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Sustainable Neuromorphic Edge Computing

Asst. Prof. Dr. Atakan Aral, University of Vienna

November 17, 2025 | Public Lecture Series: Sustainability in Computer Science

chist-era FWF Austrian Science Fund

Outline

Neuromorphic Computing

Edge AI

Off-Grid Sensing

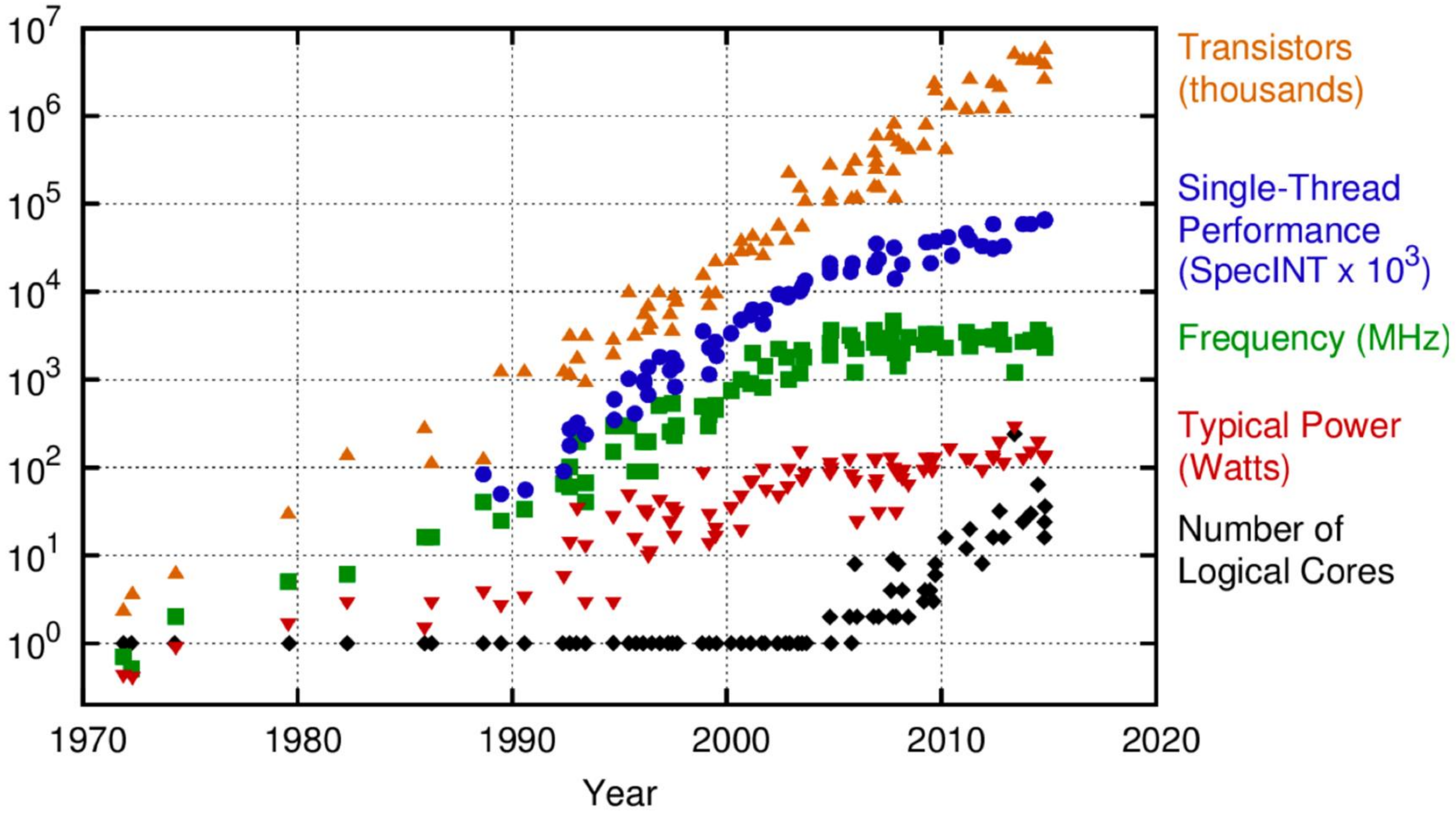
Dennard Scaling

Power use ∝ area

=

Power density is constant!

2x transistors
2x faster switching
¼ power



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2015 by K. Rupp

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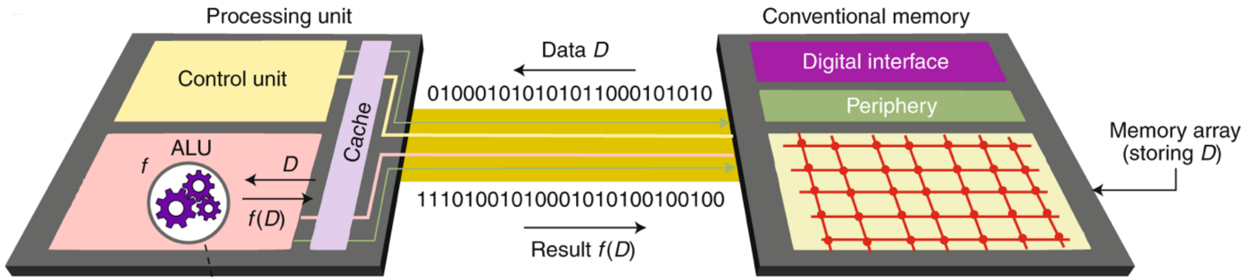
Von Neumann Bottleneck

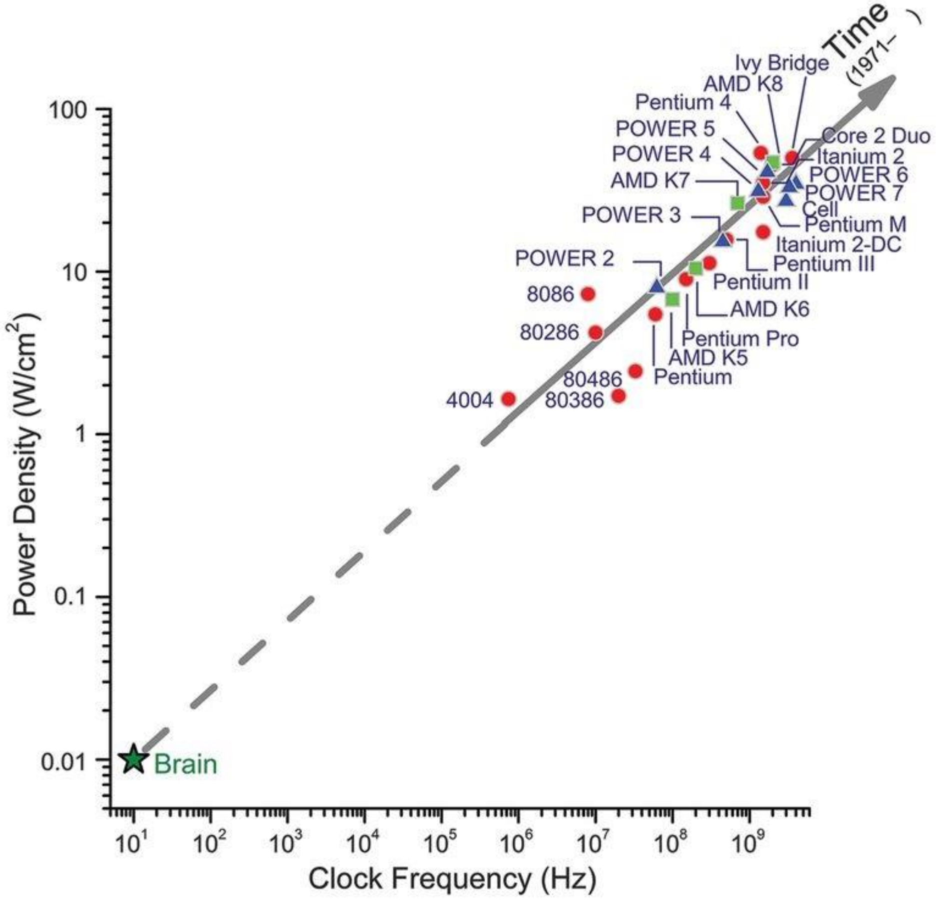


Sebastian, A., Le Gallo, M., Khaddam-Aljameh, R., & Eleftheriou, E. (2020). Memory devices and applications for in-memory computing. Nature nanotechnology, 15(7), 529-544.

