



NOKIA



4/12 Technical Panel @ Grid Connectivity Stage

5G-Enabled Grid Edge for Immersive AI Applications

Panel Chair: Xiaoyuan Fan

xiaoyuan.fan@pnnl.gov



TECHNOLOGIES
CONFERENCE & EXPOSITION

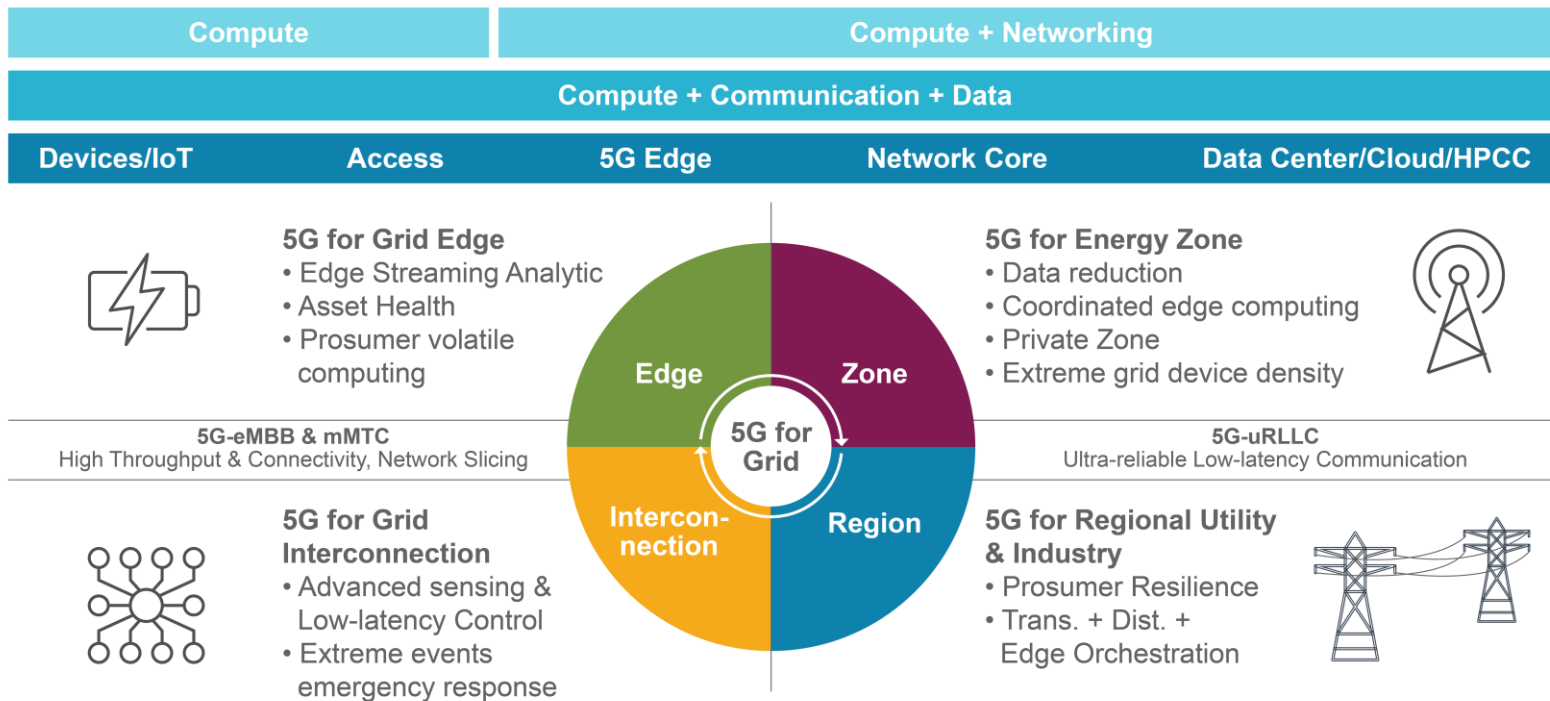


Invited Guests:
Dr. Mauricio Subieta,
Dr. Yilu Liu,
Dr. Qiuhua Huang,
Dr. Luigi Vanfretti

PNNL-SA-182932, unlimited distribution. The PNNL 5G Energy FRAME project is funded by Department of Energy, Office of Science ASCR Program.



5G Enabled Transformative Co-design and Co-simulation for Grid Decarbonization



5G Digital Continuum

IoT/Edge

HPC/Cloud

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



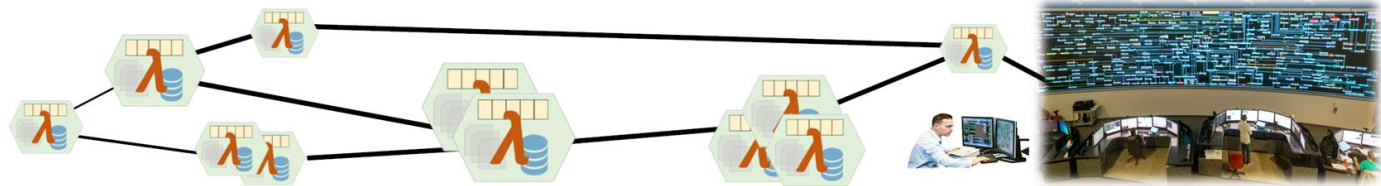
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Count = 10^1
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Sensors

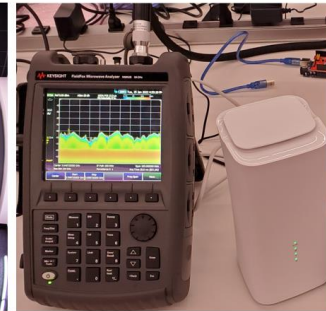
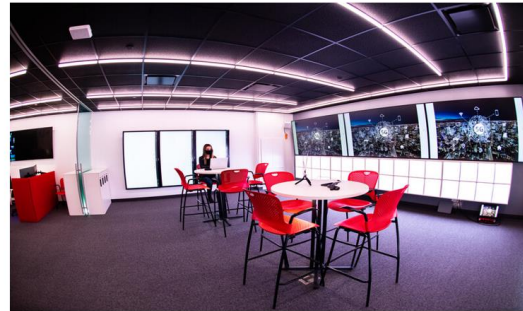
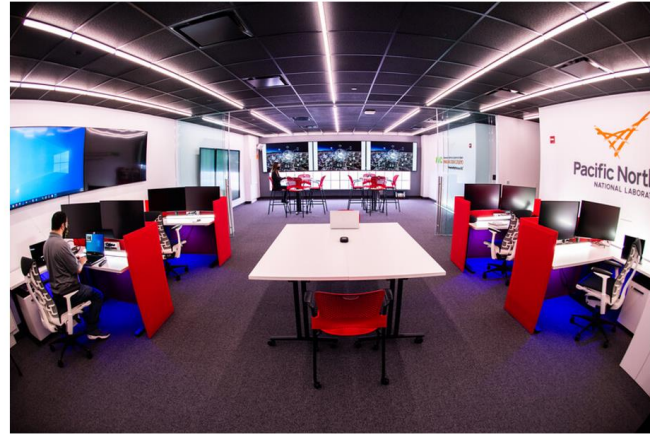
New
Programming
Model and
Runtime



Credit: DOE SC ASCR 5G-enabled Energy Innovation Workshop Report, 2020.

5G Innovation Studio @ PNNL

- Online October 2020
- First National Lab with Ultrawideband Verizon 5G
- Full R&D, modeling & simulation, testing/eval, development and demo capabilities
- Edge and cloud compute resources
- 1,000 sq ft of testing & evaluation space to support R&D, and partner demonstration
- Multi-sponsor R&D funded
- Active industry engagement



5G testbed 1st example from PNNL: AI/ML enabled Grid Data Anomaly Detection

5G Studio testbed setup for conceptual validation and preliminary testing:

Sensor Layer

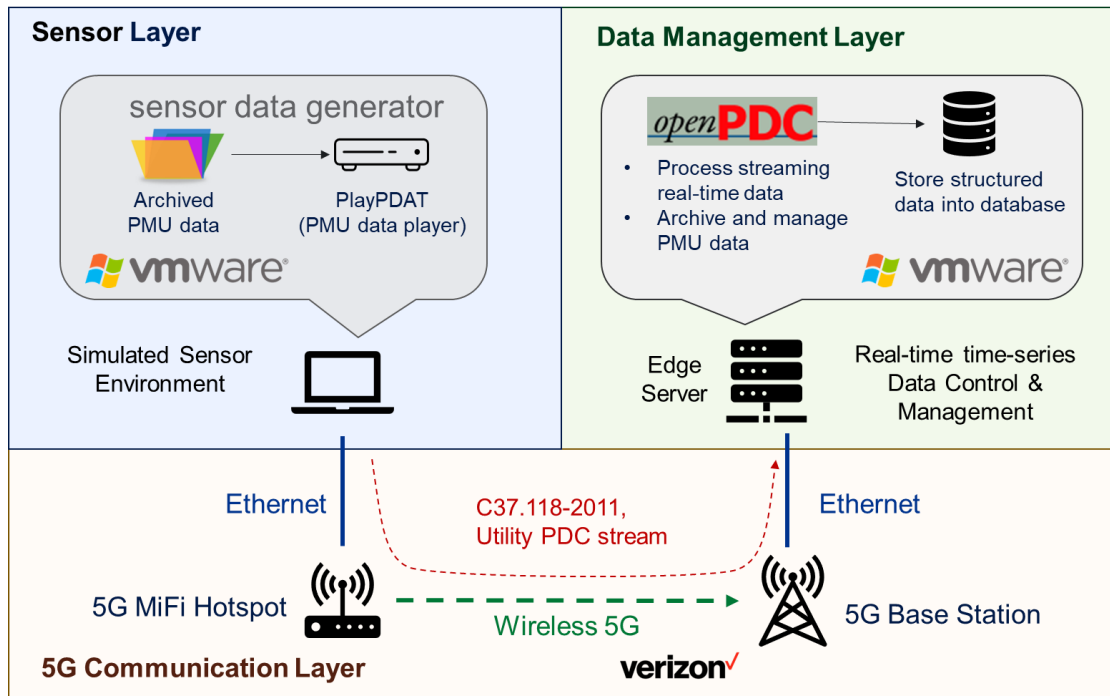
- Windows OS in VMware
- PlayPDAT: PMU data player provided by BPA

Communication Layer

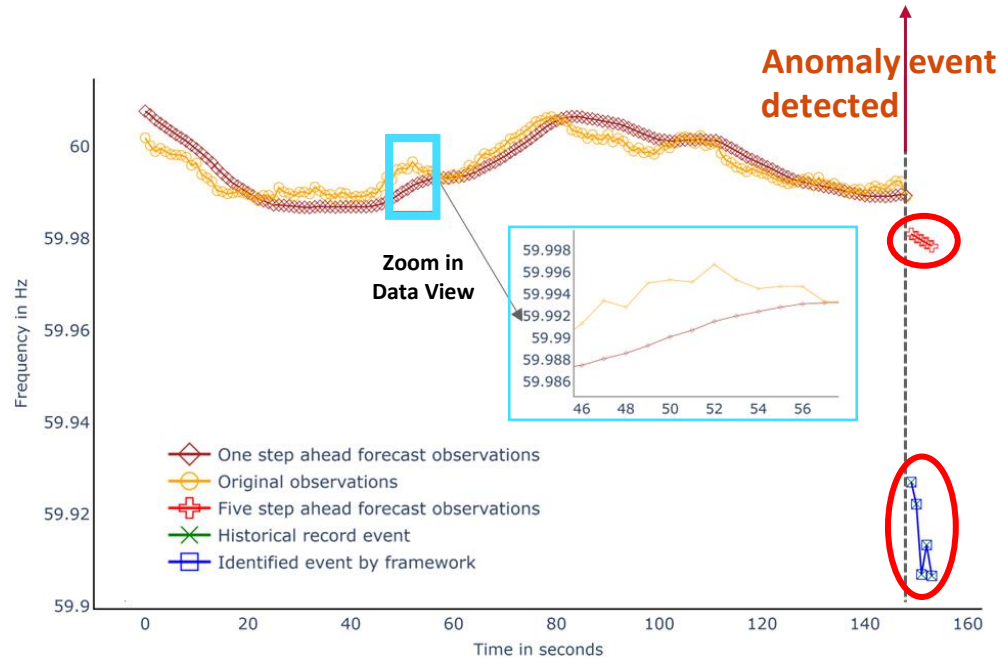
- Verizon 5G core, antenna, and MiFi hotspot.

Data Management Layer

- Windows OS in VMware
- Grid Protection Alliance OpenPDC
- Microsoft SQL Server



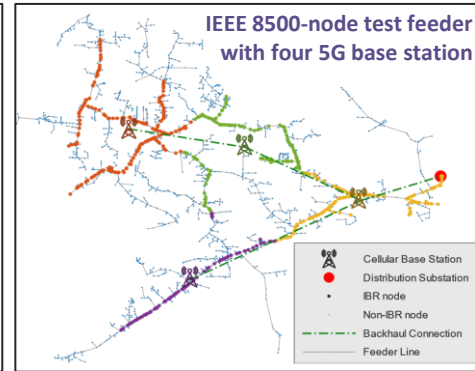
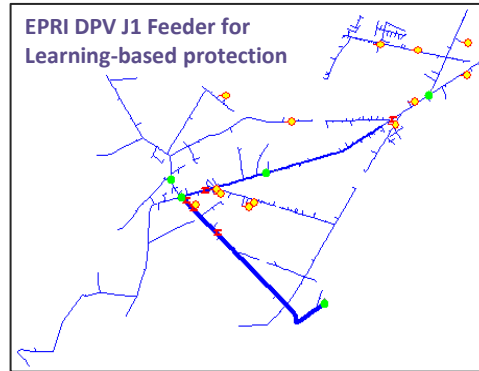
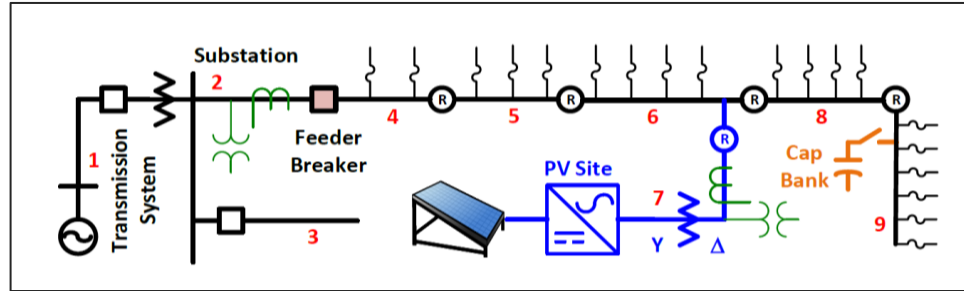
5G testbed 1st example from PNNL: AI/ML enabled Grid Data Anomaly Detection



- Edge server through 5G base station receives and processes the streaming PMU data continuously (for 1-hr PMU archive) from the sensor.
- Online AI/ML model is running at individual second, within it the past five minutes parsed data is ingested to predict grid frequency behavior of next five seconds
- **5G hardware and AI/ML works seamlessly to enable such online AI/ML based detection implementation**

5G testbed 2nd example (*in progress*): AI/ML enabled Distribution Grid Fault Detection & Control

- Leveraged existing DOE EERE SETO funded project 34233, adopting/testing their developed AI/ML algorithm as next 5G testbed example.
- 5G may enable AI/ML implementation, providing high bandwidth and edge connectivity, and seamless yet powerful computing continuum.
- Distribution system requires reliable and distributed protection elements/algorithms, to enable customer safety and reliable operation, as well as supporting significant new load and generation integration.



THANK YOU

And welcome our panelists today:



Dr. Mauricio Subieta
Chief Technology Officer
Nokia



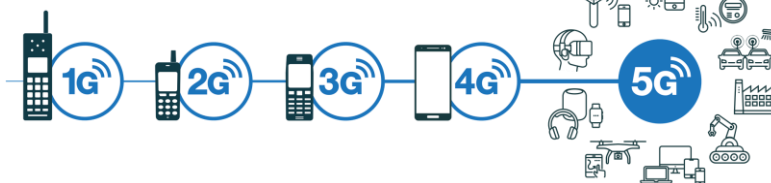
Dr. Yilu Liu
Governor's Chair/Professor
University of Tennessee



Dr. Qihua Huang
Associate Professor
Colorado School
of Mines



Dr. Luigi Vanfretti
Professor
Rensselaer Polytechnic
Institute



NOKIA

The reality and future of 5G for Power Utilities

Mauricio SUBIETA, PhD
Energy CTO



Currently supported use cases

Distribution
Automation (SCADA
- Traditional and
IEC 61850)



Superscript

CCTV - Physical
Security and Safety
Monitoring
(NERC/CIP)



Mobile Workforce
Voice, Data, Video



Advanced Metering
Infrastructure (AMI)



Synchrophasors
and FLISR



Distributed
Generation and
Storage, EV
Stations



Microgrids and
Home Area
Networks



Smart Poles and
Sensors



Fallen Power Line
Detection



LMR
Upgrade/Migration
to Mission Critical
PTT/PTV



Leased Line
Replacement



Drones and UAVs

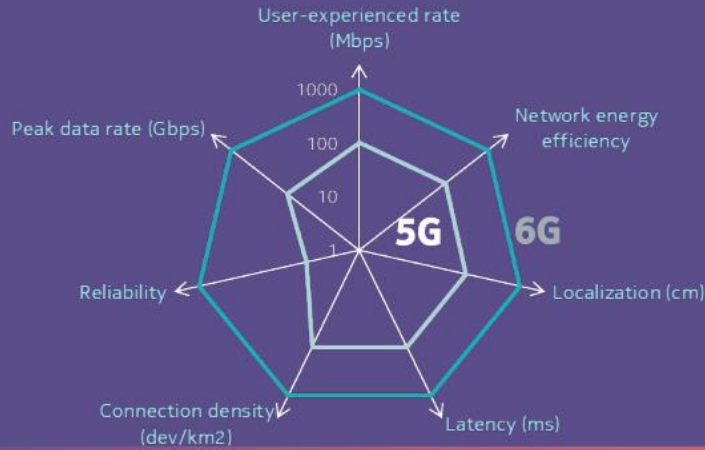


On the path to 6G... already?



