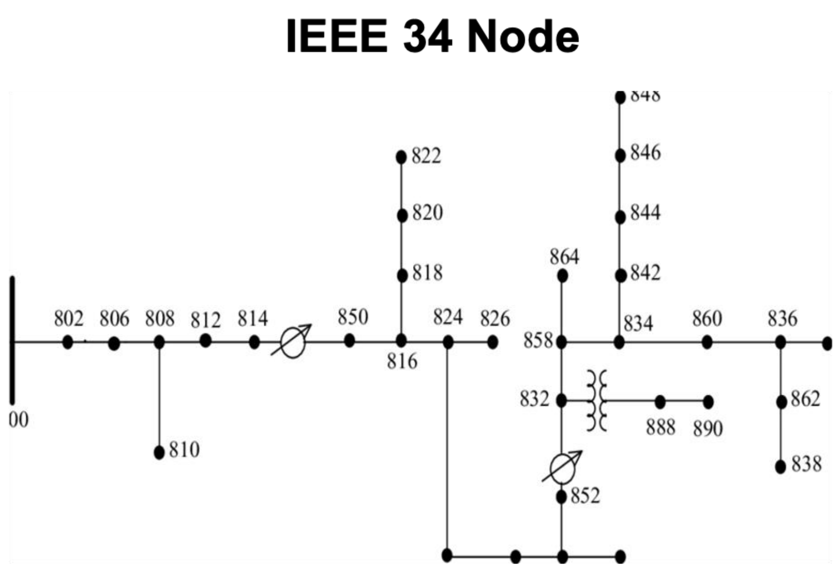

Figure 3-5: The single line diagram of the IEEE 34-node distribution feeder [45].

3.2.1 IBR Tripping without Faults

The purpose of this study is to ensure the T&D co-simulation platform can capture the impacts of distribution-level IBR trippings on frequency regulation and bus voltages of the bulk transmission system.

First, we only consider IBR tripping cases without accounting for other disturbances, as outlined below:

1. Both IBRs are tripped at 2 seconds, representing a worst-case scenario in terms of system frequency regulation.
2. One IBR is tripped at 2 seconds, and the other at 4 seconds.
3. Only one IBR is tripped at 2 seconds to simulate an AI/ML-based solution with the assumption that tripping one IBR is sufficient if the action is taken earlier.

The frequency response of two conventional generators (G3 at bus 32 and G6 at bus 35 in Figure 3-4) to the IBR tripping scenarios is shown in Figures 3-4 (a) and 3-4 (b), respectively. Additionally, Figure 3-4 (c) depicts the voltage behavior during various IBR tripping scenarios. The T&D co-simulation platform effectively captures all IBR tripping events at 2 and 4 seconds. Notably, tripping both PV farms (600 kW total) at 2 seconds leads to the most significant frequency drop, while tripping 300 kW at 2 seconds results in the best performance (least significant frequency drop).

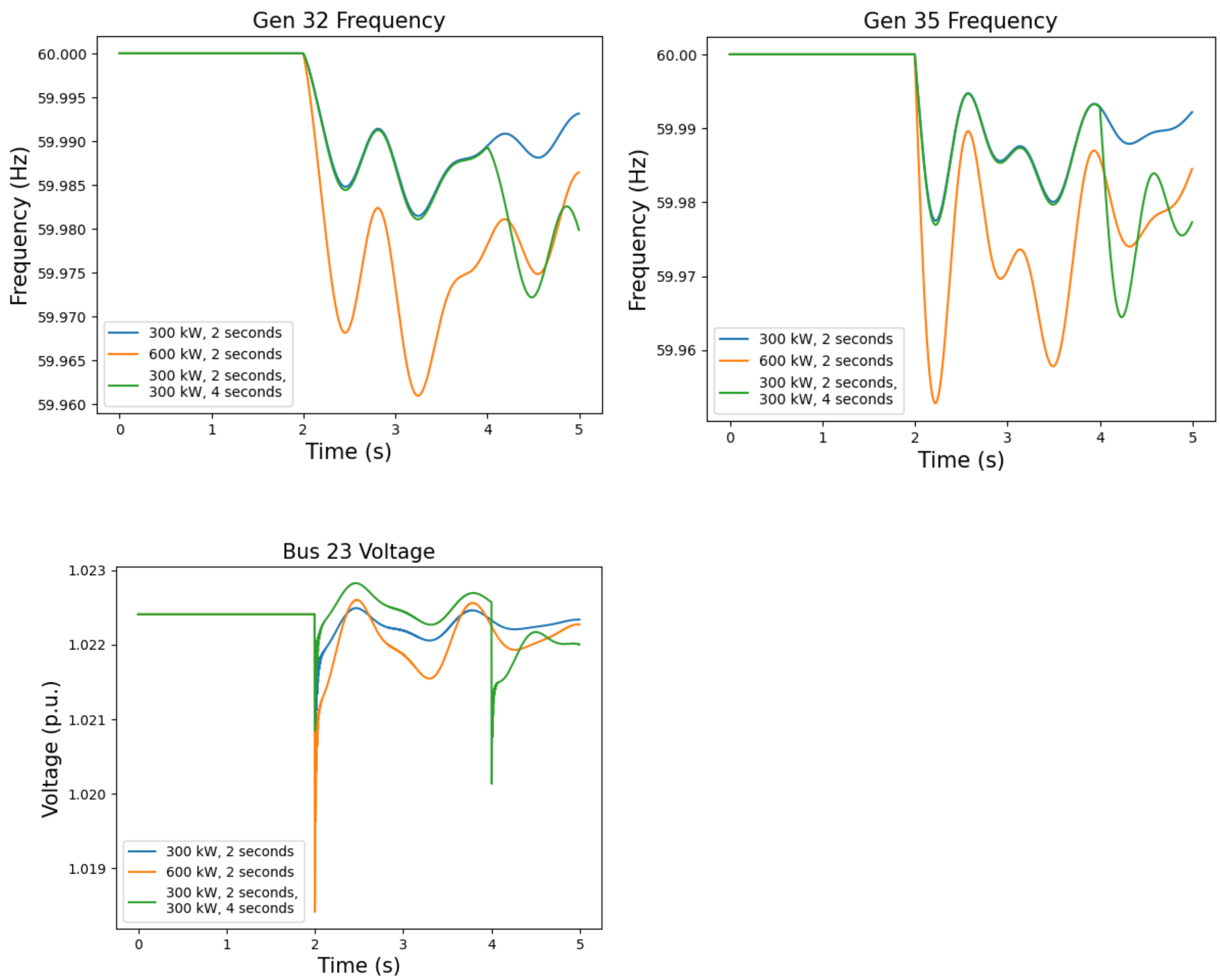

Figure 3-4 Frequency and voltage simulation results of two GFM IBRs tripping, each rated at 300 kW, using the example given in Figure 3-2 [41].

