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# Energy-efficient in-situ monitoring using on-device and distributed learning

**Antoine Bonneau**<sup>1,2</sup>   Frédéric Le Mouël<sup>1</sup>   Fabien Mieyeville<sup>2</sup>

Contact : [antoine.bonneau@insa-lyon.fr](mailto:antoine.bonneau@insa-lyon.fr)

<sup>1</sup>Univ Lyon, INSA Lyon, Inria, CITI, EA3720, 69621 Villeurbanne, France

<sup>2</sup>Univ Lyon, Université Claude Bernard Lyon 1, INSA Lyon, Ecole Centrale de Lyon, CNRS, Ampère, UMR5005, 69622 Villeurbanne, France

GreenDays - Lyon - March 2023

## 1 Thesis and Research keypoints

- Research keypoints
- On-Device Learning
- Intermittent Learning
- Federated Learning

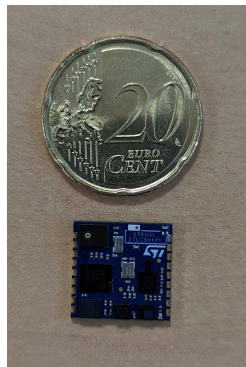
## 2 Bottom-up Approach

- Use case : Ampere's active control platform
- Data and tools
- Preliminary Results
- Evaluating Trade-offs
- Constrained hardware and Distributed Solutions

- ▶ Research keypoints
  - ▶ Deployment of a WSN as a monitoring and adaptive action solution
  - ▶ Minimal footprint energy aiming for autonomy
  - ▶ Exploiting networking AI to improve and maintain itself
- ▶ Energy efficiency as a cross-cutting topic
- ▶ Focus on Time Series data (reduced feature set and samples)

# On-Device Learning : Resources constrained learning

- ▶ Memory constraints → Compressed Models [Profentzas et al. 2022]
  - ▶ Pruning (adaptative, distributed, ...)
  - ▶ Quantization (aware training, partial, ...)
  - ▶ Huffman Encoding.
- ▶ Computation constraints → Preprocessed Models [Lin et al. 2022]
  - ▶ Use pre-trained models on boards.
  - ▶ Sparsely fine tune model.



Target : WSN Nodes / IoT low-end devices

MCU Arch	Clock speed	Storage	RAM	Current
16 or 32 bit	$\leq 50$ MHz	$\leq 512$ KB	$\leq 64$ KB	$\leq 10$ mA

# Intermittent Learning : Duty cycling

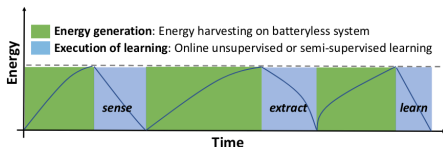
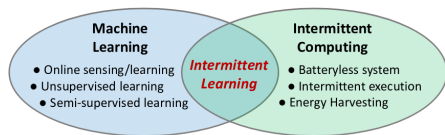


Figure 1: Intermittent Learner duty [Lee et al. 2019]

- ▶ Extreme power scarcity → Energy Harvesting
  - ▶ Save computations through gradient / energy-aware checkpointing
  - ▶ Decompose monolithic ML with task-based approaches [Lee et al. 2019]
- ▶ Changes in energy availability → Energy-aware reconfiguration [Bakar et al. 2021]
  - ▶ Power on / off different peripherals and change sensors sampling rates
  - ▶ Adapt compute complexity through early exiting
  - ▶ Change focus from learning to inference

# Federated Learning : Bypass computational weaknesses

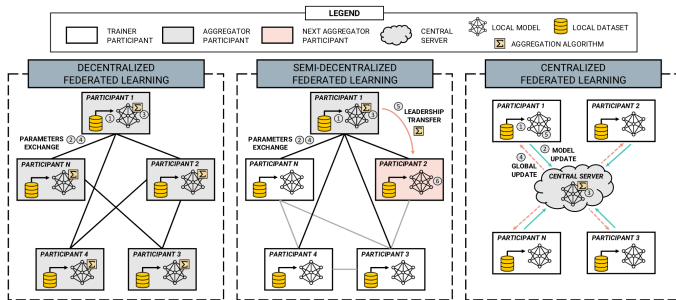


Figure 2: DFL architectures [Beltrán et al. 2022]