5G-Advanced is an evolution, not a revolution

5G-Advanced will deliver on the original expectations for 5G with enhanced system performance and network efficiency



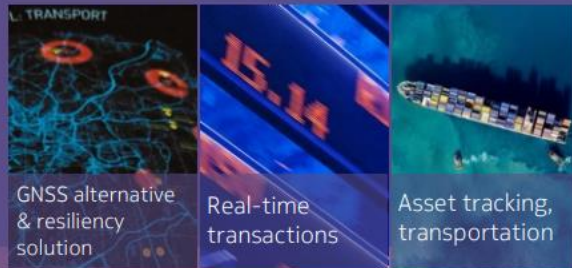
5G-Advanced will prepare for 6G by bridging performance, studying the key technology concepts and supporting early 6G use cases

5G-Advanced introduces new usage areas, new use cases, boosted resiliency and operability

Extending global 5G-Advanced reach for IoT and basic MBB



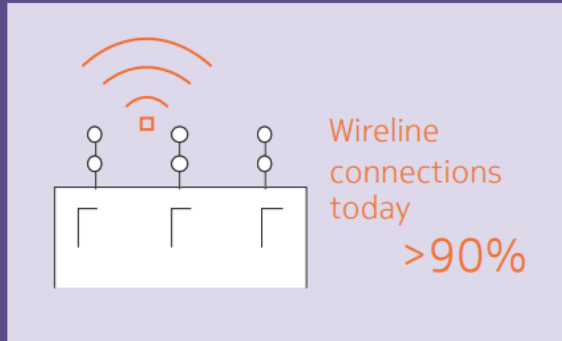
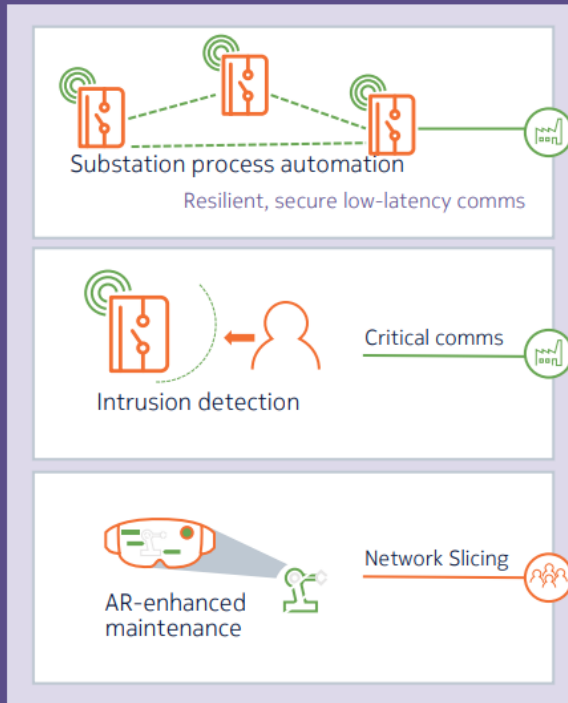
Expansion to support positioning, Time Sync aaS also without GNSS – enabling new use cases



UAV Unmanned Aerial Vehicle
NTN Non-Terrestrial Network
HAPS High Altitude Platform Systems
GNSS Global Navigation Satellite System

5G-enabled use cases for electric utilities

Resilient, secure low-latency communication



Overall costs for greenfield
2-5 times lower

of sensors \uparrow
= Payback period \downarrow

Break even for wireline replacement
1 year

Reconfiguration cycle \downarrow
= Payback period \downarrow

\$ Business case

Ultra-low latency at scale

<1ms; 99.999% reliability

Inherent security
by dedicated network slices

Single company network
for all kinds of industrial applications

5G Advantage

Removing cost
of cabling installation and maintenance

Less reconfiguration time

Less production capacity overprovisioning

Benefits

Thank you!

Questions?

- Contact

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New Prospective on Grid Edge Sensing

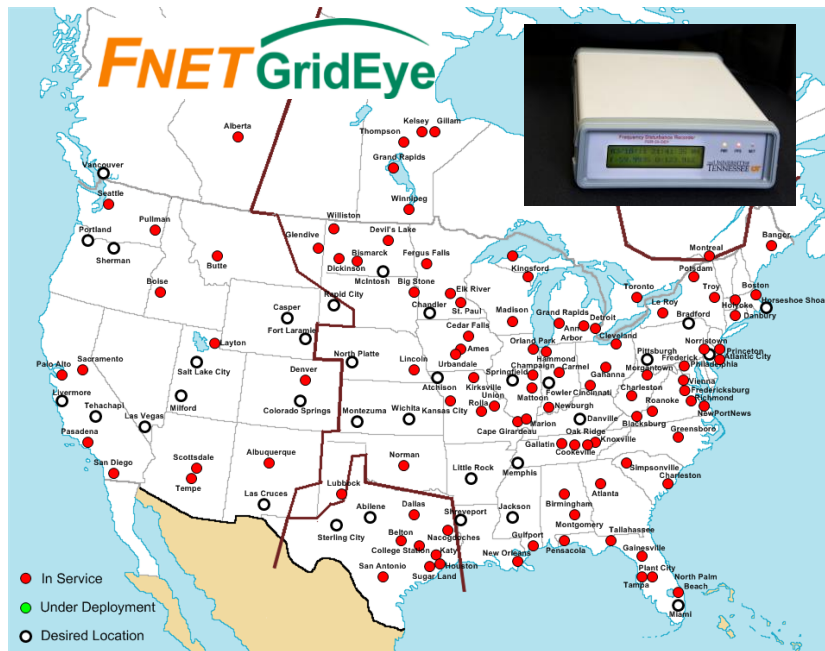
Yilu Liu, UT/ORNL Governor Chair

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April 2023



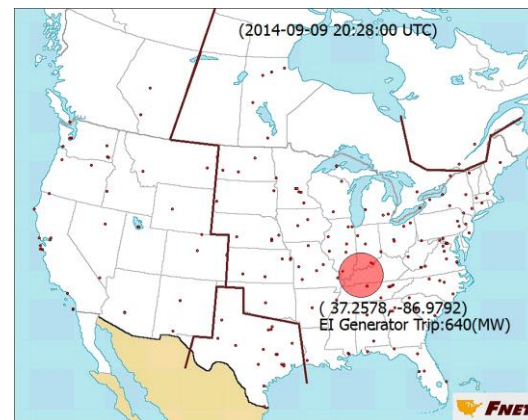
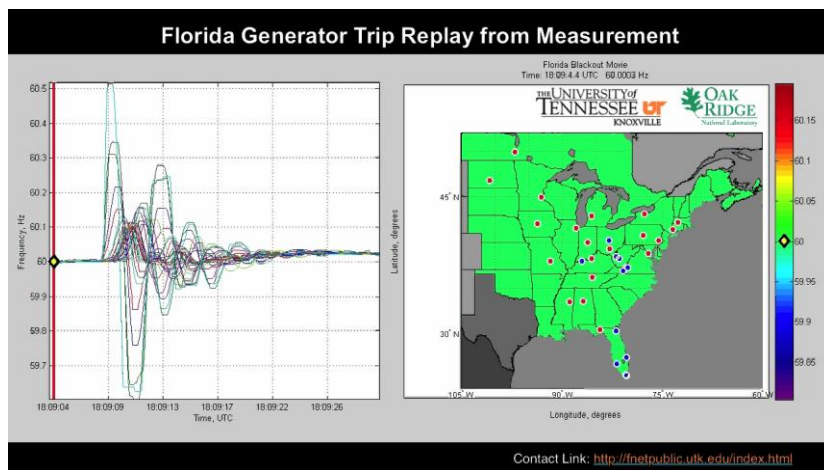
Deployed Grid Edge Monitors in US and World Wide