- Limited bandwidth between processor and memory
- Excessive heat due to high clock rates and intensive data transfer
- Designed primarily for sequential processing

Inspiration from brain

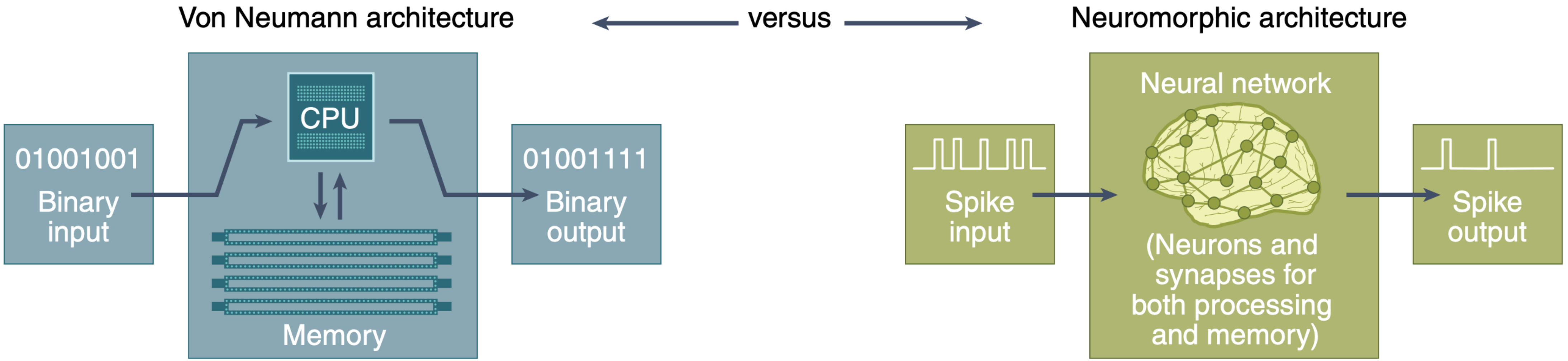
Can we copy some of the principles of the brain to avoid the power wall that halted Dennard-era scaling?



Merolla, P. A., Arthur, J. V., Alvarez-Icaza, R., Cassidy, A. S., Sawada, J., Akopyan, F., ... & Modha, D. S. (2014). A million spiking-neuron integrated circuit with a scalable communication network and interface. Science, 345(6197), 668-673.

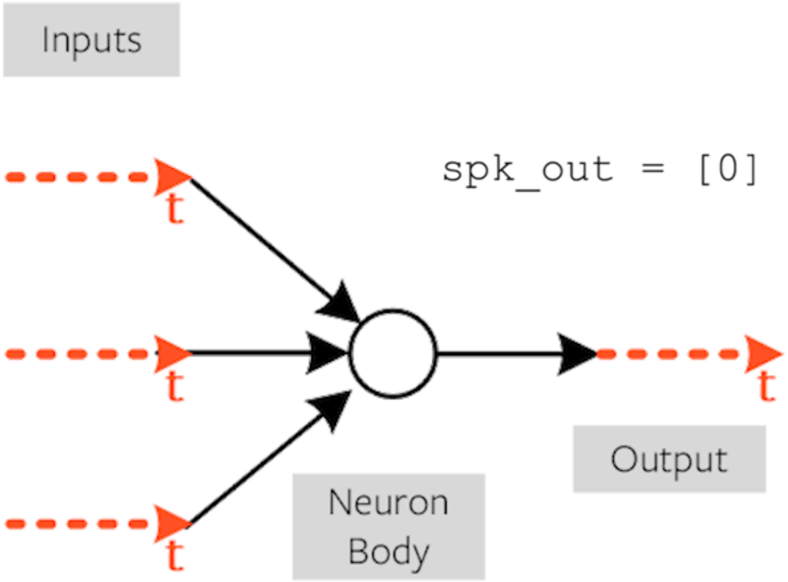
Neuromorphic Computing

Schuman, C. D., Kulkarni, S. R., Parsa, M., Mitchell, J. P., Date, P., & Kay, B. (2022). Opportunities for neuromorphic computing algorithms and applications. *Nature Computational Science*, *2*(1), 10-19.

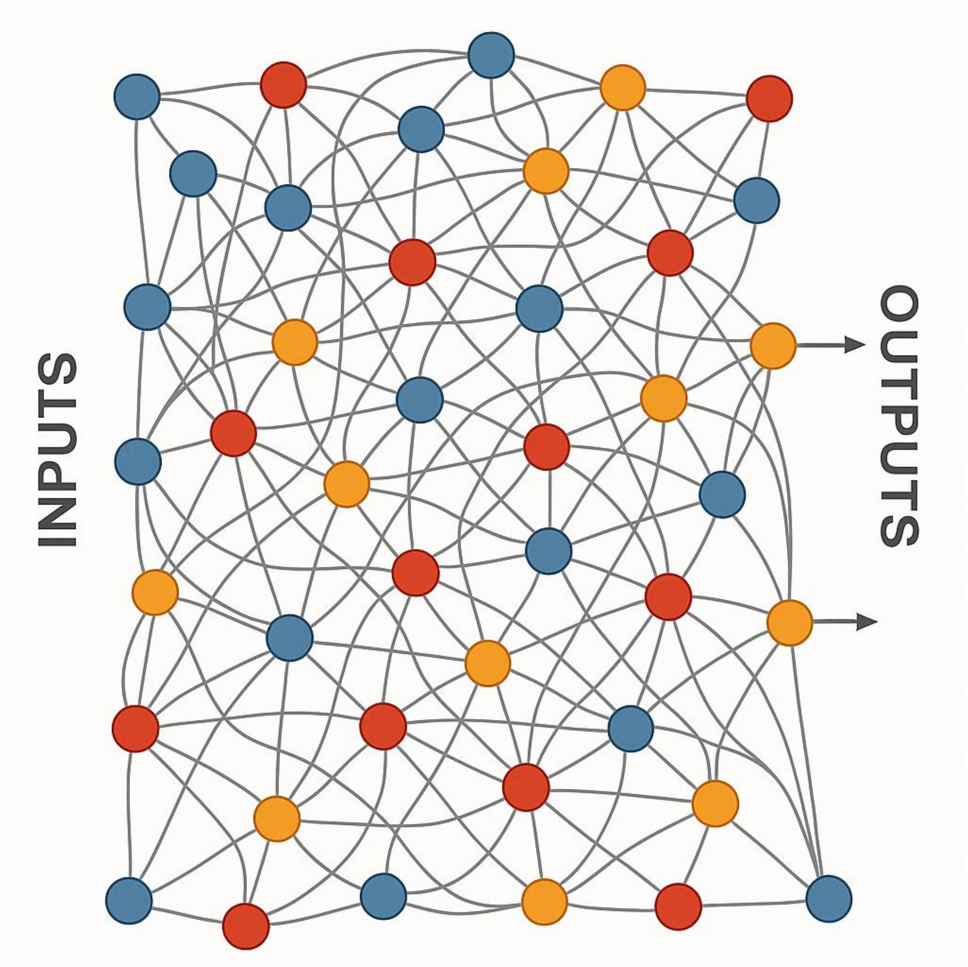


- **Processing:** Sequential → Massively parallel
- **Computation and memory:** Separated → Collocated
- **Programming:** Binary instructions → SNN
- **Communication:** Binary data → Spikes
- **Timing:** Synchronous (clock) → Asynchronous (event)
- **Determinism:** Deterministic → Quasi-Stochastic

Spiking Neural Networks



Eshraghian, J. K., Ward, M., Neftci, E. O., Wang, X., Lenz, G., Dwivedi, G., ... & Lu, W. D. (2023). Training spiking neural networks using lessons from deep learning. Proceedings of the IEEE, 111(9), 1016-1054.



Neuromorphic Hardware

- **Digital:** Implements spiking neural networks using digital circuits
  - Intel Loihi
  - IBM True North
  - SpiNNaker (University of Manchester, UK)

- **Analog:** Uses continuous electrical signals to represent neuron behavior

- **Mixed-Signal:** Combines digital control with analog computation
  - BrainScaleS (Heidelberg University, Germany)

Outline

Neuromorphic Computing

Edge AI

Off-Grid Sensing

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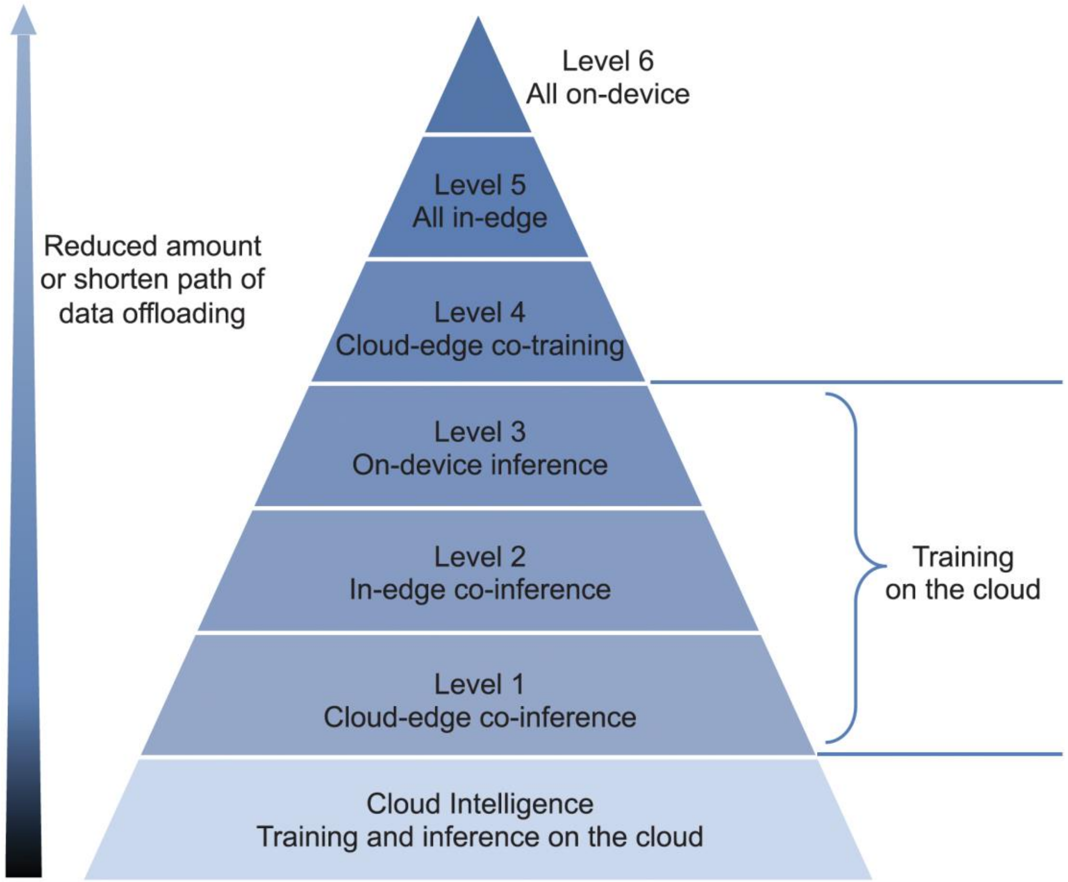
Edge AI