This case study clearly demonstrates the capability of the T&D co-simulation platform to capture the important dynamic interactions between T&D systems. Now, it is time to consider the impact of 5G-enabled end-to-end delay discussed in Section 2.

3.2.2 IBR Trippings Followed by Two Sequential Three-Phase Faults

To study the impact of the 5G-enabled AI/ML-based tool, it is deployed at the feeder 10 of this T&D system with one transmission system and 16 distribution feeders.

A three-phase fault is introduced at t = 2.0 seconds, cleared at t = 2.1 seconds, reintroduced at t = 3.0 seconds, and cleared again at t = 3.1 seconds. It is assumed that the IBR installed at bus 812 is tripped after the first fault and the IBR installed at bus 806 is tripped after the second fault. The detailed tripping logic for the protection is not simulated, and the IBRs are manually tripped based on the three end-to-end delay values mentioned in the Table 2-1 in Section 2.

The total end-to-end delay times in Table 2-1 (656 ms, 471 ms, and 919 ms—rounded to the nearest integer values of 700 ms, 470 ms, and 920 ms) are considered in our study. For convenience, the simulation without any IBR tripping is used as a reference. Table 3-1 shows the timing details of all four scenarios.

Table 3-1: Simulation scenarios that consider two sequential faults and tripping of two IBRs based on different communication delays (time: seconds).

Scenario index	Fault 1 starting	Fault 1 clearing	IBR 1 tripping	Fault 2 starting	Fault 1 clearing	IBR 2 tripping
1	2.0	2.1	N/A	3.0	3.1	N/A
2	2.0	2.1	2.47	3.0	3.1	3.47
3	2.0	2.1	2.7	3.0	3.1	3.7
4	2.0	2.1	2.92	3.0	3.1	3.92

The purpose of this case study is to demonstrate the platform's ability to simulate communication delays, enabling the simulation of IBR behavior under different 5G delay conditions to assess their impact. While the case setup may not fully represent real-world scenarios, it is designed to showcase the platform's potential capabilities.

Like the no-fault cases in Section 3.2.1, the generator frequency at generator 32 and generator 35, as well as the voltage magnitude at the Bus 23, are monitored to compare different scenarios. To show the impact on distribution systems, the active power at the feeder 10 and the frequencies of the two IBRs are also created for comparison.

3.2.2.1 Transmission Network Bus Voltage Magnitude

The voltage magnitudes at bus 23 for all four scenarios are plotted together in Figure 3-6, focusing on the time interval between 2.0 and 4.0 seconds. These voltage curves clearly capture the dynamic behavior introduced by the faults. Although the differences are subtle, the impact of the IBR tripping on the voltage magnitude is still noticeable. This is reasonable, given that the size of the IBRs is relatively small compared to the overall T&D co-simulation system. However, as the system’s dependency on distribution-level IBRs continue to increase, the effects of such IBR tripping will become more significant.

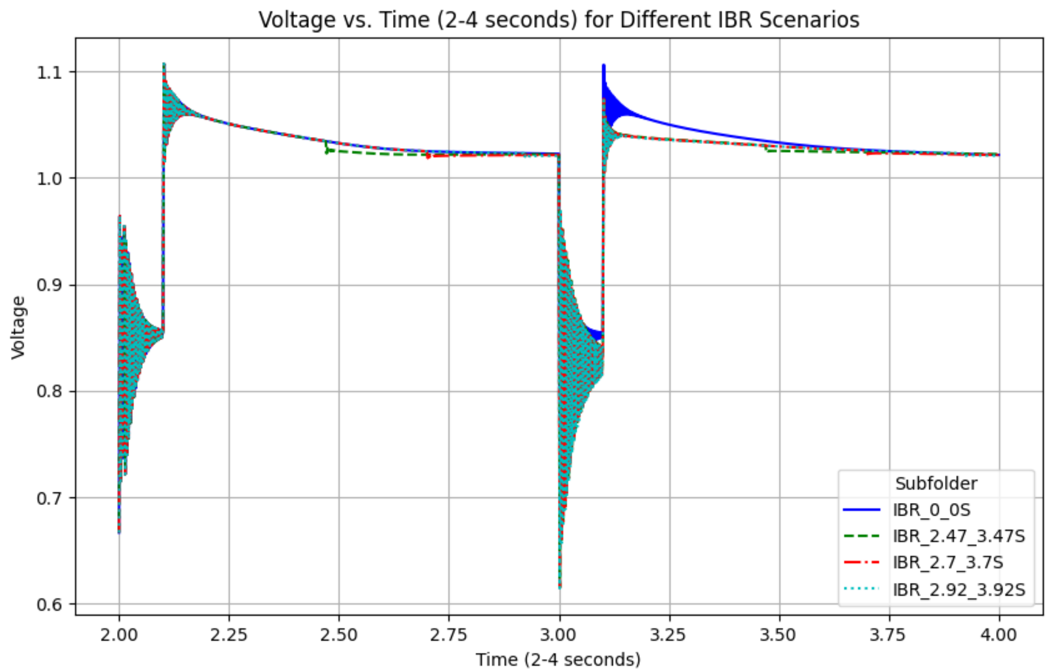

Figure 3-6: Comparison of voltage magnitudes at bus 23 for four scenarios: no IBR tripping, and tripping with delays of 0.47 seconds, 0.7 seconds, and 0.92 seconds after fault 1 at 2.0 seconds and fault 2 at 3.0 seconds, with each fault lasting 0.1 seconds. The figure is zoomed in between 2.0 and 4.0 seconds.