Live data streaming

<https://fnetpublic.utk.edu/>

Edge Sensors for Transmission Level Dynamics



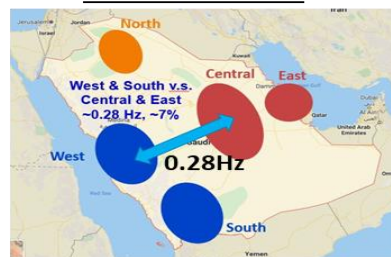
Event location



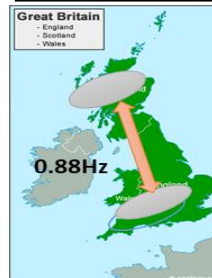
Continental Europe



Saudi Arabia

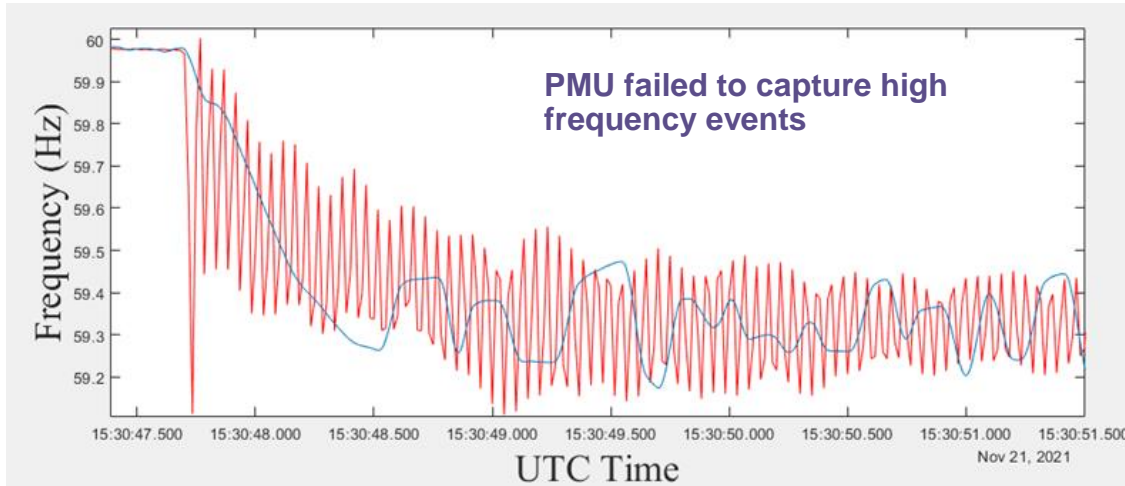


Great Britain



Oscillation damping

Grid Edge Needs High Speed Monitors

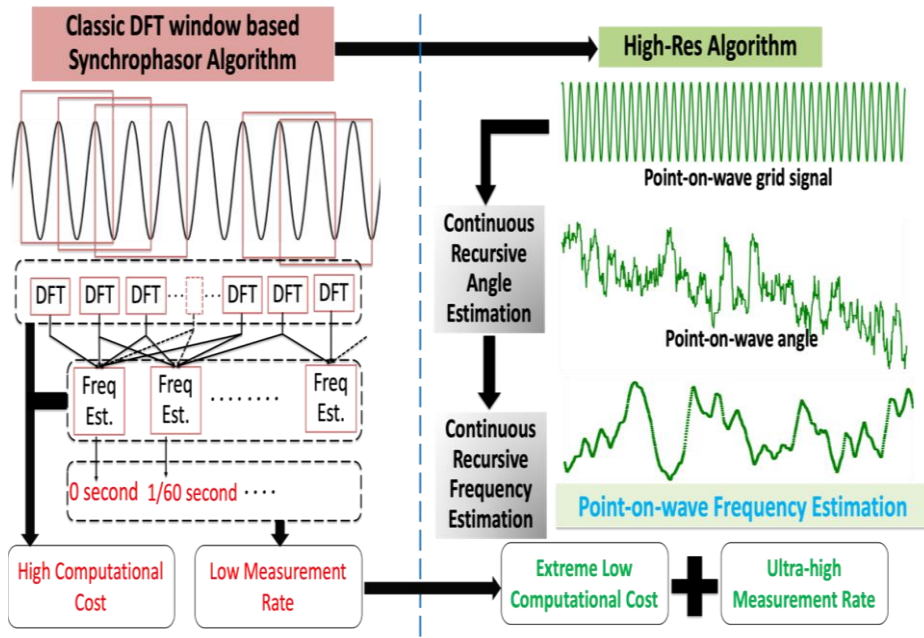


- syn gen oscillation at ~30 Hz mechanical triggered by LC resonance on electrical side.
- 13 Hz oscillations at two nearby wind plants.
- 19 Hz oscillation at island grid from grid following IBRs.
- PV inverter 20/80 Hz oscillations

DFRs are trigger based, non-continuous data recording,
Will miss unknow events

Example Oscillations

High-speed Recursive Algorithms



Extremely Low Computation Cost

Sampling Rate	Window Size (cycle)	Computation Time (second)		Faster
		DFT Algorithm	Proposed Algorithm	
1440 Hz	5	1.279	0.002	650x
	10	2.396	0.002	1200x
	20	4.611	0.002	2300x
2880 Hz	5	2.590	0.002	1300x
	10	4.870	0.002	2400x
	20	9.240	0.002	4600x

- ✓ ~ 3 orders of computation time reduction compared to popular DFT based algorithms.
- ✓ Measurement rate: kHz vs typical 60 Hz
- ✓ Easy hardware integration into grid edge devices.
- ✓ Enhanced grid edge visibility, high-frequency event detection, accurate RoCoF, fast DER control/protection, stability predication.

UTK New Generation Grid Edge Monitor



- Continuous syn wave up to 36k s/s
- Voltage and current
- 1440 s/s phasor
- Ethernet or wireless
- GPS time synchronization
- 5G communication possible
- 5G time synchronization coming....

Thanks For Your Attention!

Yilu Liu, UT/ORNL Governor Chair
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IEEE GridEdge Technical Panel
**5G-Enabled Grid Edge for Immersive AI
Applications**

5G and AI For Grid Emergency Control

Qiuhua Huang
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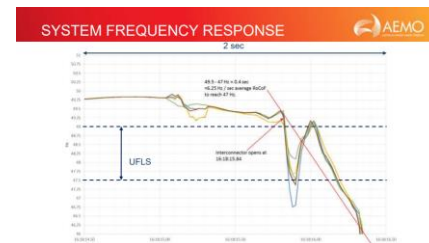


Future grid demands intelligent and faster emergency control

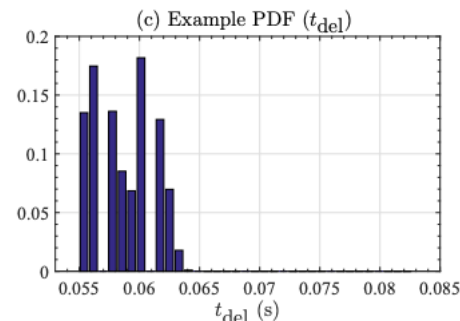
- Faster dynamics due to increasing penetration of inverter-based resources (IBRs) and reduced system strength(e.g., frequency response during South Australia blackout)
- Wide-area measurement is critical for achieving intelligent and effective grid emergency control
- More delays to obtain wide-area measurements than local measurements
- The challenge is to ensure acceptable delays even when transmitting a large amount of data

[1] https://windintegrationworkshop.org/berlin2017/wp-content/uploads/sites/6/2017/11/WIW17_4B_1_Analysis_of_the_South_Australian_Blackout.pdf

[2] F. Wilches-Bernal, et al, "Time Delay Definitions and Characterization in the Pacific DC Intertie Wide Area Damping Controller", IEEE PES GM 2017,

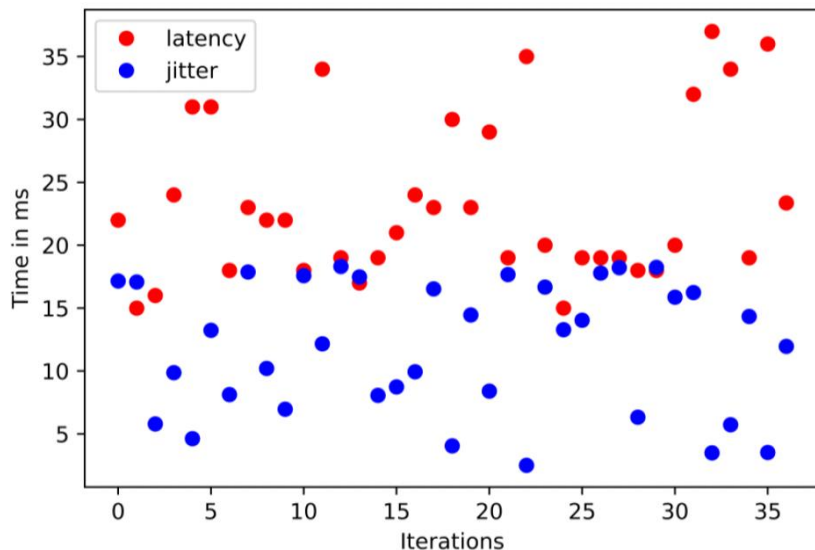


South Australia blackout [1]



PMU Signal delays in PDCI[2]