"edge computing with machine learning and advanced networking capabilities" *—IEC*

"Instead of entirely relying on the cloud, Edge AI makes the most of the widespread edge resources to gain AI insight." *—Zhou et al. (2019)*

- Edge servers are located much closer to the data sources compared to cloud
    - Higher data transmission rate
    - Lower computational power



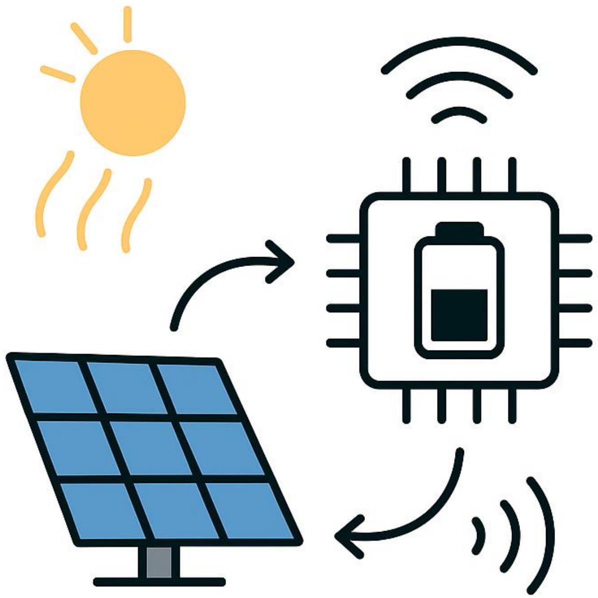
Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge intelligence: Paving the last mile of artificial intelligence with edge computing. *Proceedings of the IEEE*, *107*(8), 1738-1762.

Ultra Low Power Operation

- Sub-milliwatt “always-on” operation for battery-powered or energy-harvesting devices
- Compact devices without fans

How?

- No spike → no computation, no memory access, no energy use
- Very low firing rates (e.g., 1–10% of neurons active at a time)
- Cheap operations: additions or binary events instead of floating-point multiply-accumulate
- No data movement between memory and compute



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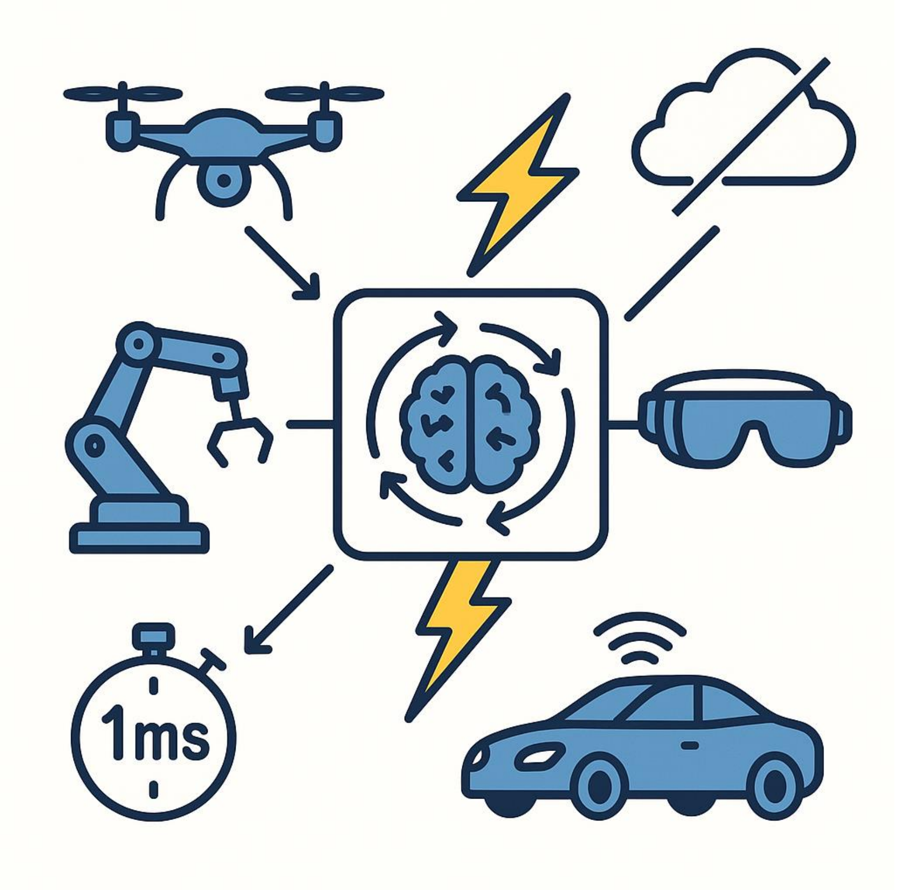
Real-Time Responsiveness

- Micro- to millisecond latency for robotics, drones, AR/VR, autonomous vehicles, etc.
- No cloud round-trip
- No von Neumann bottleneck
- Enhanced on-device learning and adaptation

Especially for graph-based tasks!

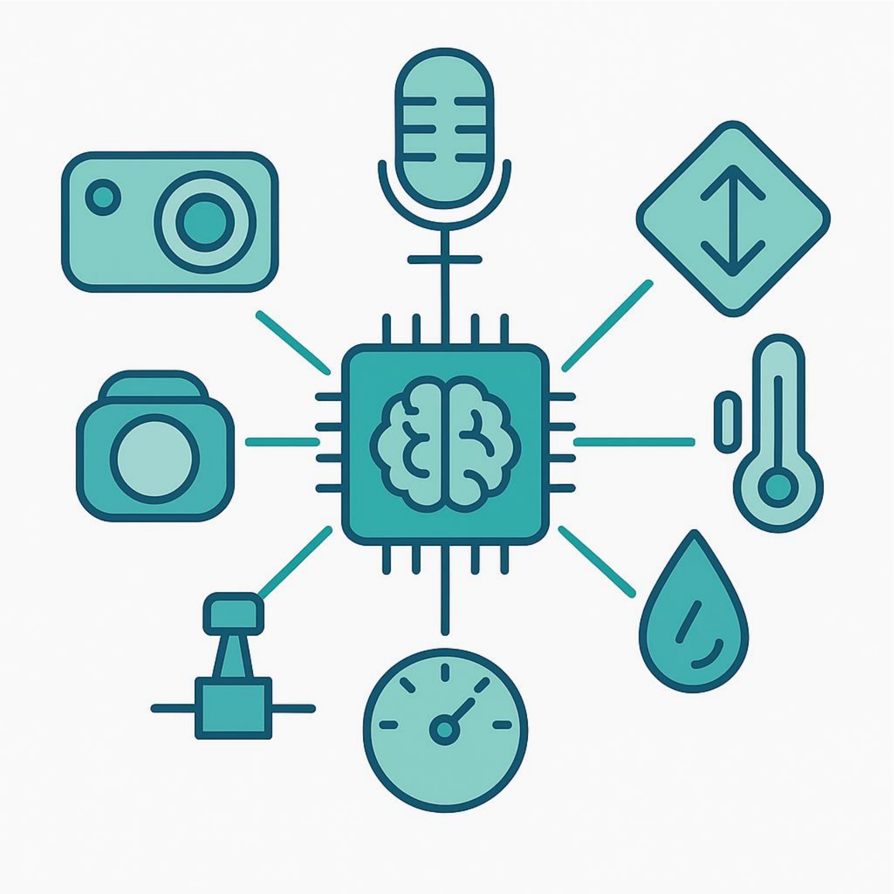


Better Privacy Preservation

- Less reliance on the cloud
- More on-device data processing

High Fan-In / Fan-Out Connectivity

- One spiking neuron can accept inputs from thousands of presynaptic neurons
  - Loihi-2 supports >16k fan-in per core
- Sensor fusion
- Noise robustness (e.g., majority voting)



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Challenges

- New tool-chains & developer workflows
- New training algorithms for SNNs (currently slow convergence)
- Data dispersion at the edge
- Heterogeneous Edge SoCs
- Ecosystem fragmentation
- ...