3.2.2.2 Generator Frequency

Next, we compare the frequencies of generator 32 and generator 35. All four scenarios are shown in Figure 3-7, with a zoomed-in view between 2 and 4 seconds. Similar to the voltage curves at bus 23, these figures demonstrate that while the T&D co-simulation effectively captures the dynamics of three-phase faults and IBR tripping, but the differences across the four scenarios are small due to the relatively minor size of the IBRs.

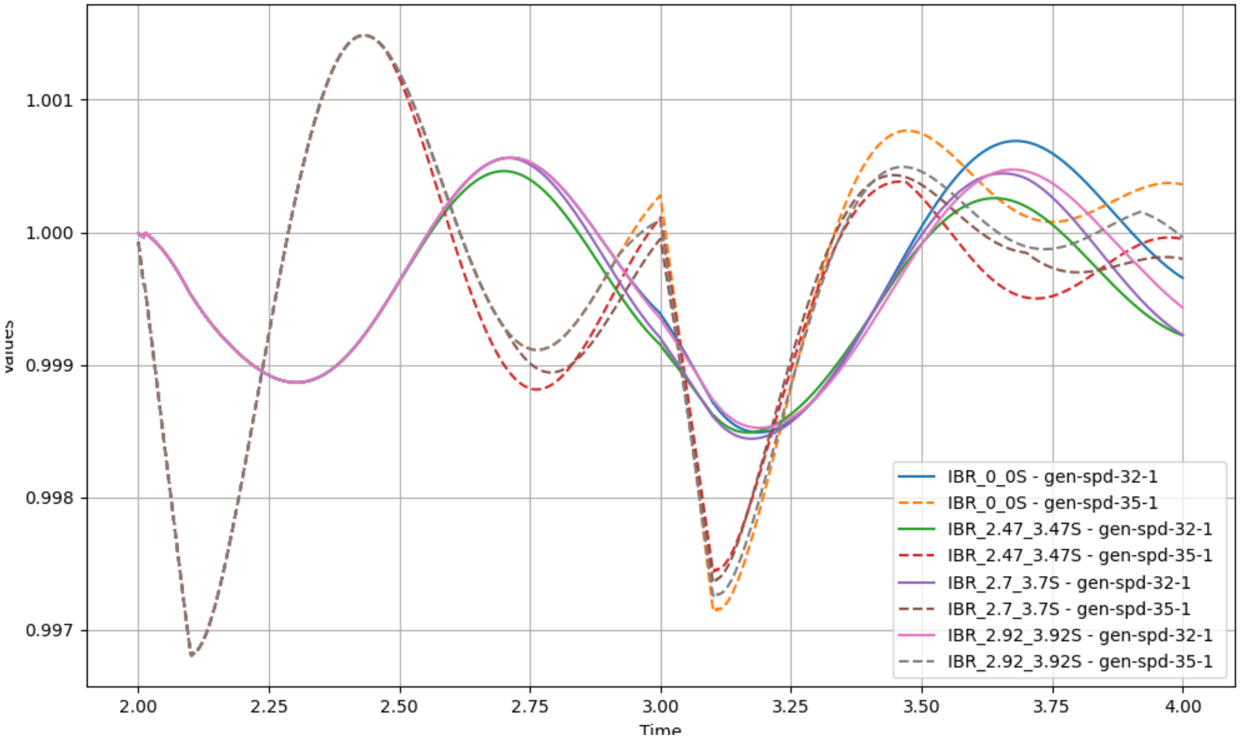

Figure 3-7: Comparison of generator frequencies at generator 32 and generator 35 for four scenarios: no IBR tripping, and tripping with delays of 0.47 seconds, 0.7 seconds, and 0.92 seconds after fault 1 at 2.0 seconds and fault 2 at 3.0 seconds, with each fault lasting 0.1 seconds.

3.2.2.3 Active Power at Feeder

To show the impact of IBR tripping at the distribution side, Figure 3-8 displays the active power (P) at feeder 10 for all four scenarios between 2 and 4 seconds. A comparison that focusing on IBR tripping differences between 2.25 seconds and 2.95 seconds is shown in Figure 3-9.

Based on these two figures, the following observations can be made:

- The 0.47-second delay (orange curve) provides the most balanced response to the fault, with a quick dip in active power followed by a relatively smooth recovery. This scenario offers the least amount of instability post-tripping.
- As the tripping delay increases (0.7 seconds and 0.92 seconds), the system experiences a delayed response to the fault, leading to increased post-fault instability.
- Without IBR tripping, the system adjusts gradually but at the cost of reduced active power over the time window, showing that IBR tripping is essential for maintaining power levels and stabilizing the system after faults.