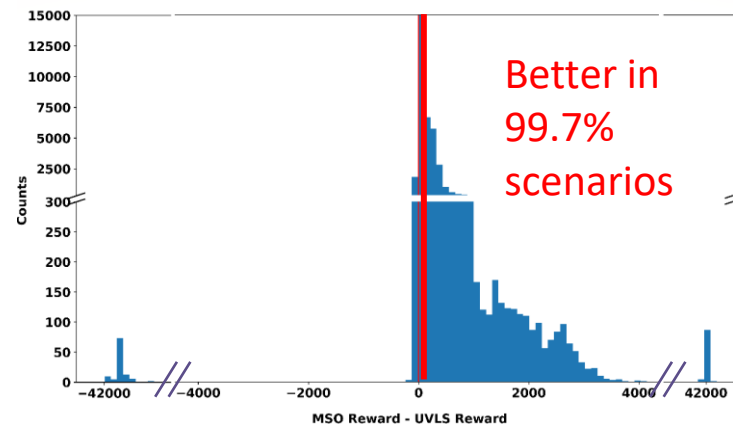
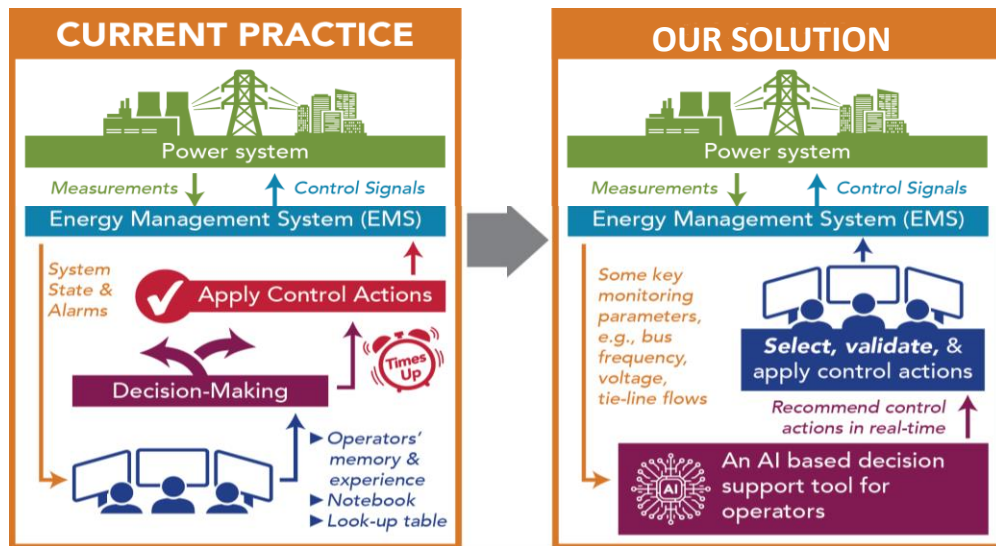
The low-latency of 5G is critical for time-sensitive emergency control



Performance of roundtrip latency and jitter, using DER VM as Client and internal LibreSpeed speed test server [1].

[1] Fan X., J.P. Ogle, J.V. Cree, D. Wang, Y. Chen, E.S. Peterson, and T. Fu, et al. 2022. Technical Characterization and Benefit Evaluation of 5G

AI-based wide-area grid emergency control

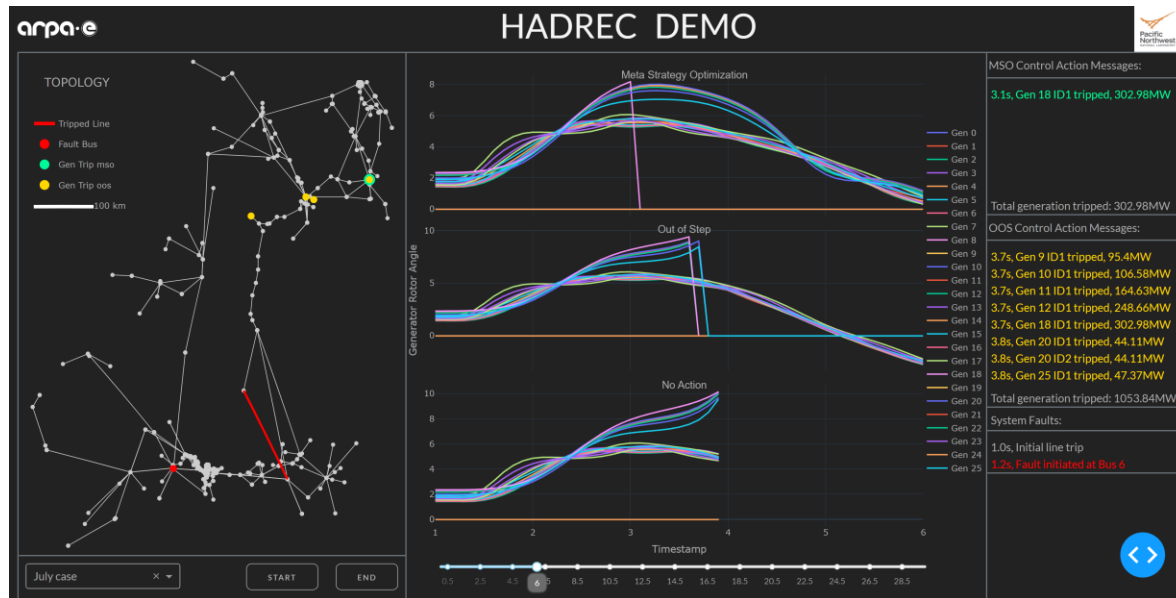


Objective value (total reward) differences (positive is better)

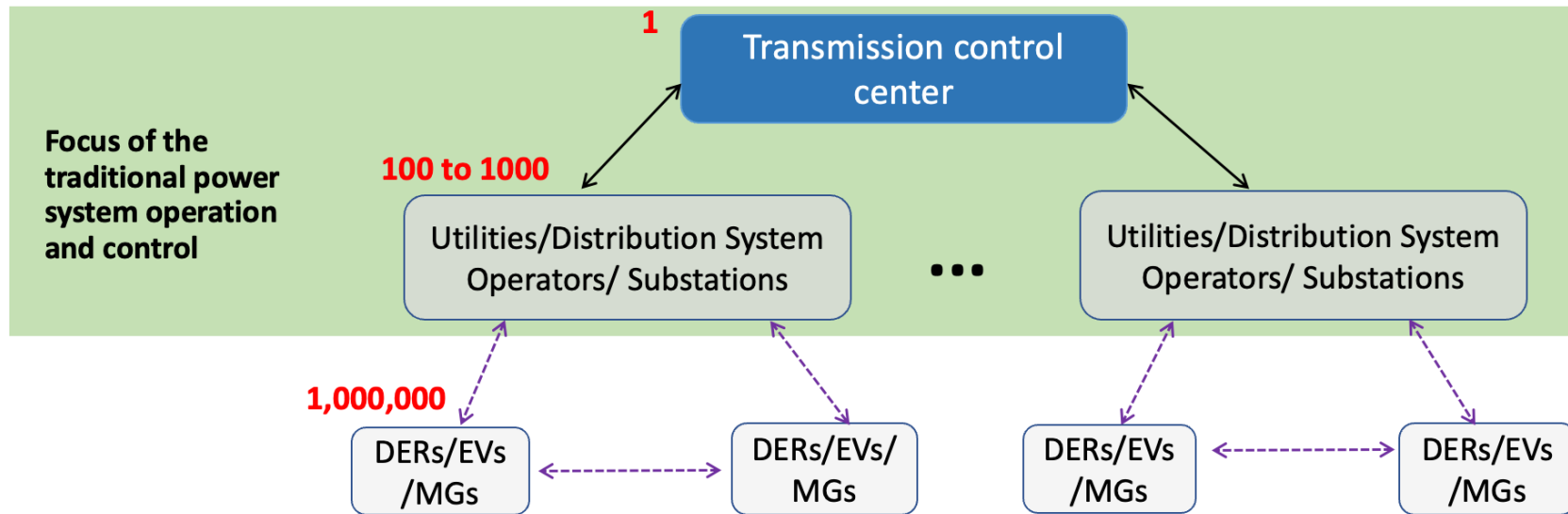
Demo in the PacifiCorp System

Generation tripping
for angular transient
stability

70% reduction in
tripped generation
(300 MW vs 1000
MW)



Challenge and opportunity: connect and coordinate with resources at the grid edge