Ferdowsi, A. and Aral, A. (2025) *An Exact Gradient Framework for Training Spiking Neural Networks*. arXiv preprint

Outline

Neuromorphic Computing → Edge AI → Off-Grid Sensing

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Off-Grid Sensing

- Collecting data in geographically remote regions with limited energy availability and network connectivity
  - Environmental Monitoring
    - Water pollution
    - Forest fires
    - Avalanches, landslides, etc.
  - Remote Infrastructure Monitoring
    - Water distribution networks
    - Agriculture
    - Oil and gas well

Off-Grid Sensing

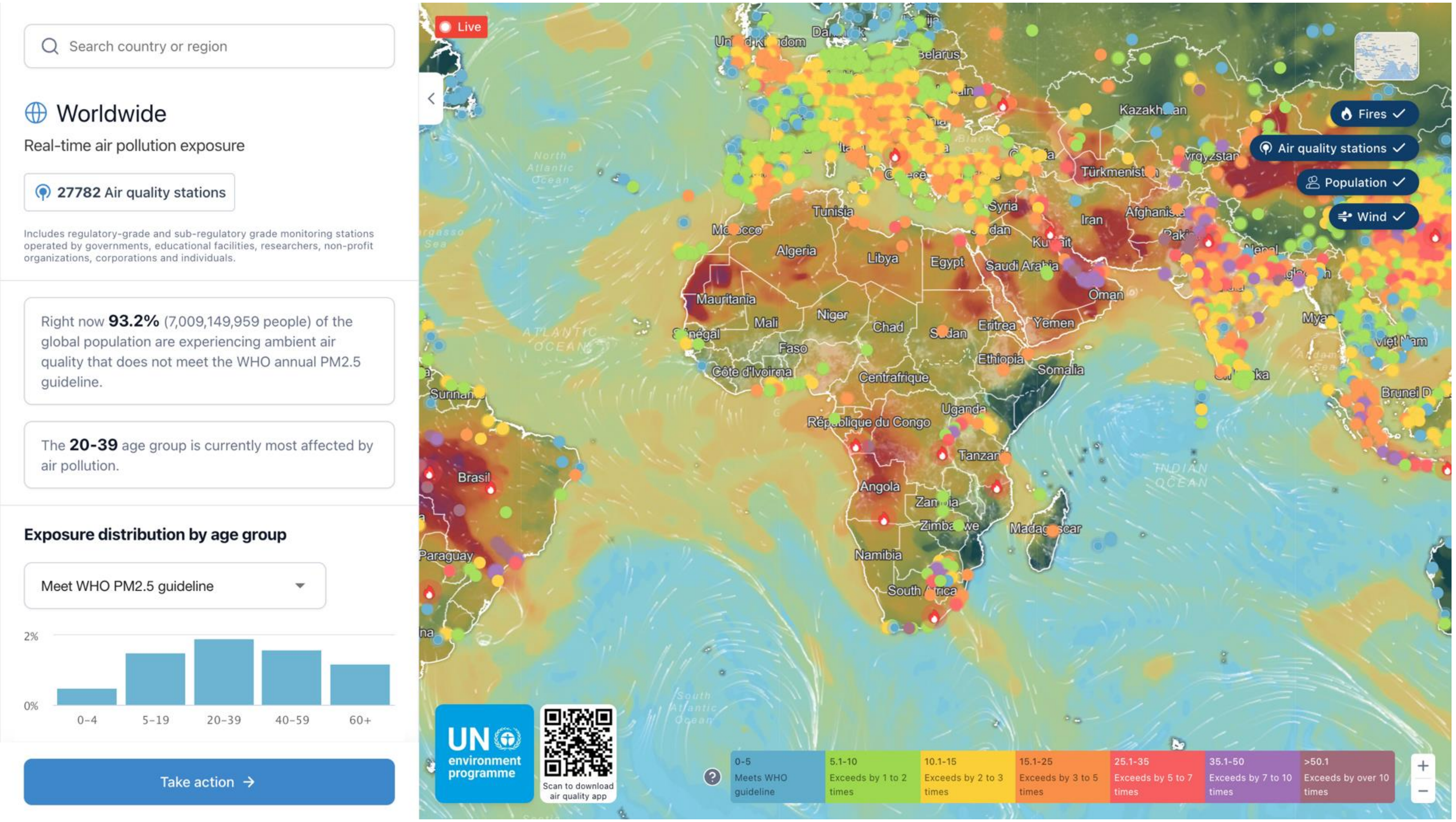
Rural Environmental Monitoring Use Case	Number of Stations	Dispersion	Real-Time Constraint	Proximity to Urban Areas	Potential for Electricity Access	Potential for Internet Access	Safety Risk	Data Sensitivity
Air Quality (GEMS/Air)	10s of 1000s	Global	Hour	Any	Moderate	Moderate	Moderate	Low
Water Quality (SWAIN)	30 to 75	Regional	Minute	Any	Low	Low	High	Low
Seismic Activity (EMSC)	$\geq$ 2500	Continental	Minute	Any	High	Moderate	High	Low
Avalanche (SLF IMIS)	186	Regional	Hour	Mid to Far	Low	Low	High	Low
Nuclear Explosion (CTBTO)	337	Global	Hour	Mid to Far	Low	Low	High	High
Agriculture	$\approx$ 1 per 2 ha	Local	Hour	Near to Mid	Low	Low	Moderate	Low
Oil and Gas Well	$\approx$ 1 per well	Local	Minute	Mid to Far	High	Low	High	High

Aral, A. 2024. The Promise of Neuromorphic Edge AI for Rural Environmental Monitoring.
Environmental Data Science, vol. 3, e34. Cambridge University Press.

GEMS/Air

- Part of UNEP
- 27 782 air quality stations
- Hourly measurements

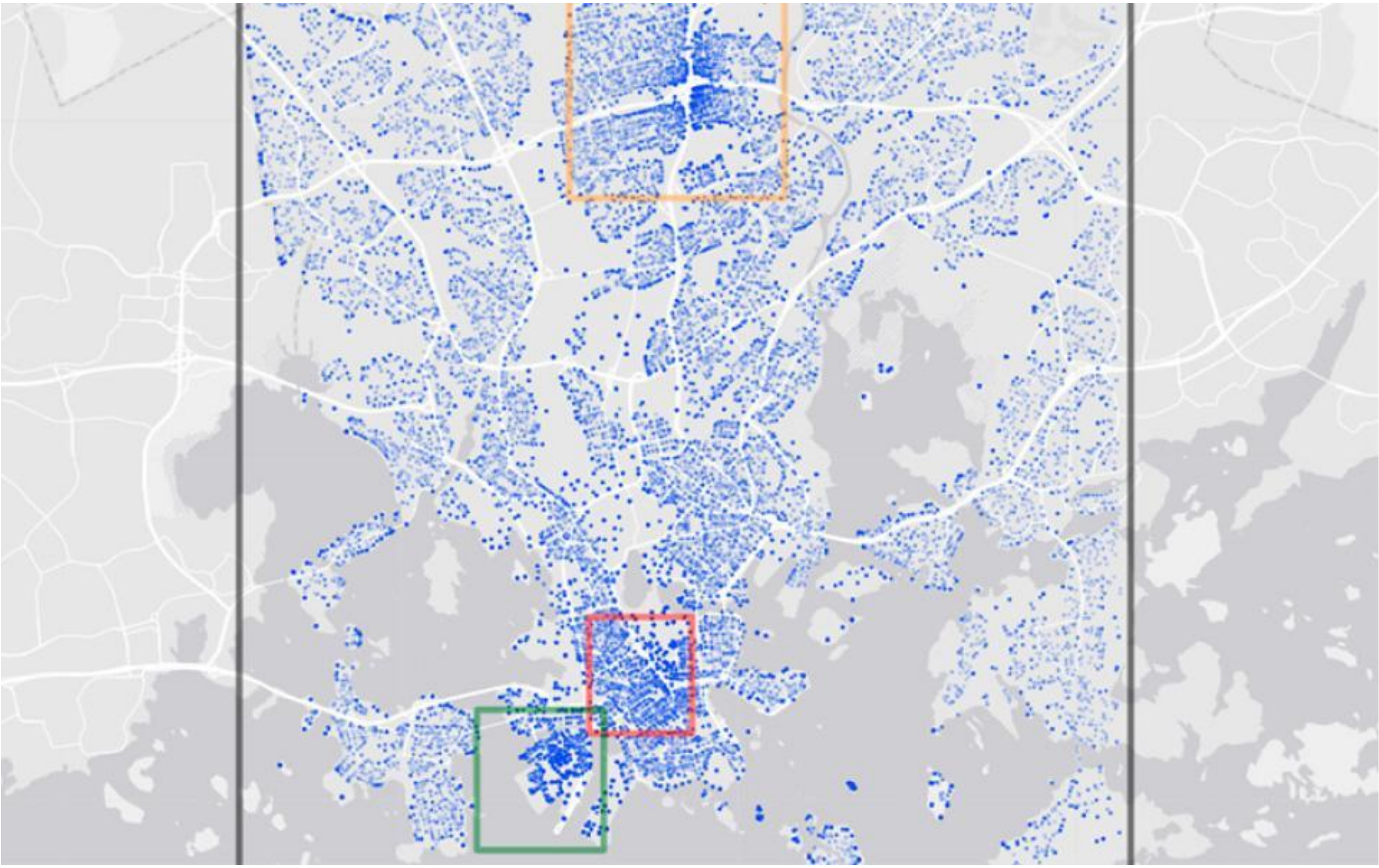
- https://www.iqair.com/unep



MEGASENSE

- Scalable real-time 5G air pollution sensing as a service for megacities
- Use ML to calibrate many low-cost sensors (e.g., wearables) with a few highly accurate measurement stations.