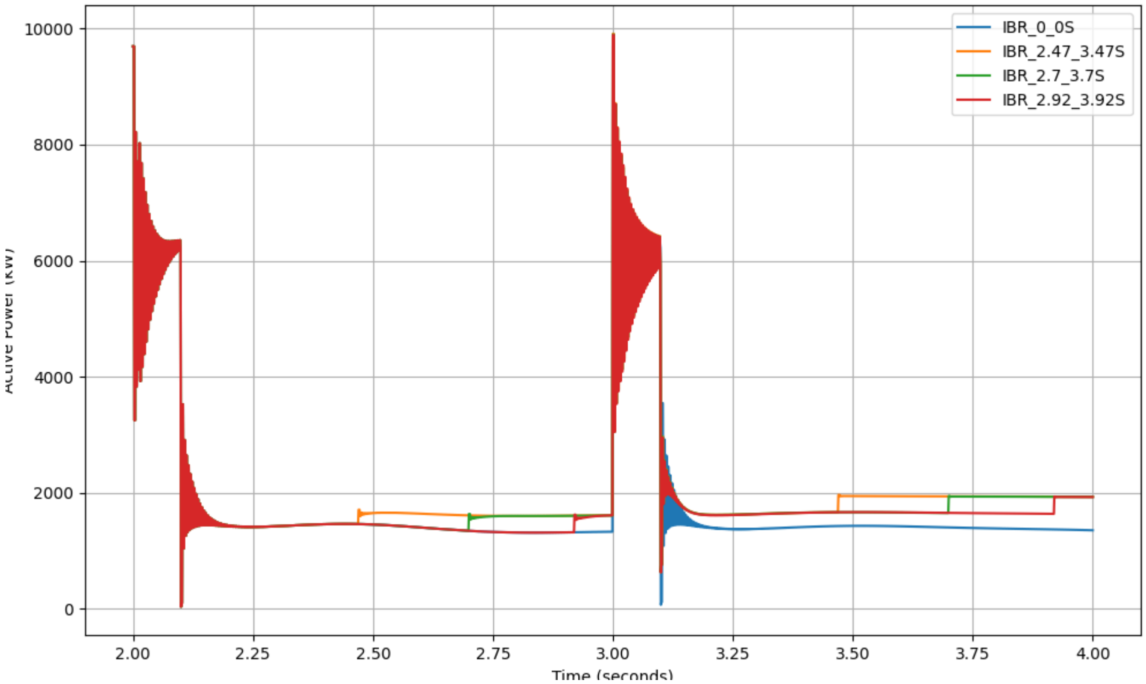

Figure 3-8: Comparison of active power at feeder 10 for four scenarios: no IBR tripping, and tripping with delays of 0.47 seconds, 0.7 seconds, and 0.92 seconds after fault 1 at 2.0 seconds and fault 2 at 3.0 seconds, with each fault lasting 0.1 seconds.

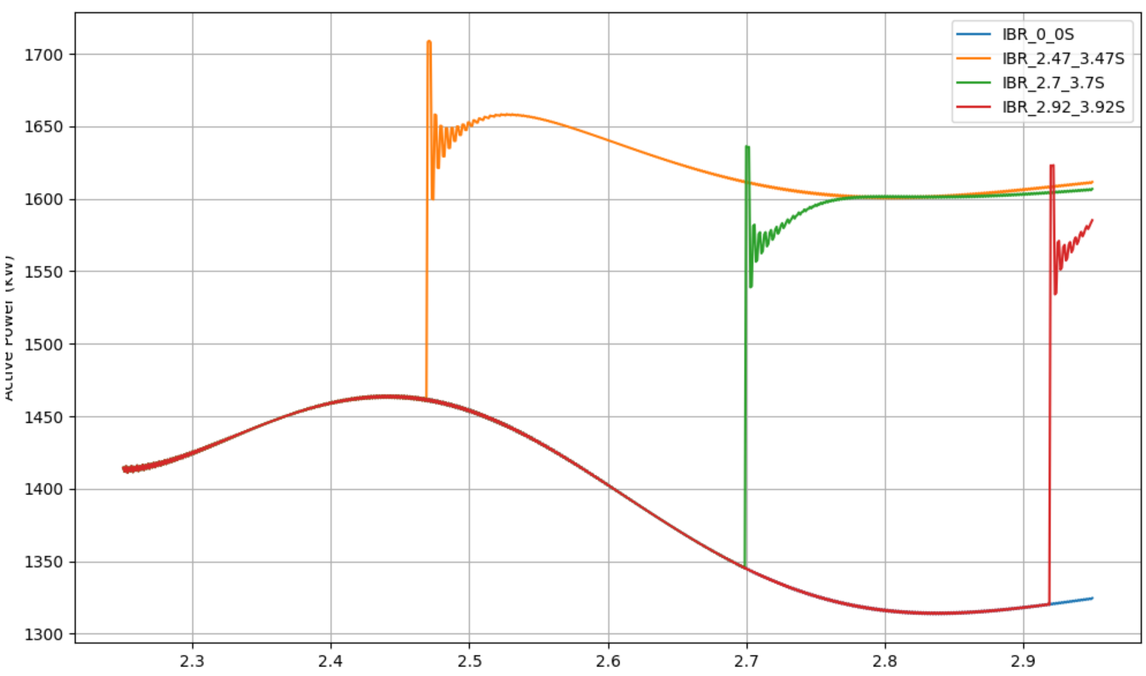

Figure 3-9: Comparison of active power at feeder 10 for four scenarios: no IBR tripping, and tripping with delays of 0.47 seconds, 0.7 seconds, and 0.92 seconds after fault 1 at 2.0 seconds and fault 2 at 3.0 seconds, with each fault lasting 0.1 seconds, focusing on four IBR tripping scenarios during 2.25 seconds to 2.95 seconds.

3.2.2.4 Frequency at IBR

To illustrate the impact on the distribution, the frequencies between 2 and 4 seconds at the second IBR tripping (located at node 806 on feeder 10) are shown in Figure 3-10 for four scenarios: no IBR tripping, and tripping with delays of 0.47 seconds, 0.7 seconds, and 0.92 seconds after fault 1 at 2.0 seconds and fault 2 at 3.0 seconds, with each fault lasting 0.1 seconds. The tripping times are 3.47, 3.7, and 3.92 seconds, respectively. Please note that the first IBR tripped at 2.47, 2.7, and 2.92 seconds, respectively. The no-IBR tripping scenario (IBR_0_0S) is shown as a reference.