THANK YOU

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Rensselaer



A ML-Based Edge Appliance for Detection of Converter-to-Grid Oscillations

Prof. Luigi Vanfretti
Rensselaer Polytechnic Institute
Troy, NY

<http://ALSETLAB.com>

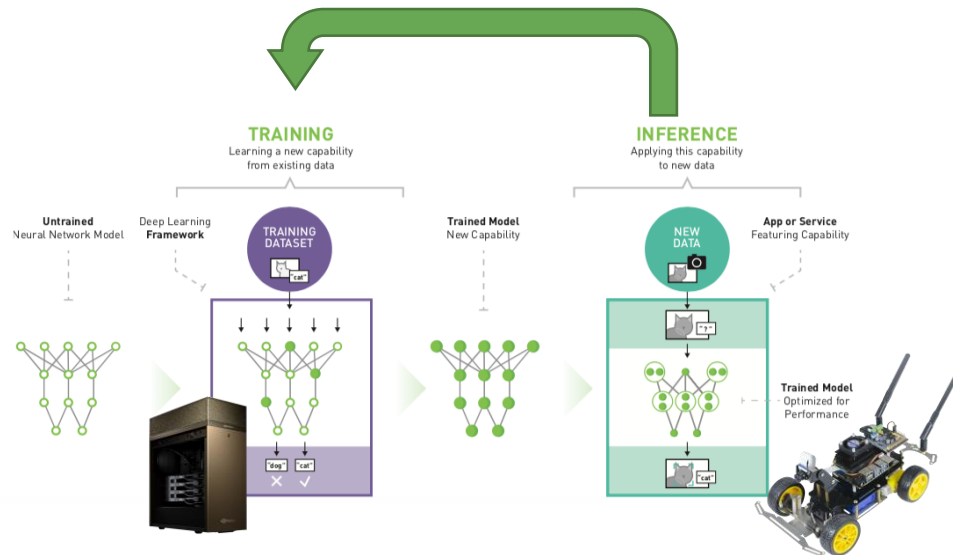


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Outline

- Motivation
- Exploiting ML Technologies:
 - Data Acquisition into ML-hardware.
 - Exploiting Hardware using Conventional (FFT-based) Methods
 - Exploiting ML Methods & Hardware for Classification for Detection
- HW Testing:
 - Impact of DAQ Chain on ML Appliance
- Conclusions



Source: NVIDIA

Motivation

Problem:

Identify oscillations product of the interaction between power electronic-based converter controls and the grid (under changing operating conditions and topology).

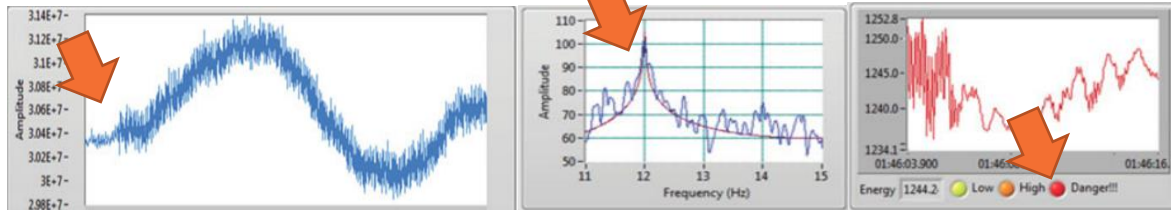
Examples:

- Wind turbine rotor controller rings against grid when line in grid trips (change of impedance) [A]
- PV Inverter controller rings against grid when operating in constant PF mode [B]

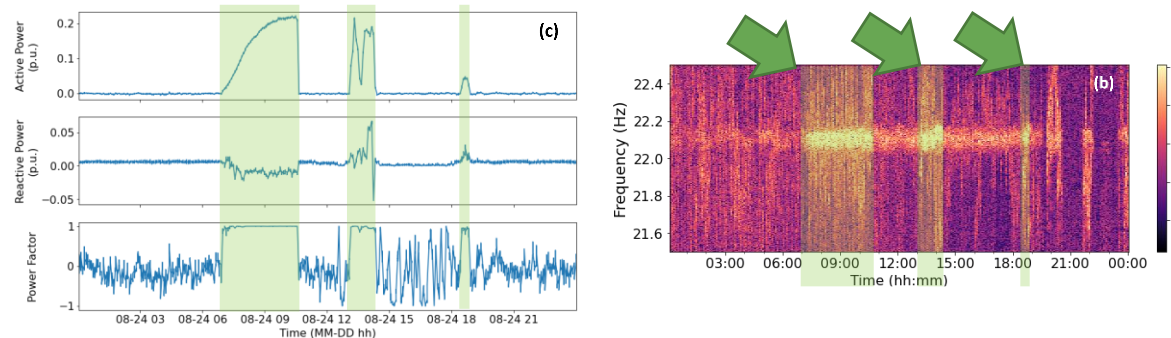
Previous Works:

- FFT [A], statistical signal processing-based methods (e.g., energy-based detection [A]), spectral analysis [B], etc.
- **Pros:** experience with “slower” oscillations (e.g., electromechanical mode estimation) → has gained trust from utilities.
- **Cons:** limited on-board computational capabilities on the edge, centralized data collection (e.g., PMU-to-PDC-to-X), processing has inherited delays from filtering and RMS-energy computation, signal processing methods needs careful parametrization/tuning from experts, decision making is slow (human operator driven)...

~12 Hz Oscillation between the grid and a wind farm/turbines in Oklahoma [A]



~22 Hz Oscillation between the grid and a utility scale PV plant in Virginia [B]



AI/ML and 5/xG tech can help here!



Data Acquisition to Exploit ML Edge Hardware

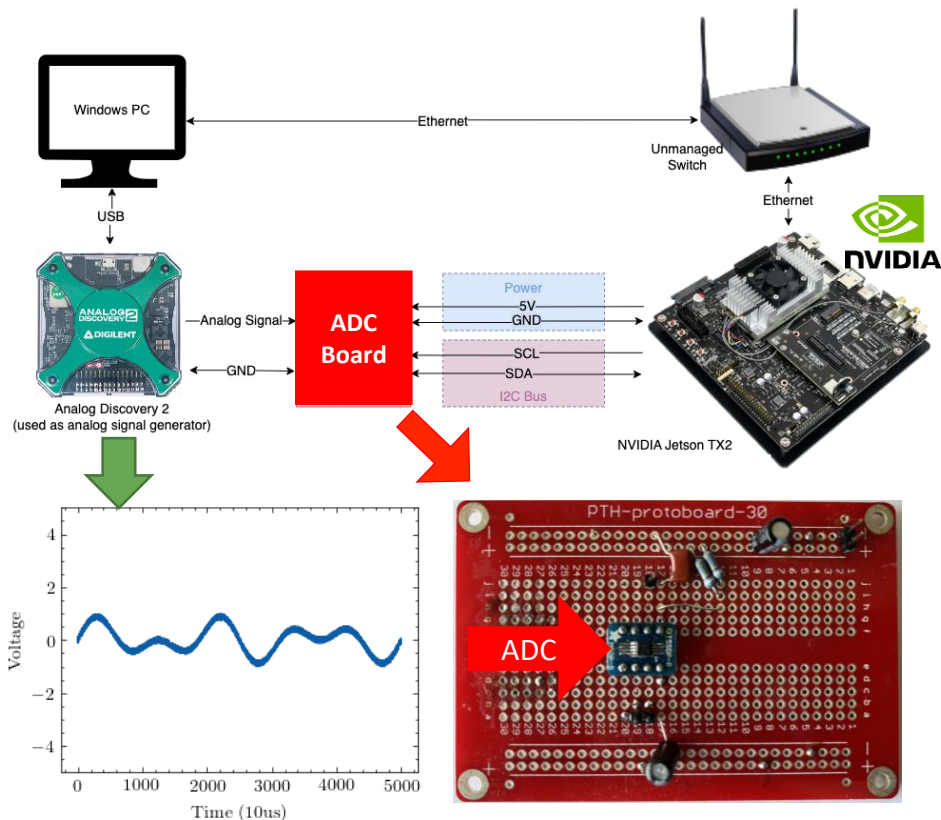
Goal: to exploit onboard edge capabilities of ML Edge HW (i.e., here only the NVIDIA Jetson family) to perform GPU-based computations (FFT) and deploy ML-based classification/detection algorithm (after training offline).

Challenge: AI/ML boards mainly target apps outside power grid, e.g., autonomous vehicles uses cameras/images. The HW is not “plug-and-play” for our use case.

- *Need to develop analog DAQ and data ingestion pipeline* (e.g., can't directly read low voltage/current signals).
- *Need to test* components that will affect oscillation detection at high frequencies, i.e., *what is the impact of different types of ADCs.*

Low-Cost Testing Setup (due to COVID!):

- From Win. PC the Waveforms SDK + Python control the AD2.
- The Analog Discovery 2 (AD2) then acts as a configurable analog signal generator → sweep signal amplitude and freq.
- ADC Board couples the analog (test) signals via the I2C bus of different ADCs to the NVIDIA Jetson TX2.
- NVIDIA Jetson TX2 performs computations (FFT and ML-algos)



Exploiting HW in FFT-based Methods

FFT-Based Computations: with data being streamed to the NVIDIA Jetson TX2, we aim to quantify the benefit of using onboard GPU for FFT computations for detection using two C++ libraries: FFTW and cuFFT.