- ▶ Learning in correlated groups → Adaptive Neighbor Matching
  - ▶ Select neighbors based on similar performances (gossip and PENS)
  - ▶ Selection to significantly improve convergence speed and training loss.
- ▶ Communication is energy-consuming → Optimize transmission
  - ▶ Reduce shared payload size with compressed sensing [Li et al. 2021]
  - ▶ Choosing communication-efficient aggregators (e.g Dynamic Average Consensus-Based)

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# Ampere's active control platform

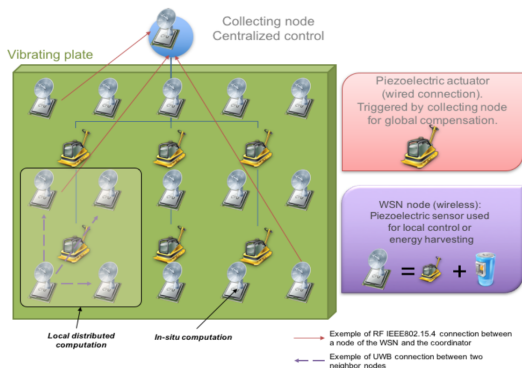


Figure 3: Ampere's vibrating rig [Zieliński 2015]

## ▶ Experimental Issues

- ▶ Low power / High EH potential
- ▶ Reduce vibration (locally, collaboratively and globally)
- ▶ Keep WSN up through piezoelectric EH and energy balancing

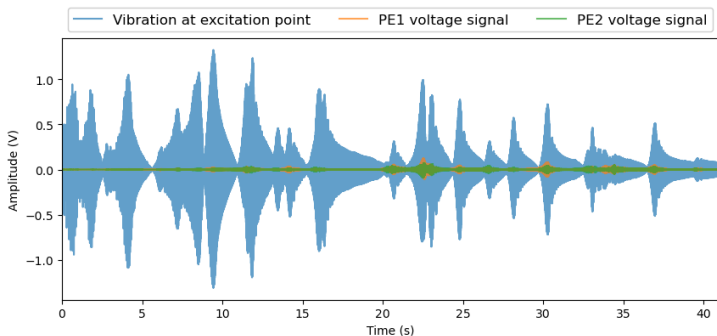


Figure 4: Dataset 1 / 30 ( $f_{sampling} = 1.6$  kHz,  $f_{exc} = 10$  Hz  $\rightarrow$  500)

## ► Tools

- tsai: Time Series AI framework (fastai + PyTorch)
- Software Wattmeters : carbontracker vs. codecarbon

# Preliminary Results

- ▶ Anomaly detection
- ▶ Regression
- ▶ **Classification**

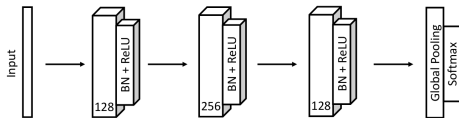


Figure 5: FCN [Wang et al. 2016]

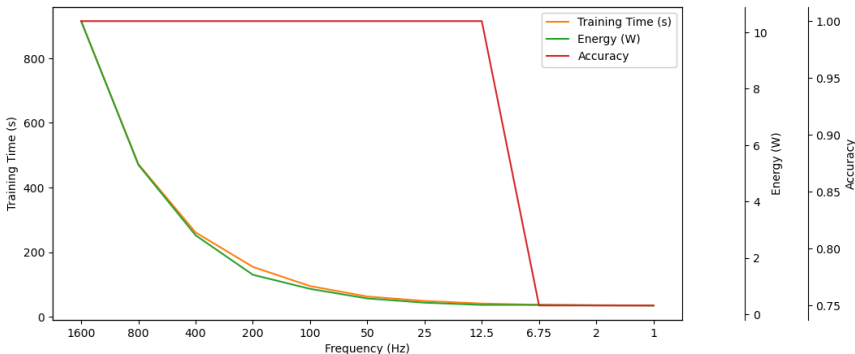
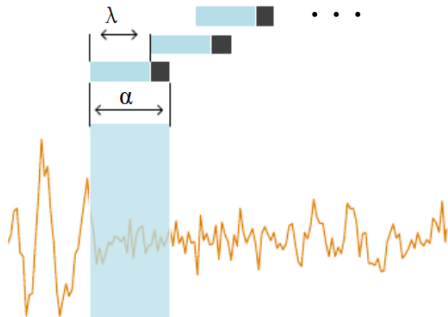