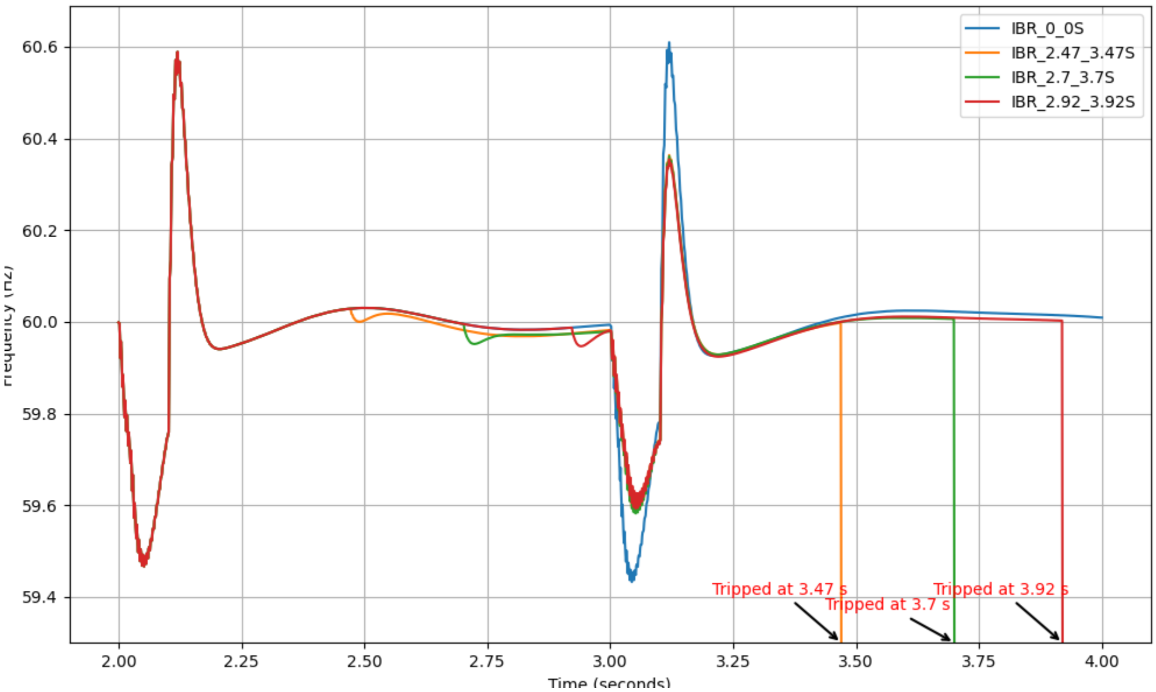

Figure 3-10: Comparison of inverter frequencies at node 806 (IBR 2) at the feeder 10 for four scenarios: no IBR tripping, and tripping with delays of 0.47 seconds, 0.7 seconds, and 0.92 seconds after fault 1 at 2.0 seconds and fault 2 at 3.0 seconds, with each fault lasting 0.1 seconds.

The variations across cases in Figure 3-10 illustrate the following nuances that can be properly studied using co-simulation:

1. The earlier tripping events at 2.47 seconds (orange curve), 2.7 seconds (green curve), and 2.92 seconds (red curve) cause minor frequency variations, but these tripping events prevent larger frequency deviations. These early trips limit the severity of the frequency oscillations compared to the no-tripping scenario. These initial trips dampen the impact of the disturbances, allowing the system to stabilize more quickly.
2. When the second fault happens, the IBR tripping scenarios have better frequency response than no-IBR tripping scenario as the frequency peak values are lower.
3. The blue curve (no-tripping scenario) experiences more significant frequency deviations during the fault events. Although it recovers naturally, the frequency swings are more pronounced compared to the tripped curves. This suggests that the tripping mechanism helps mitigate larger frequency disturbances.

In summary, early tripping events effectively mitigate the impact of faults by reducing the severity of frequency oscillations. This is particularly beneficial for maintaining system stability and preventing larger deviations that could potentially escalate into more severe consequences. While the no-tripping scenario (represented by the blue curve) eventually recovers, it is more susceptible to significant frequency deviations during fault events. The scenarios studied here are based on the results obtained in Section 2, where the delays are likely different than what would typically occur in real-world applications.

The purpose of this study is to demonstrate the capability of the T&D co-simulation framework, which incorporates communication delays to simulate realistic conditions. When integrated with actual models and real-world data, the framework is expected to produce more accurate and representative simulation results. By replicating the complexities of both power and communication systems, this co-simulation approach offers valuable insights into how various delay factors can impact system behavior, ultimately leading to more robust protection strategies in practical implementations.

3.3 Data Availability and Sharing

The model and data used for the 5G for Grid Use Case study are obtained from publicly available sources.

Open-source simulation tools:

- GridPACK: https://github.com/GridOPTICS/GridPACK
- GridLAB-D: https://github.com/gridlab-d/gridlab-d
- HELICS: https://github.com/GMLC-TDC/HELICS

Power system models used in the 5G for Grid Use Case:

- IEEE 39-bus system: https://icseg.iti.illinois.edu/ieee-39-bus-system/
- IEEE 34-node feeder: https://cmte.ieee.org/pes-testfeeders/resources/

Other power system models have been used in T&D co-simulation studies:

- mini Western Electricity Coordinating Council transmission network model: https://ieeexplore.ieee.org/abstract/document/9299666/
- IEEE 8500-node test feeder model: https://cmte.ieee.org/pes-testfeeders/resources/
- EPRI J-1 feeder model (used for AI/ML tool development and validation): https://sourceforge.net/p/electricdss/code/HEAD/tree/trunk/Distrib/EPRITestCircuits/epri_dpv/J1/

3.4 Future Opportunities

The integration of 5G technology into power systems represents a transformative step forward in enhancing protection, control, and operational efficiency due to its ultra-low latency and high bandwidth. The faster communication capabilities enabled by 5G can facilitate quicker responses to fault events, allowing for earlier tripping and improved system stability. As demonstrated in the analysis, the earlier the tripping, the better the frequency response, which ultimately contributes to a more reliable and resilient power system. Therefore, advanced communication technologies, like 5G, can further optimize these tripping mechanisms, leading to enhanced protection and operational efficiency in modern power systems.

Looking ahead, the synergy between 5G technology and AI/ML-driven applications offers substantial potential to improve power system operations. The ultra-low latency and high data throughput offered by 5G are critical in supporting real-time data processing and decision-making capabilities, making AI/ML systems more efficient and reliable. This is particularly relevant in key applications, such as predictive maintenance, dynamic load management, and real-time grid monitoring, where the combination of 5G and AI/ML algorithms can enable faster, more accurate responses to changing grid conditions.

Additionally, 5G technology can enhance the integration of DERs by facilitating seamless communication between devices, enabling more effective coordination and control across the grid. This capability is crucial in the context of decentralized energy systems where grid-edge intelligence is becoming increasingly important.