FFTW: Fastest Fourier Transform in the West, <http://fftw.org/>

- Used to FFT computations using the onboard CPU
- CPU: Dual-core NVIDIA Denver 2 64-bit CPU and quad-core Arm Cortex-A57 MPCore

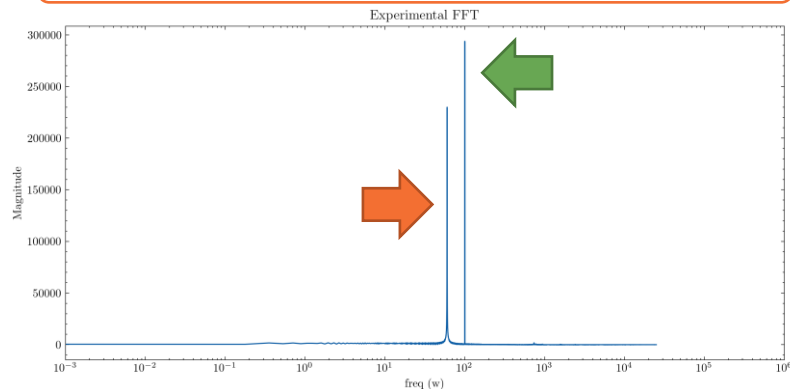
cuFFT: CUDA Fast Fourier Transform library, [here](#)

- Used to perform FFT computations using the onboard GPU
- GPU: 256-core NVIDIA Pascal architecture

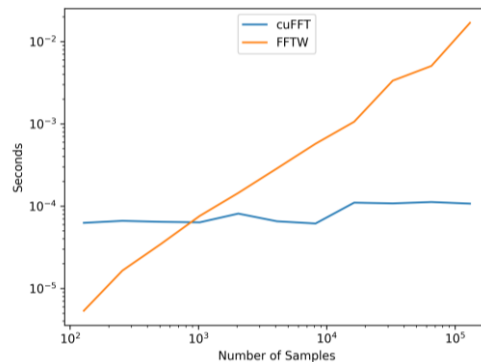
cuFFT vs FFTW

- **Left lower figure:** as more data samples are used (e.g., higher frequency signal sampled faster), FFTW will become slower while cuFFT will maintain acceptable performance ~ 0.12 msec
- **GPU-based capabilities:** key enabler for high frequency power grid monitoring at the edge.

Sample FFT Computed with cuFFT containing both a 60 Hz (fundamental) and 100 Hz Component



FFT Execution Time (table in msec): cuFFT (GPU-based) vs FFTW (CPU-based)

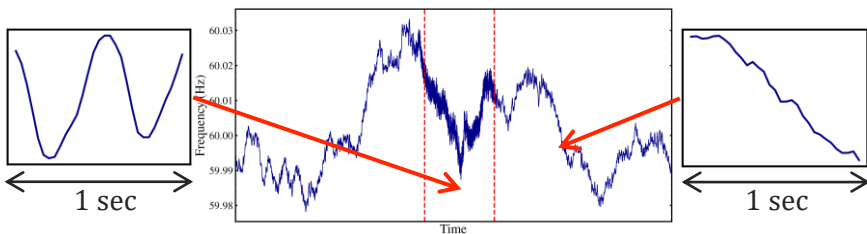


# of Samples	cuFFT	FFTW
128	0.062495	0.005344
256	0.066143	0.016448
512	0.064319	0.034720
1,024	0.063391	0.075807
2,048	0.080960	0.144447
4,096	0.065311	0.286462
8,192	0.061375	0.572155
16,384	0.109983	1.057940
32,768	0.107743	3.343330
65,536	0.111967	5.039600
131,072	0.107007	16.866400

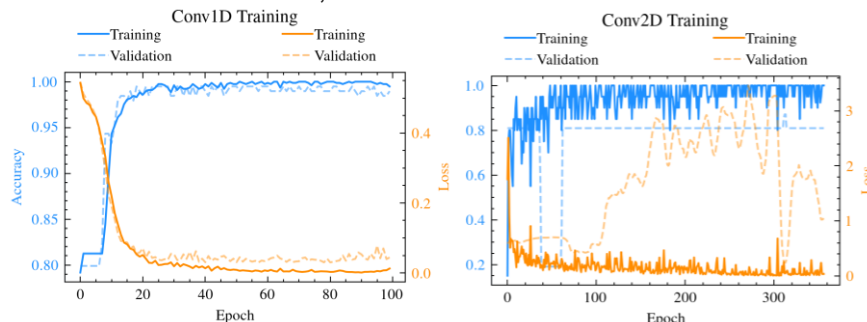
ML-Based Oscillation Detection

Data: build training and testing data sets from a wind farm in Oklahoma [A], manually labeled by utility expert.

Example: Vertical red dotted lines indicate the oscillation event inset and offset, with samples labeled.

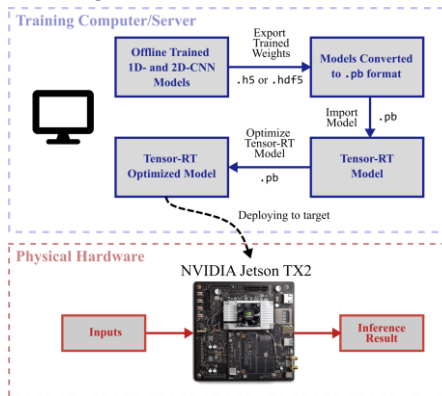


Training and Validation: 1D and 2D CNN models are trained and validated, results are shown below for each.



CNN Model Optimization: after training and validating the models, they need to be prepared for deployment in a target (i.e., NVIDIA Jetson TX2) for real-time inference

- **TensorRT** is used to convert the TensorFlow models to CUDA-compatible code.
- Without optimization the average inference is of the same order in the TX2 than in a Windows PC.
- With optimization the code runs approximately 10 times faster.
- The CNN capabilities of detecting oscillations in less than 10 msec, **this performance is approximately 3X faster than the state of the art** using other methods [E]



Hardware/Model	1D-CNN	2D-CNN
Windows PC Intel i7-7700HQ 2.80 GHz NVIDIA GeForce GTX 1060 (TensorFlow/Keras Model)	96.931 ms	67.312 ms
NVIDIA Jetson TX2 Non-optimized by TensorRT	74.290 ms	38.379 ms
NVIDIA Jetson TX2 Optimized by TensorRT	9.787 ms	3.410 ms

Average Inference Time using Different HW Devices with and without TensorRT Optimization

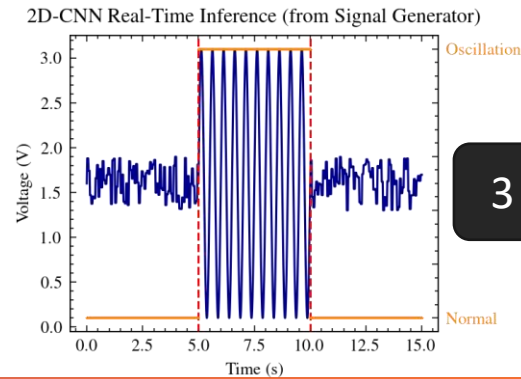
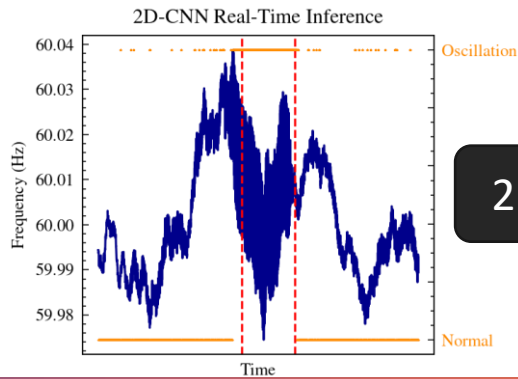
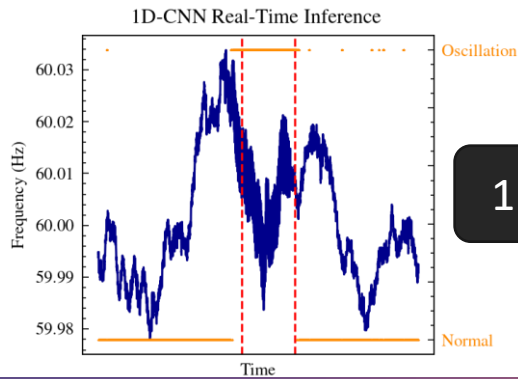
ML-Based Oscillation Detection Experiments

Detection Experiments: two different experiments.

- **Experiment 1 - Figures 1 and 2:** real-world measurements from the wind farm [A] including both the oscillations and ambient data, **never seen neither during training or validation** are played back as inputs.
- **Experiment 2 - Figure 3:** Waveforms emulating oscillations are created using the testing setup (shown previously [C]), labeled (from Signal Generator). This aims to emulate end-to-end testing for real-time performance of the entire solution.

Detection Performance:

- **Figs. 1 and 2:** CNNs succeed at detection and provide correct predictions while the oscillation is active. However, accuracy is not 100%, as expected. A simple running window algorithm can be used to discard false positives by comparing with past predictions.
- **Fig. 3:** shows how oscillations can be detected with real-time data. Accuracy is superior compared to the real-world data experiment, as the signal is less “challenging”. But more importantly, this **shows that CNNs can learn the patterns of an oscillation using data from one “system” and then identify similar events in another system, i.e., transfer learning.**



Impact of ADC on ML-Based Osc. Detection Performance



Hypothesis: ADCs are the components that will affect oscillation detection at high frequencies.

To understand their impact:

- We test two different ADCs, 8-bit PFC8591 and 12-bit ADC.