- https://helsinki.fi/en/researchgroups/sensing-and-analytics-of-air-quality



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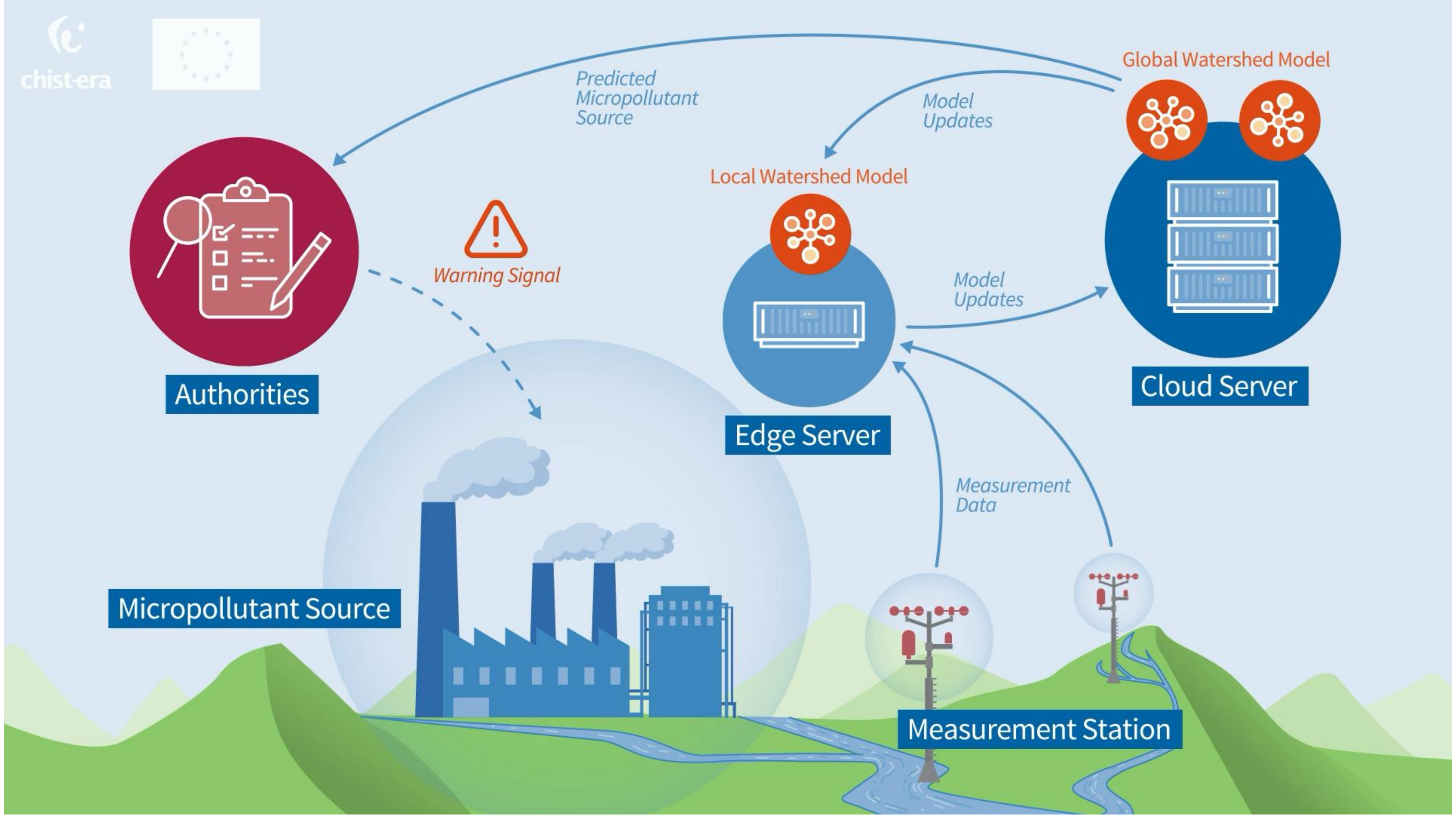
SWAIN

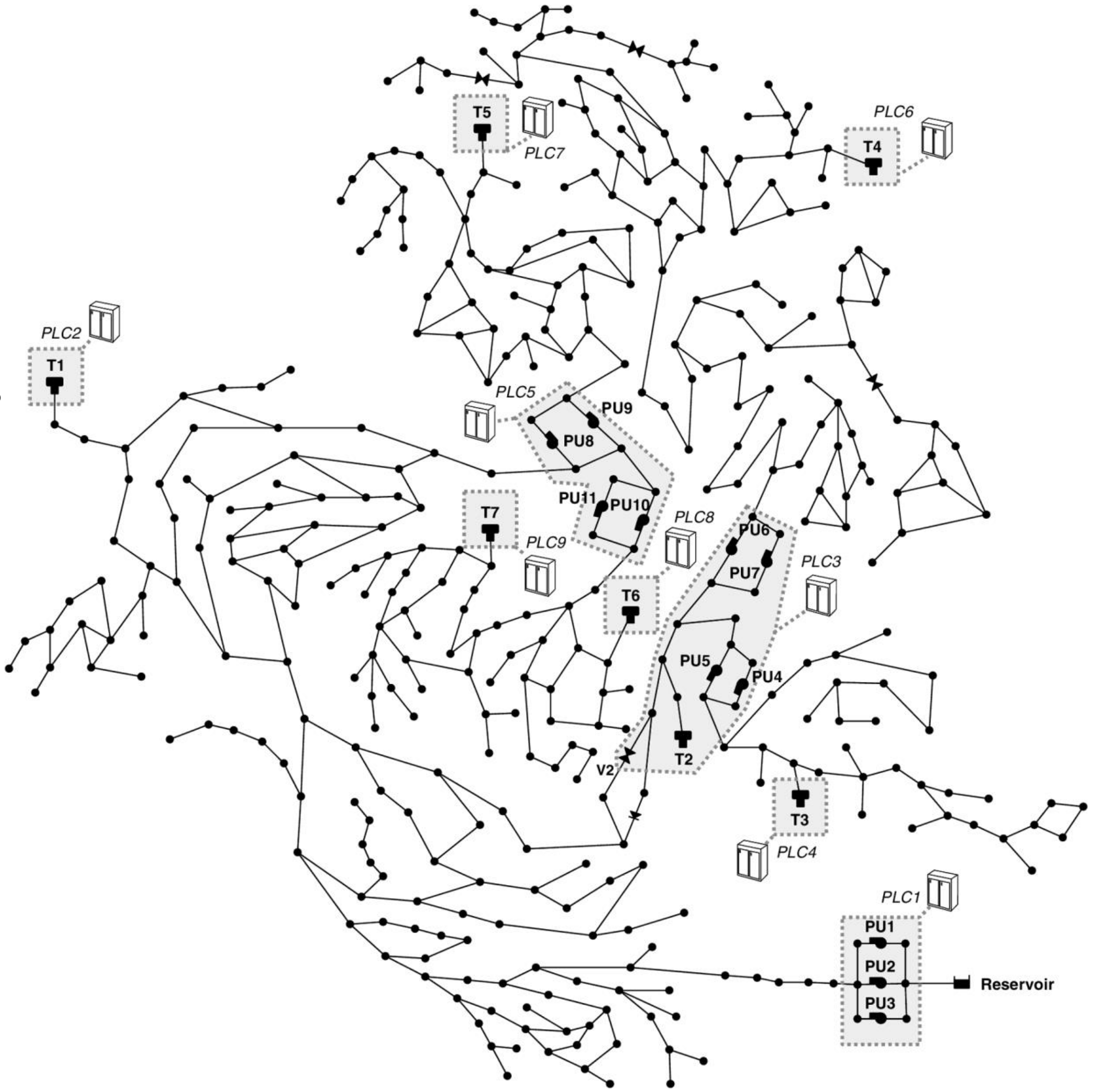
- Up to 100 sensors
- Two prototype deployments
- Sub-minute measurements
- Feedback loop
- https://swain-project.eu/



TROCI

- Cyber attack protection for critical infrastructures
- Water distribution networks
- Federated anomaly detection