Grid-edge has been recognized as “an unprecedented opportunity to drastically enhance the reliability, availability, and efficiency of the electric grid with the rise of decentralized energy systems” in a recent report of AI/ML technology for power system applications [46]. Along this direction, AI-driven smart edge devices that are powered by 5G offer significant potential to enhance grid monitoring and decentralized decision-making. By processing data locally, these devices reduce the load on central servers, enabling faster, more responsive interventions and improving grid resilience. Meanwhile, the integration of 5G with AI/ML can better manage the uncertainties of renewable energy. AI/ML algorithms, especially those for risk management, can benefit from 5G’s rapid data exchange, improving adaptability to fluctuations in renewable energy output.

Combining 5G with HPC, including edge computing, can accelerate complex simulations and data processing in power systems. This synergy enhances real-time applications like grid stability analysis and DER optimization. The integration with 5G and edge computing is an ideal approach to balancing the computational and data transmission burden. Grid edge workflow management presents another opportunity to handle the increasing data volume and complexity across power systems [47].

Last but not least, ensuring safety in AI/ML-driven power systems is crucial. 5G’s robust communication supports the development of safety-constrained learning algorithms, reducing risks in critical power system operations.

In conclusion, integrating 5G technology with AI/ML in power systems holds promise for building a more resilient, efficient, and reliable power grid. By enabling faster communication, real-time data processing, and intelligent decision-making, these advancements pave the way for smarter power systems that can adapt quickly to routine operations and disruptions. As these technologies evolve, the power grid will become more robust and adaptive, ensuring stability and reliability in a complex energy landscape.

4.0 Project Summary and Technology Roadmap

In this section, the three-year project activities are summarized and reviewed, including the publications, collaborations with research partners, and data and tools used for simulations. In addition, an extended discussion on the convergence of microelectronics and power electronics is provided to explore the technology roadmap that may realize the co-design of energy, communication, computing to deliver the decarbonization goal with science-driven methodologies.

4.1 Technical Achievement and Outcome

Since the inception of this three-year research project in 2021, the PNNL project team has been delivering the innovation and technology development based on the unparalleled capabilities offered by 5G. The PNNL in-house 5G NSA and SA hardware testbeds were employed to generate simulation data to qualitatively and quantitatively evaluate the network performance and impacts on power grid applications to explore the feasibility of enabling AI/ML applications through 5G platform and edge devices.

Besides the hardware enabled R&D work, the project team and research partners also developed a series of research work centered around the grid communication infrastructure modeling and design, especially the 5G platform, in support of power grid planning, monitoring, and control.

As a result, a group of research publications, presentations, collaboration and outreach activities, are listed in Appendix A, B, and C at the end of this report.

4.2 Project Data and Tools

5G hardware testing and performance data is fundamental and important for scientific and engineering applications. With the access to both PNNL 5G NSA and SA testbeds, the PNNL project team collected communication system performance data sets, including latency, jitter, varying bitrates, user datagram protocol and transmission control protocol configurations, device sleep time variations, and three different UE. All data was saved in spreadsheets and shared through the project website[1]. There is also a short introduction document and associated python scripts attached in these datasets for initial data analysis and plotting functions. For more details, please refer to [7, 40, 48].

Besides the 5G hardware testbeds and platform at PNNL, there is also a collection of research tools and software being adopted and customized by the project team in support of power grid modeling and communication infrastructure modeling. For example, power grid T&D co-simulation tools [10], including HELICS [49], GridPACK [50], and GridLAB-D [51], had been employed to represent the physical behavior of power grid as part of the 5G for Grid Use Case, in which the communication network behavior was configured based on our hardware testing data in Section 3. In addition, customized graph analytics [6] for critical node ranking and black-start impacts were developed and applied for large-size grid network models; such analytics were implemented with task parallelism on PNNL's HPC cluster *Deception*. Last but not least, AI/ML models had been adopted and revised to be compatible with a 5G-enabled edge

[1] Data section on the PNNL 5G Energy FRAME project publication web page: https://www.pnnl.gov/projects/5g-energy-frame/publications

computing platform to demonstrate the feasibility of real-time anomaly data detection [14] and distribution grid protection configuration in Section 2.

To expand from the hardware and software simulations performed in this project, Figure 4-1 shows a conceptual design on the data fusion framework. The project team recognizes that it is challenging to find accessible and high-quality datasets in support of cross-infrastructure network modeling and applications, and it often comes to the multi-source data that is being siloed (i.e., power grid, population and census block statistics, geolocations, and community specific representations). In reflection of the co-design of energy, communication, and computing, the multi-level fusion model for cross-domain datasets features FAIR dataset requirements (Findability, Accessibility, Interoperability, Reusability) and three technical blocks to ensure reliable, valuable, and accurate information from multi-source data:

1. Data pre-processing block: this is the lowest and basic level, which contains data redundancy, completeness, cleaning, transformation, and so on. The main purpose is to prepare the data in proper level for further processing and reduce the system load.
2. Machine-based information extraction fusion block: this contains all static information, identification, and characteristics of the raw data
3. Feature and decision fusion block: this aims to achieve the characteristics/patterns/determinations/actions to the decision level. Human-machine interaction can be involved as needed.

It is also seen that 5G enabled dynamic network slicing, edge connectivity and computing capabilities, cloud integration, and HPC accessibility are playing their roles in this model. To deliver AI/ML as a service offering, there are an expanded list of AI/ML R&D work [46] funded by DOE Office of Electricity Advanced Grid Modeling program that may benefit such framework; therefore, expediting the industrial adoption through 5G.