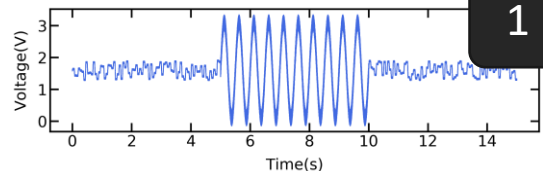


Experiment: to valuate the performance of the entire ML-based solution under inputs from the two ADCs, we perform:

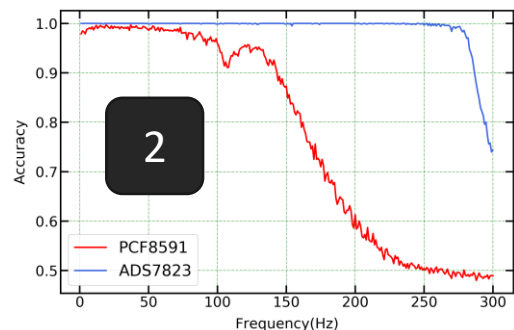
- 300 experiments varying the frequency of the signal from 1 to 300 Hz, keeping the sinusoidal. **Example signal in Fig. 1.**
- **CNN inference is performed on 1000 windows of the produced signal.** Half of the windows correspond to normal conditions, and the other half is a sustained oscillation. After the NVIDIA TX2 computes 1000 inferences, a message is sent to the client (host computer) to start the next experiment by varying the signal frequency.

Results:

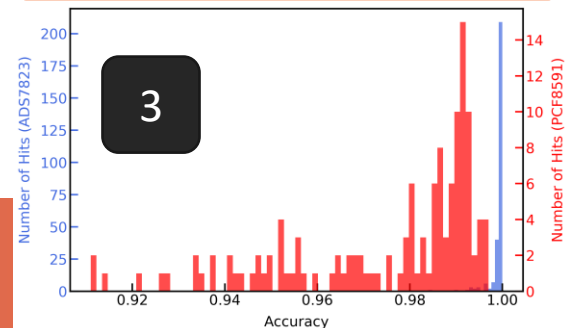
- **Figure 2** – y-axis: average accuracy for 1,000 inferences. PCF8591 performance degrades rapidly ~ 100 Hz, while ADS7823 has acceptable accuracy up to ~ 250 Hz.
- **Figure 3** – histogram, x-axis is accuracy. Both histograms lean towards 1.0 accuracy, they are effective, however, PCF8591 have a larger distribution → larger uncertainty.
- **The CNN model is unchanged: this emphasizes the importance of appropriate HW selection at every stage when an ML solution is being developed and deployed for real-world grid applications.**



Average Accuracy for 1,000 Inferences



Accuracy Histogram (PCF: red, ADS: blue)



Conclusions

ML Edge Hardware. Can be used to exploit GPU-based computations even if ML-based algorithms are not used, with *substantial computational benefits for oscillation detection*.

Real-Time F.O. Detection using ML. Fast and accurate, can be deployed on the edge, *outperforming 3X in detection speed* existing methods and with similar accuracy.

Not all data is created equal. Unless the data has the behavior that we want the AI/ML to recognize, even if you have Terabytes, it is of relatively low value. *Real-world grid expert curated data sets are critical for development.*

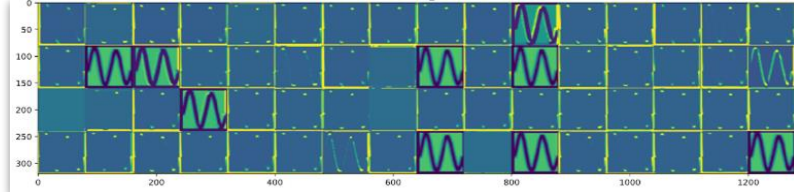
Labeling: *It is very time consuming and requires expert knowledge!* However, it is the key for ML-based detection performance.

ML Models/Methods:

- Wealth of methods and technologies that need to be carefully adapted for power applications: seek power grid expertise.
- **Transfer Learning:** One can get very far using simulations data for training, *but accuracy improvements require real data.*

Inference at the Edge: *ML HW/SW platforms have great potential for grid automation at the edge.*

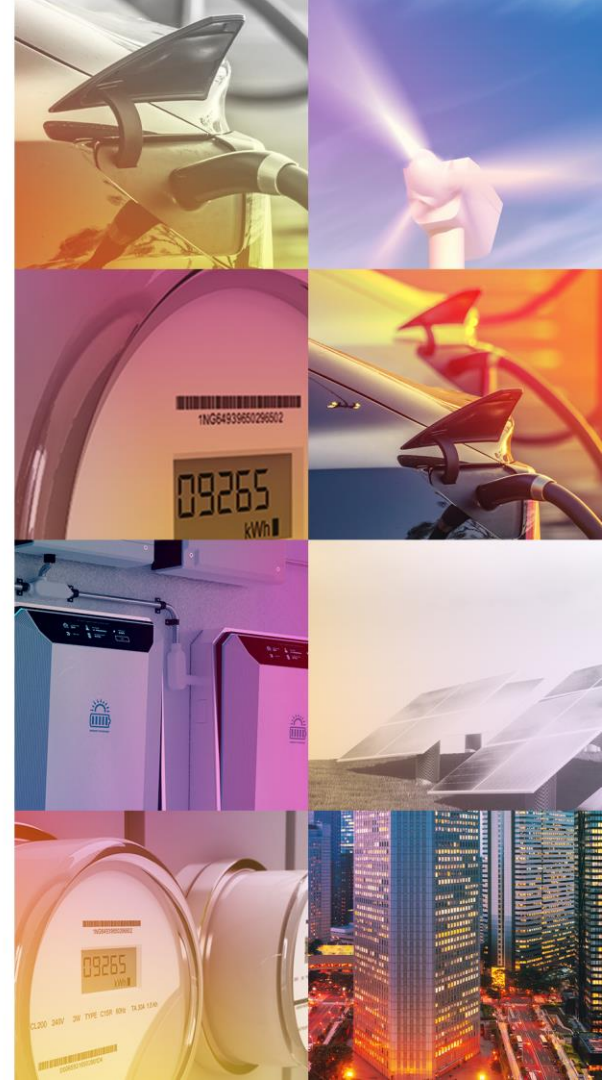
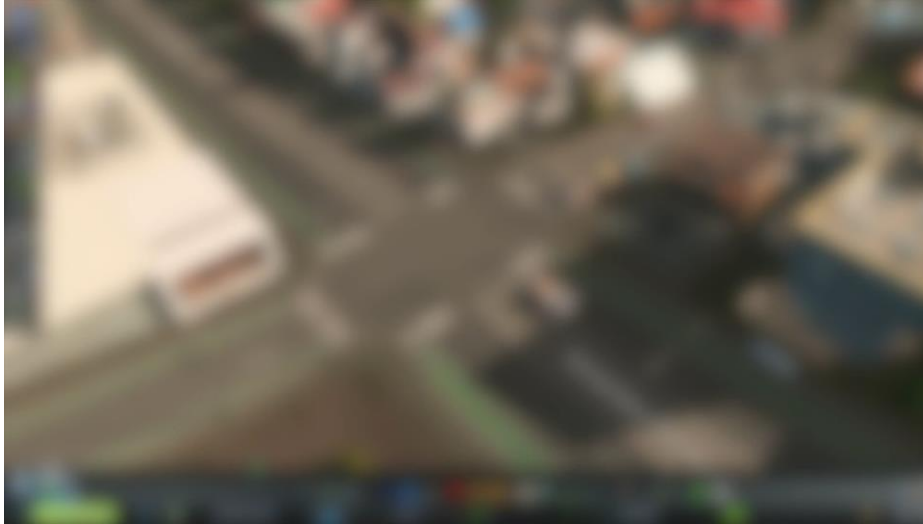
- Poses an entirely new paradigm for grid automation, protection and control based on AI/ML, with the ability to adapt to changing grid conditions by updating deployed models with new data from the field.
- Engineering know-how, ML HW/SW and IT/Comm. infrastructure to deploy and train at scale is **relatively more complex and costly** than in existing automation/protection/control engineering practice: it will be a challenge to "win hearts and minds", train and develop the process to maintain/operate the technology within the electrical power industry constraints.



THANK YOU

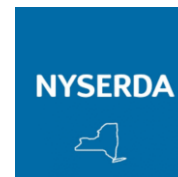
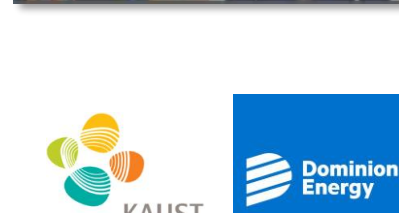
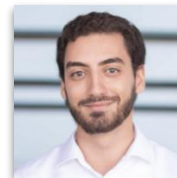
Questions?

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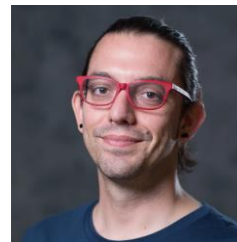
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