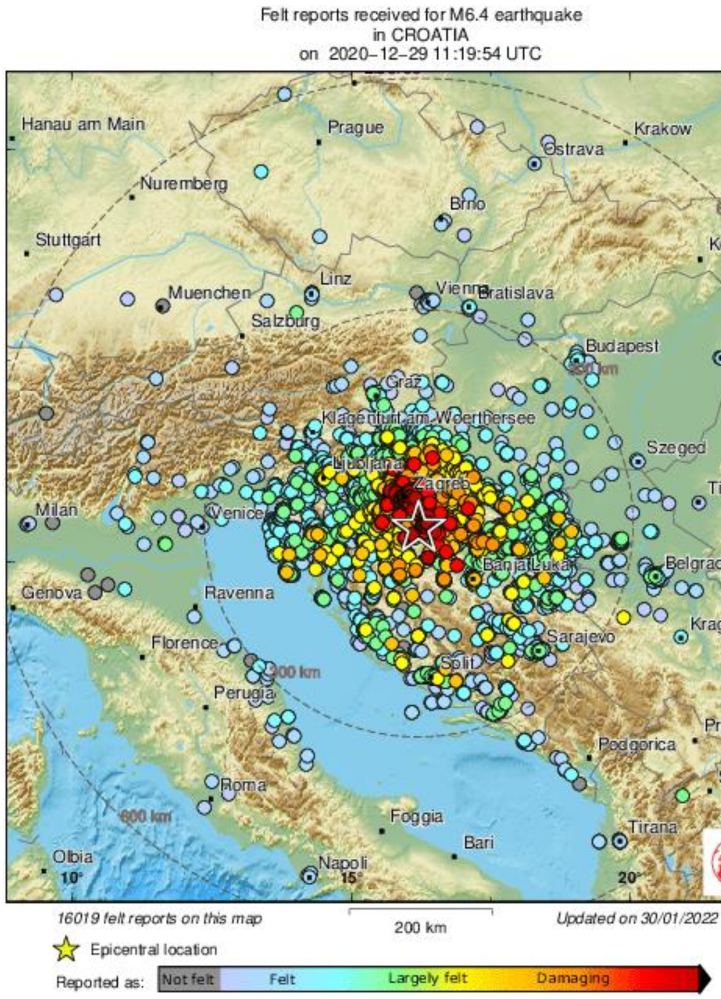
- https://troci.holisun.com/

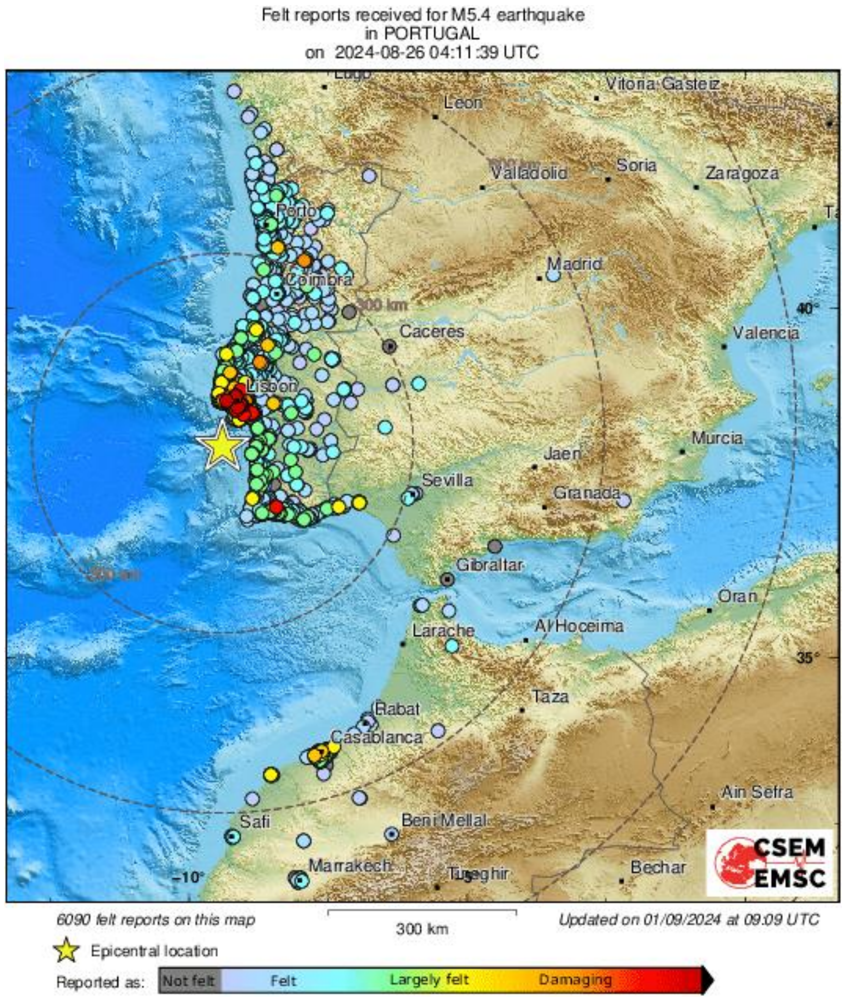


EMSC

- More than 2500 sensors
- Sub-minute measurements
- Sensors deployed in urban areas

- https://emsc.eu/

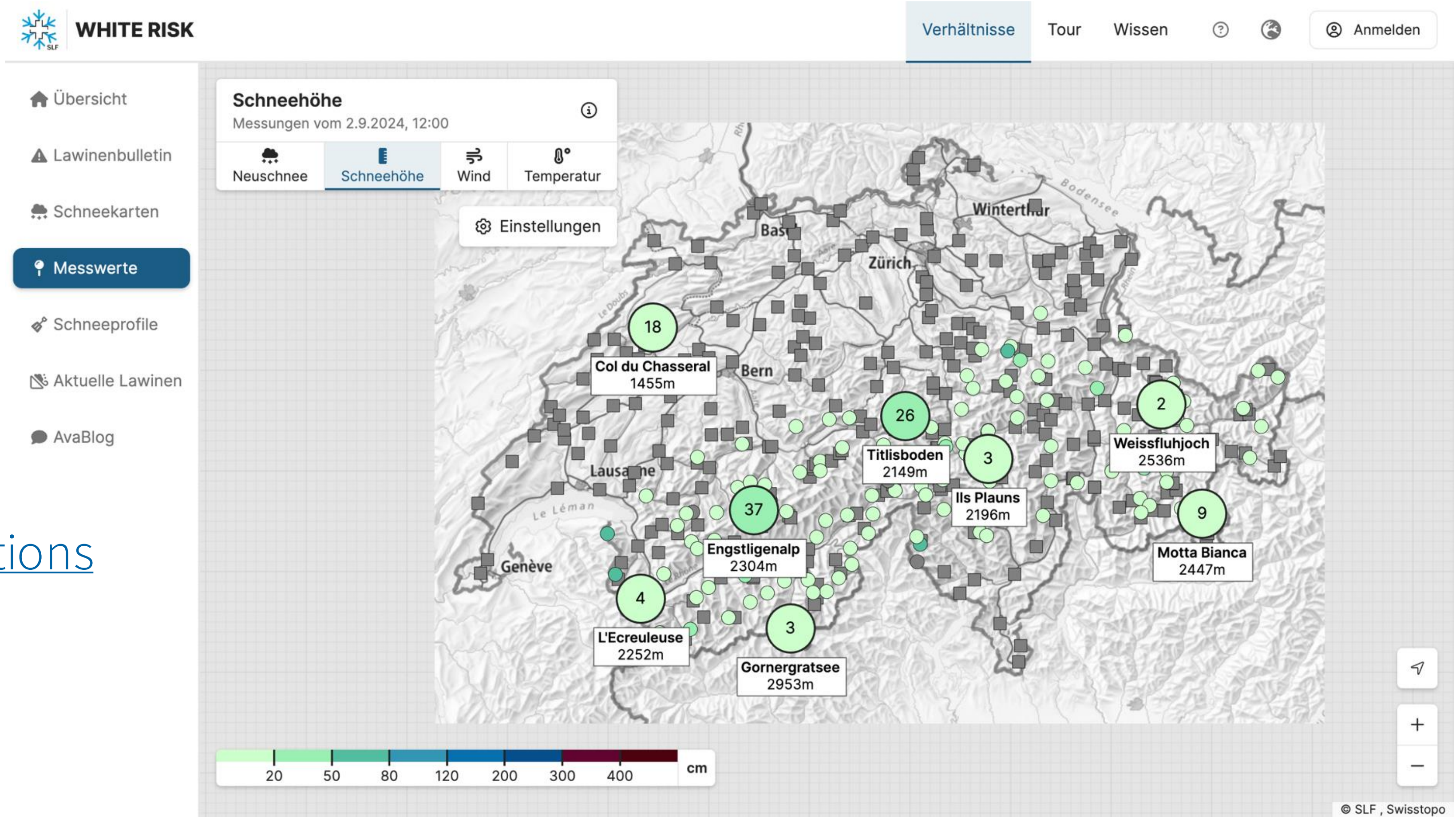




SLF IMIS

- 189 stations in the Swiss Alps and Jura Canton
- Highly remote areas
- Every 30 minutes

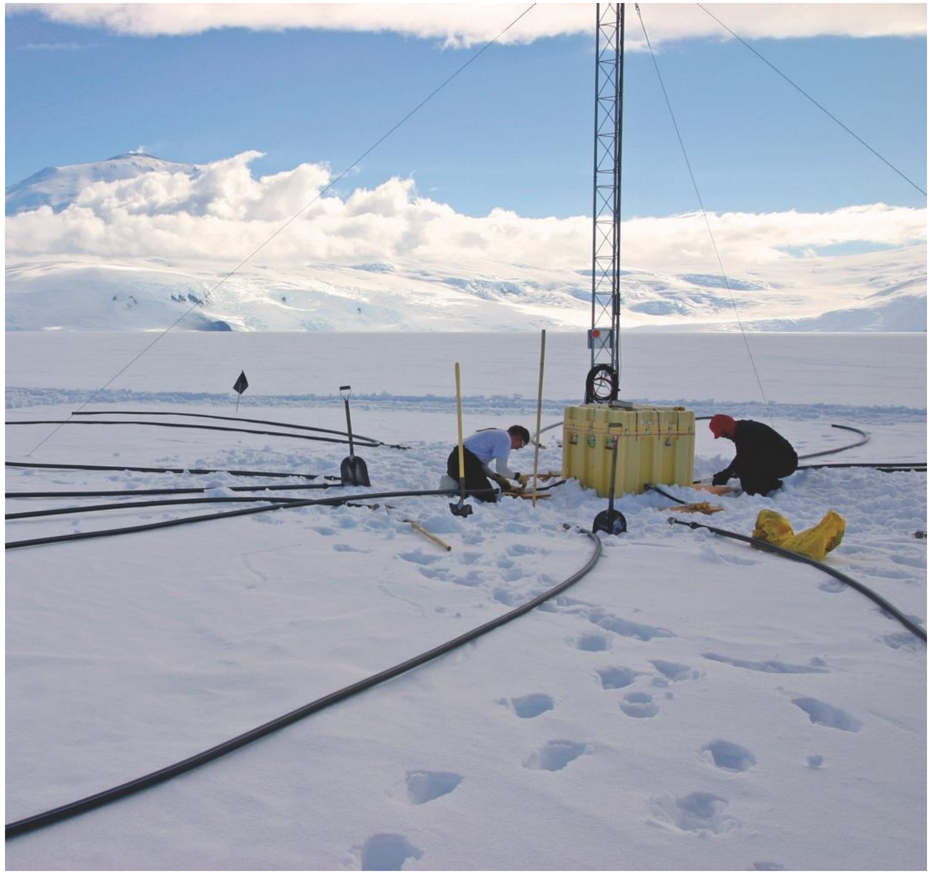
- https://whiterisk.ch/en/conditions



CTBTO

- 337 facilities worldwide
- Hourly measurements
- Homogenously distributed around the earth