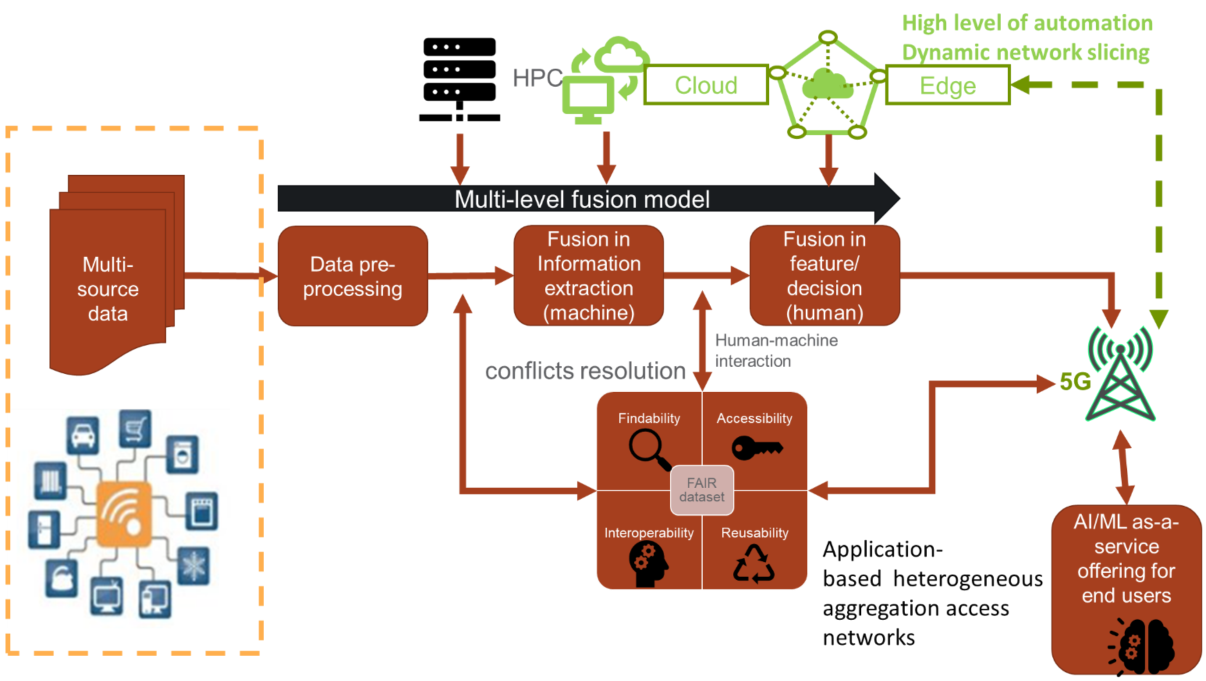

Figure 4-1 Data fusion framework integrated with various computing sources and 5G [48].

4.3 Exploring a Technology Roadmap by Technical Workshop

In the year two report of this project, it is recognized that more workshops centered around the co-design of microelectronics and power electronics (e.g., an energy-efficient and resilient data center) could benefit the research and industry stakeholders so that a better future grid can be visioned, designed, assessed, validated, and coordinated in support of technology innovation and the overall decarbonization goals [40].

Similar to the interconnection of the power grid through its generation, transmission, distribution networks, and the end-users, there is no physical or electrical separation among those during the day-to-day operation for reliable services; this also applies to the power-electronics dominated power grid [52], in which all participating components and entities may rely on autonomous control, distributed and edge computing, and communication infrastructure for wide-area coordination and service provision. As a result, either at the device level or the interconnection system level, there is no physical or electrical boundary among its microelectronics portion and power electronics portion—all those must be designed, integrated, coordinated, and managed to deliver the same day-to-day operation for reliable services. Figure 4-2 illustrates the performance and capabilities of different semiconductor material types considering the natural connection of such material in support of power electronics and microelectronics. The scientists and engineers in those two domains may experience less barriers among such cross-domain collaborations.

In this subsection, the team will explore a technology roadmap following the suggested technical workshop venue and leveraging two technical reports by collaborative efforts of many industry and academic experts:

- ***Solid State Power Substation Technology Roadmap***: this report shares the vision of future power grid with solid state power substations (SSPS), and discusses technology challenges and potential benefits, and the necessary broad participation from industry, academia, and government laboratories for a collection of R&D work "spanning hardware design and development, real-time simulation, control algorithms, system protection, power electronics, thermal management, magnetics and passive components, network architecture, communications, cyber-physical security, and computation. Expertise in analysis, markets, regulations, standards, testing, and education [53]".

  In particular, SSPS formulates the connecting node for any equipment in power generation, transmission, and distribution, bridging all forms of electricity service and energy storage. In short, SSPS will be critical to grid with its ubiquitous nature, no matter it is alternating current or direct current system. Moreover, the very fundamental enabling technology for SSPS is the power electronics or power semiconductors, including thyristors, IGBTs, MOSFETs, and wide-band-gap semiconductor materials (e.g., silicon carbide and gallium nitride). Such understanding and technology origin naturally depicts the underlying tone of co-design of

  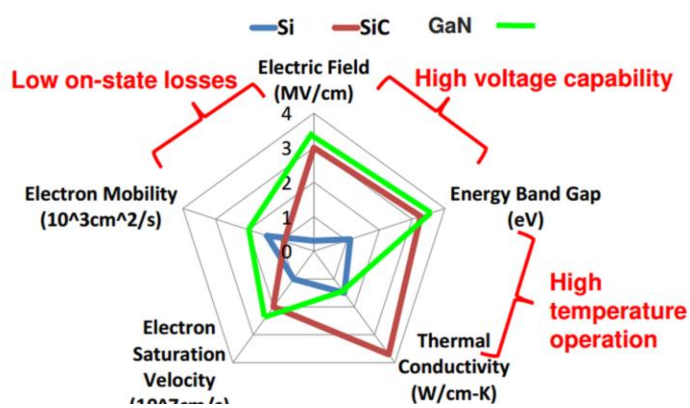

  Figure 4-2 Performance comparison of semiconductors from power electronics perspective [53].

power electronics and microelectronics centering around semiconductor technology and supporting emerging applications.

Lastly, there are three stages of roadmap activities being identified in the report; they are covering near-term (within 5 years), midterm (within 10 years), and long-term (within 20 years). For more details, please refer to [53].

- ***MAPT: Microelectronics and Advanced Packaging Technologies Roadmap [54]***: this report is provided by the Semiconductor Industry Association and extends the work of the Semiconductor Research Corporation's 2030 Decadal Plan for Semiconductors [55]. The MAPT roadmap shows a high-level concept on the semiconductor R&D ecosystem in Figure 4-3, in which a multidisciplinary strategy considering critical enablers, needs and drivers, and the overall elements of success for chips, chiplets, and system-in-packages. One significant feature of the MAPT roadmap is its attention to sustainability, including energy sustainability, environment sustainability, and workforce sustainability.

Figure 4-3 A high-level concept on the MAPT roadmap and its ecosystem [54].