Figure 6: FCN subsampling comparisons

# Evaluating Trade-offs

- ▶ Training carbon impact : 0.1 - 1 gCO<sub>2</sub>e (total : 6.2 gCO<sub>2</sub>e ; 24 run)
- ▶ Down-sampling strategies impact
  - ▶ Signal decimation ( $\frac{1}{2}$ ,  $\frac{1}{4}$ , ...)
  - ▶ Random pruning
  - ▶ Cluster-distributed resampling
- ▶ Processing complete time series vs. using windows



# Constrained hardware and Distributed Solutions

- ▶ Simulation (flower, ns3) vs Real world (RaspberryPi, STM32 F302R8)

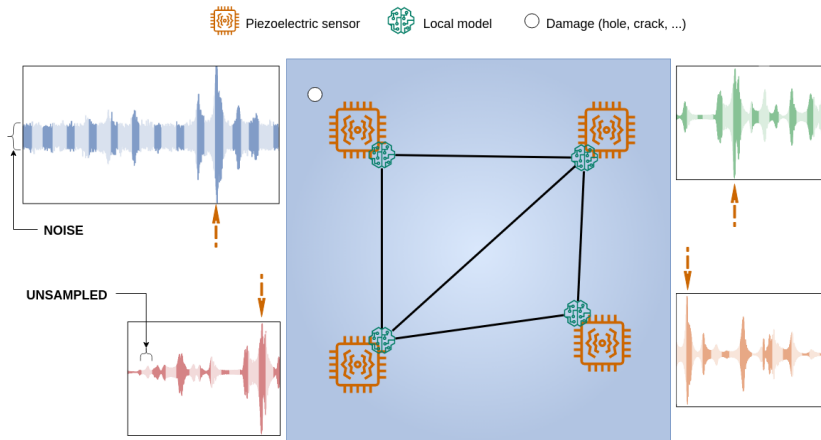


Figure 7: Federated Learning objectives

- ▶ Signature synchronization with localized monitoring / modeling
- ▶ Anomaly detection from noise shifting → Reinforcement Learning

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# References I

-  Bakar, Abu et al. (Sept. 2021). “REHASH: A Flexible, Developer Focused, Heuristic Adaptation Platform for Intermittently Powered Computing”. In: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* DOI: 10.1145/3478077.
-  Beltrán, Enrique Tomás Martínez et al. (Nov. 2022). “Decentralized Federated Learning: Fundamentals, State-of-the-art, Frameworks, Trends, and Challenges”. In: DOI: 10.48550/arXiv.2211.08413.
-  Lee, Seulki et al. (Dec. 2019). “Intermittent Learning: On-Device Machine Learning on Intermittently Powered System”. In: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* DOI: 10.1145/3369837.
-  Li, Chengxi et al. (Oct. 2021). “Communication-Efficient Federated Learning Based on Compressed Sensing”. In: *IEEE Internet Things J.* DOI: 10.1109/JIOT.2021.3073112.
-  Lin, Ji et al. (July 2022). “On-Device Training Under 256KB Memory”. In: DOI: 10.48550/arXiv.2206.15472.

## References II

-  Profentzas, Christos et al. (Sept. 2022). “MiniLearn: On-Device Learning for Low-Power IoT Devices”. In: *International Conference on Embedded Wireless Systems and Networks*. URL: <https://research.chalmers.se/en/publication/531933>.
-  Wang, Zhiguang et al. (Dec. 2016). “Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline”. In: URL: <http://arxiv.org/abs/1611.06455> (visited on 03/24/2023).
-  Zieliński Piotr, Mateusz (Oct. 2015). “Système distribué actif sans fil basse consommation pour l’amortissement des vibrations”. fr. PhD. Université de Lyon: Université de Lyon. URL: <https://www.theses.fr/2015ECDL0029>.