- https://ctbto.org/




337 Total Number of Facilities
Seismic Primary Array (PS)
Seismic Primary 3-Component Station (PS)
Seismic Auxiliary Array (AS)
Seismic Auxiliary 3-Component Station (AS)
Radionuclide Station (RN)
Radionuclide Station with Noble Gas Monitoring Capabilities (RN)
Radionuclide Laboratory (RL)
Hydroacoustic (Hydrophone) Station (HA)
Hydroacoustic (T-Phase) Station (HA)
Infrasound Station (IS)
International Data Centre - CTBTO - Vienna
Projection from the South Pole, representing accurately the size of Antarctica and the location of the stations in this region
The boundaries and presentation of material on this map do not imply the expression of any opinion on the part of the Comprehensive Nuclear-Test-Ban Treaty Organization (CTBTO) Preparatory Commission concerning the legal status of any country, territory, city or area or its authorities, or concerning the delimitation of its frontiers or boundaries.
Revised August 2021 | CTBTO.ORG

Sustainability beyond Energy Efficiency

Challenges

- Energy / network availability
- Battery life and disposal
- Hardware obsolescence and e-waste
- Physical disruption to ecosystems
- Carbon footprint of manufacturing and installation

Solutions

- Energy-harvesting
- Fewer sensors / sites
- Less frequent communication
- More efficient processing

Challenges in an Off-Grid Setting

1. Electricity Access
2. Internet Access
3. Failure Risk
4. Sustainability

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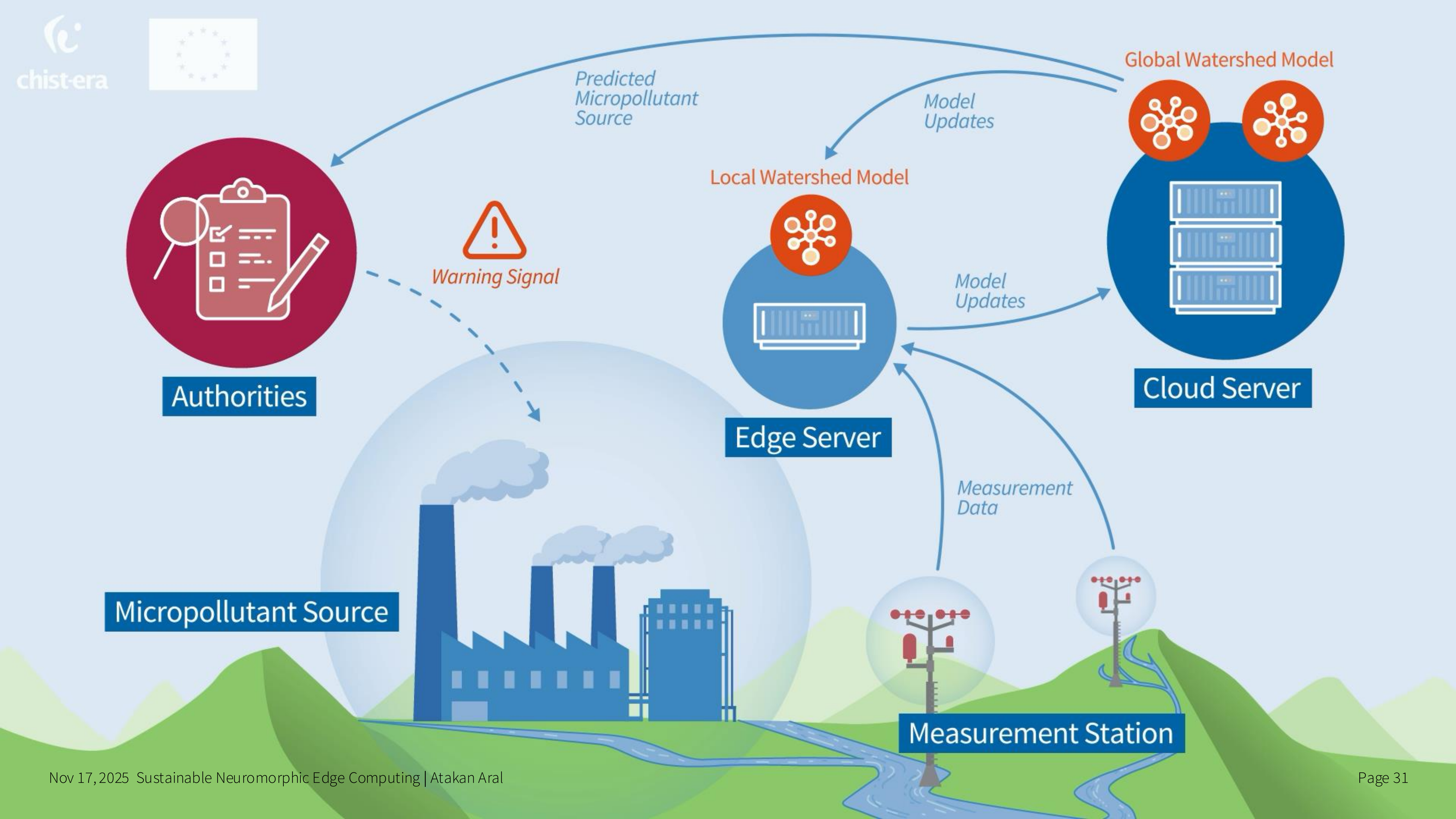
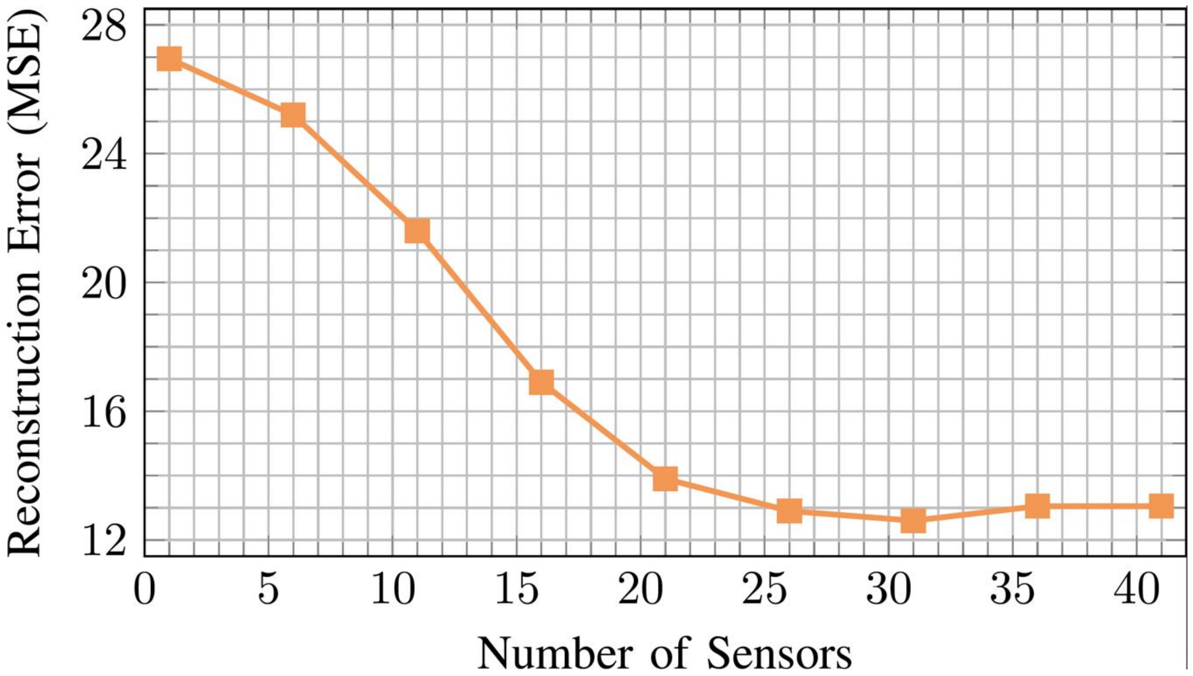
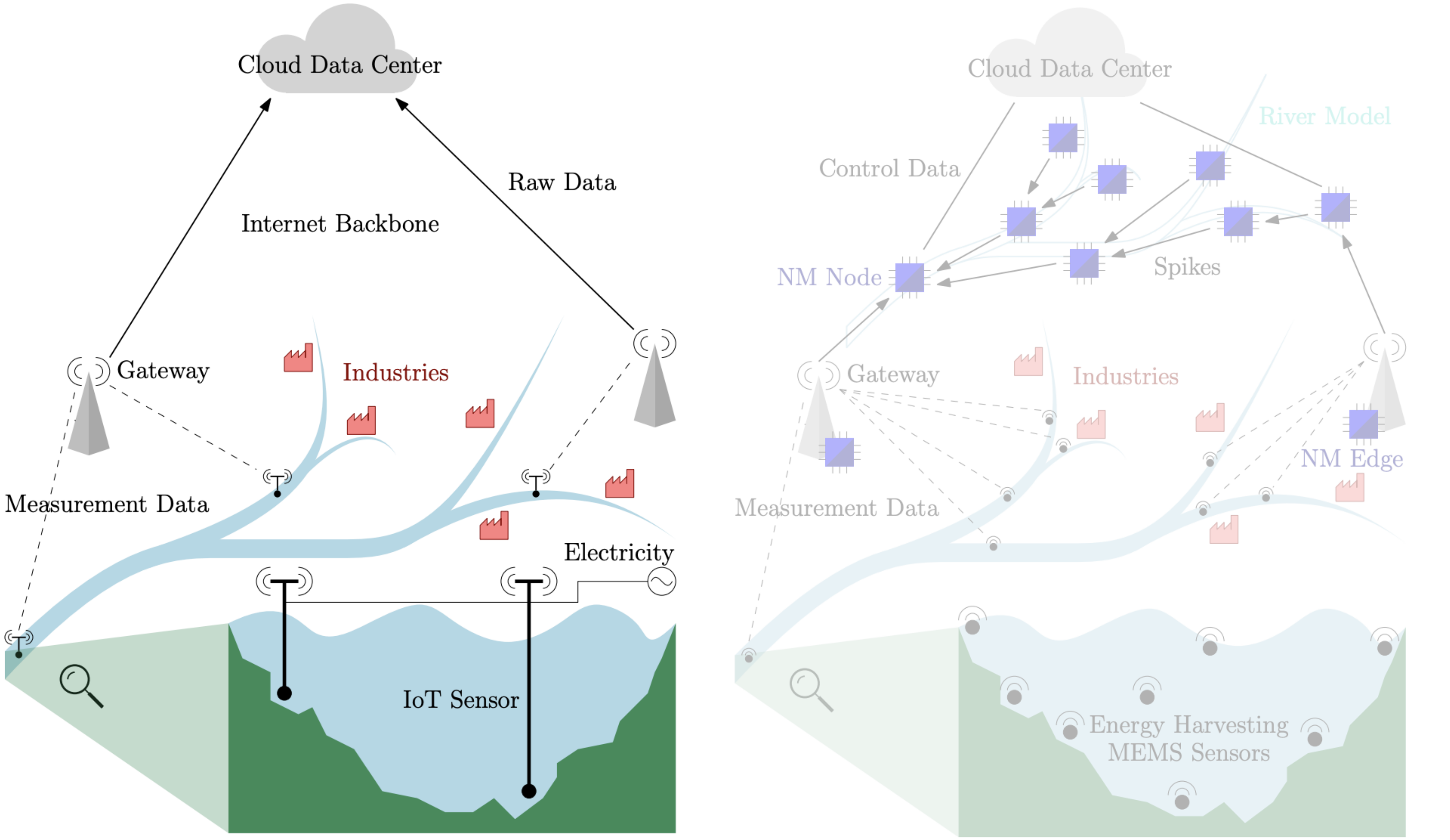