In Figure 4-3, one important topic in the needs and drivers category is sustainability and energy efficiency. For example, Figure 4-4 illustrates different data center configurations. Both computing and cooling energy consumption should be properly modeled and

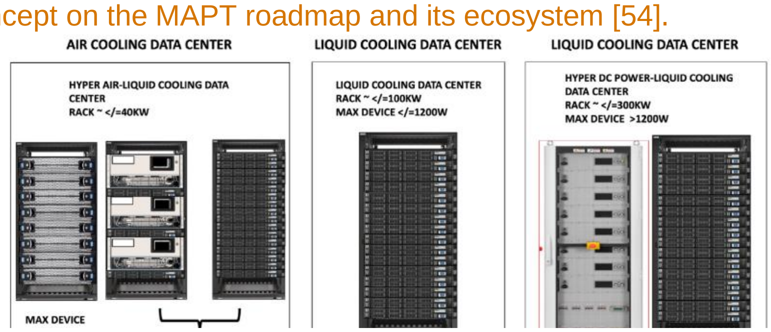

Figure 4-4 An illustration of different data center computing server rack and cooling solutions [54].

evaluated, as individual rack could surpass 60kW or even 120kW, while a combination of those racks (also known as pods) could surpass 1 megawatt (MW) power. Moreover, there are also cooling system constraints indicated by power usage effectiveness at the data center level. Moving to the regional grid and interconnection level, connection requests for hyperscale facilities of 300 – 1000MW or larger with lead times of 1 – 3 years, are emerging challenges for infrastructure planning, which stretch the capacity of local grids to deliver and supply power at that pace [56].

The continuation of energy efficiency and sustainability requires new ideas, such as how the co-design concept for the integration of power electronics and microelectronics could be a significant value to support, identify, customize, and automate many of the design, implementation, packing, and manufacturing of the end-use product. It is also important to leverage the summarized information in this report, with highlighted application spaces and new technology (see Table 4-1), which is in progress, to find the most promising pathway to explore the integrated yet accelerated innovation out of power electronics and microelectronics.

It should be noted that the MATP roadmap utilized a relatively shorter timeline which covers near-term (1 – 5 years), midterm (5 – 10 years), long term (10 – 15 years). For more details, please refer to [54].

Table 4-1 Table from the MATP roadmap shows a broad view of power electronics applications and key drivers (+++ critical, ++ important, + moderate, - modest) [54].

Application Space	Application	Efficiency (reduce loss / heat)	Power Density (reduce size/weight)	Voltage Conv. Ratio (VOUT/VIN)	Reliability	Heavy Load Performance	Light Load Performance	Process Tech. Migration
Performance Computing	Datacenter/ Cloud	++	+	+++	+	+++	+	GaN
	Desktop/Server	+	+	+	+	++	+	-
	Laptop/Personal	++	++	+	+	++	++	nm CMOS
	Networking, etc	+	+	+	+	+	+	-
Mobile/ Communication	Cell phone	++	+++	+	+	+	++	nm CMOS
	Tablet	+	+	+	+	++	+	nm CMOS
	Displays	+	+	+	+	+	+	SOI
IOT/Wearables / Biomedical	Consumer IOT	+	+	+	-	-	++	nm CMOS
	Biomedical	+	+++	-	+++	-	+++	nm CMOS
Automotive	Powertrain	++	++	+	+++	+++	+	GaN/SiC
	Battery (BMS)	+	++	+	+++	++	++	BCD/SOI
	Battery (charger)	+	++	+	+++	+++	-	GaN/SiC
	Peripheral DC-DC	+	+	++	+++	+	-	BCD/SOI
Grid Interface/ Renewable Energy	Rectifier (AC-DC) (e.g. low power)	+	++	-	+	+	+	GaN BCD/ SOI
	Inverter (DC-AC) (e.g. Solar PV)	++	+	+	+++	++	+	GaN
	Battery Storage	+	-	+	++	++	++	-
	LED Lighting	++	++	+	++	++	+	-
Wireless Power Transmission	Low power (e.g. mobile/IOT)	+	+	-	-	+	+	nm CMOS
	High power (e.g. automotive)	++	+	+	++	++	+	-
Industrial Automation	Motor Drives	++	+	-	++	++	+	GaN/SiC
	COTS DC-DC	-	+	-	++	+	+	-

Now, through the 5G Energy FRAME project and the 5G for Grid Use Case used for the grid, the research team would like to emphasize the findings in the *Basic Research Needs for Microelectronics: Report of the Office of Science Workshop on Basic Research Needs for Microelectronics* [57] published by DOE SC, the identified possible benefits are:

1. Computer and 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 [57]

By expanding such benefits into the integrated power electronics and microelectronics perspective, it is safe to predict the following:

1. Large electric loads, including data centers, could range from tens of MW to even thousands of MWs for their power rating, and possibly have a year-around high energy demand with strict service requirements. There are also incentives in which data centers may opt in demand response and/or other grid service programs to maximize economic profit through their flexible scheduling of computing loads. Such trends significantly impact how power grid planners and operators manage the infrastructure and perform resource planning.
2. The energy decarbonization goals and sustainability enhancement calls for continuous leaps of energy efficiency, which may span across multiple infrastructure domains, including energy, communication, and computing. Under the grid transition with higher penetration of renewable energy as inverter-based-resources (IBRs), it is critical to develop a coherent coordination process for the design, manufacturing, monitoring, control, and optimization of IBRs by leveraging the co-design concept for the power electronics and microelectronics within IBRs.
3. New business services and enterprise-customer architecture may be developed to properly capture the advantage of 5G RedCap deployment and edge AI/ML capabilities so that all regulated infrastructure owners and operators could evolve with engaging customers through R&D collaborations with university, national laboratories, pilot communities and municipals, and, more importantly, the continuous state and federal support to scientific discovery, engineering advancement, and technology commercialization.

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Appendix A – Technical Publications

This appendix provides a list of

https://www.pnnl.gov/projects/5g-energy-frame/publications

Appendix B – Project Collaborators

This appendix provides a list of

https://www.pnnl.gov/projects/5g-energy-frame/collaborations

Appendix C – Project Outreach Activities

This appendix provides a list of

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