Global Watershed Model
Predicted Micropollutant Source
Model Updates
Local Watershed Model
Warning Signal
Model Updates
Authorities
Cloud Server
Edge Server
Measurement Data
Micropollutant Source
Measurement Station

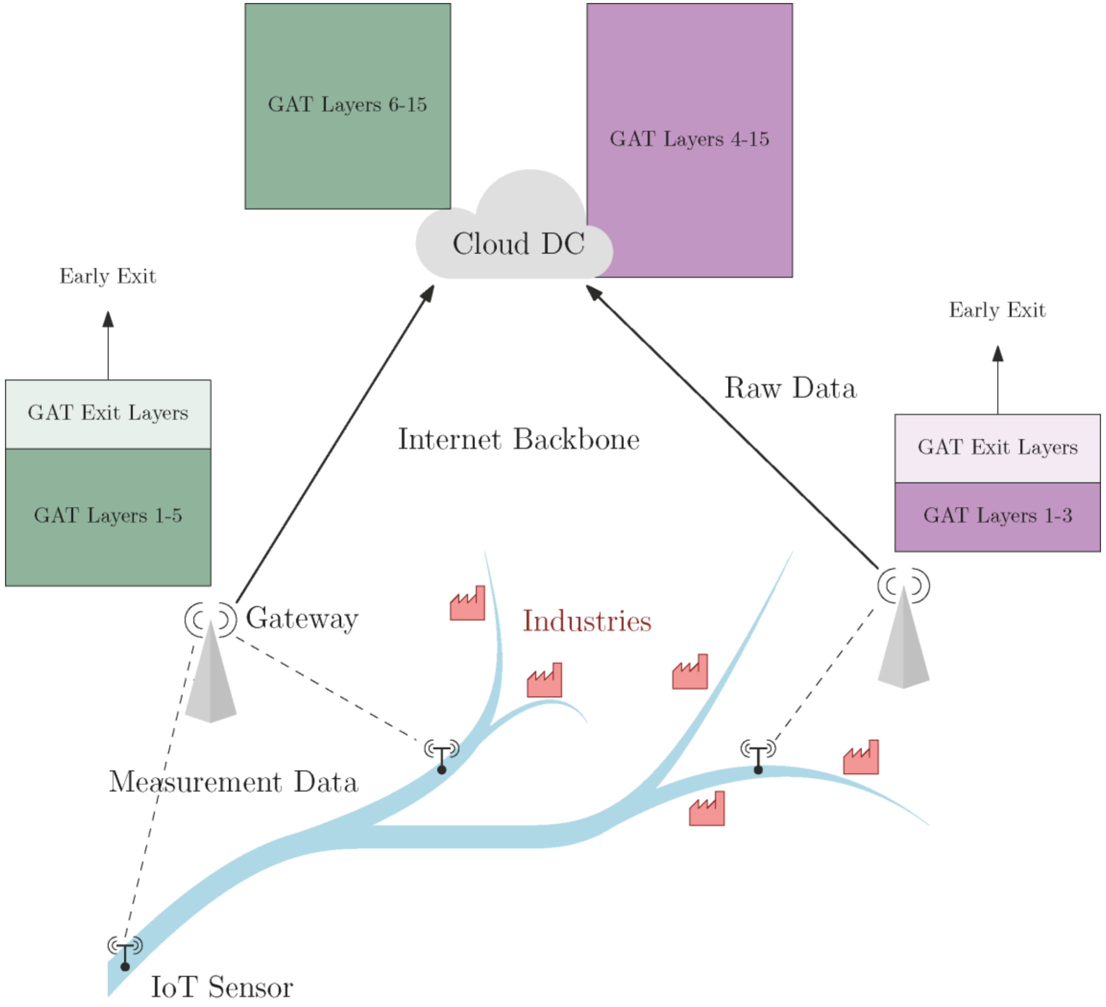
Distributed Model Synchronization

- Local models have to synchronize to form a global model.
  - Intermittent communication
  - Low bandwidth
  - Fail-prone compute nodes
- A complete synchronization is unnecessary.
  Aral, A., Erol-Kantarci, M., & Brandić, I. (2020). Staleness control for edge data analytics. *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, *4*(2), *SIGMETRICS 2020.*



Ahmad, S., Uyanık, H., Ovatman, T., Sandıkkaya, M. T., De Maio, V., Brandić, I. and Aral, A. 2023. Sustainable Environmental Monitoring via Energy and Information Efficient Multi-Node Placement. *IEEE Internet of Things Journal.*


Cloud Data Center
Raw Data
Internet Backbone
Gateway
Industries
Measurement Data
Electricity
IoT Sensor
Cloud Data Center
River Model
Control Data
NM Node
Spikes
Gateway
Industries
NM Edge
Measurement Data
Energy Harvesting
MEMS Sensors



More details:

Ferdowsi, A. and Aral, A. (2025) *Distributed Neuromorphic Edge Computing: Theory and Applications in Environmental Monitoring*. In IEEE EDGE/CLOUD Symposium on Sustainability and Resilience across the Computing Continuum.

Aral, A. (2025) *EdgeSynapse: Towards Leaky-Spike Transmission for Sustainable Edge Sensing.* In Workshop on Edge-Integrated Mobile Sensing and Applications (EdgeSense)

Conclusion

- **Neuromorphic Edge** is a promising solution to the challenges in IoT- and AI-driven monitoring, especially in off-grid environments.
  - Energy Proportionality
  - Real-Time Responsiveness
  - Better Privacy Preservation
  - High Fan-In / Fan-Out Connectivity

- Still in the early stages: success depends on open benchmarks, streamlined development tools, and cross-disciplinary collaboration.

Sustainable Neuromorphic Edge Computing

Asst. Prof. Dr. Atakan Aral, University of Vienna

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