



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

Antoine Bonneau, Frédéric Le Mouël, Fabien Mieyeville

## ► To cite this version:

Antoine Bonneau, Frédéric Le Mouël, Fabien Mieyeville. Energy-efficient in-situ monitoring using on-device and distributed learning. Green Days, Mar 2023, Lyon, France. hal-04035287

HAL Id: hal-04035287

<https://inria.hal.science/hal-04035287>

Submitted on 28 Mar 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# 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

# Outline

## 1 Thesis and Research keypoints

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

## 2 Bottom-up Approach

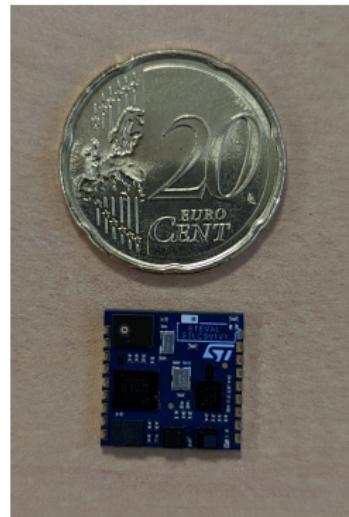
- Use case : Ampère's active control platform
- Data and tools
- Preliminary Results
- Evaluating Trade-offs
- Constrained hardware and Distributed Solutions

# Ultra Low Power Ambient Artificial Intelligence

- ▶ 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	$\leq 50 \text{ MHz}$	$\leq 512 \text{ KB}$	$\leq 64 \text{ KB}$	$\leq 10 \text{ mA}$

# Intermittent Learning : Duty cycling

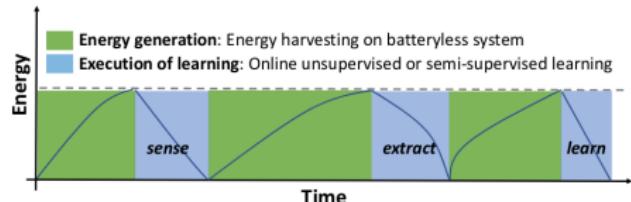
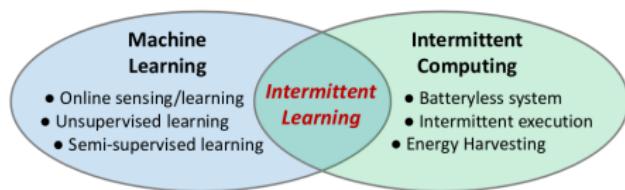


Figure 1: Intermittent Learner duty [Lee et al. 2019]

- ▶ 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

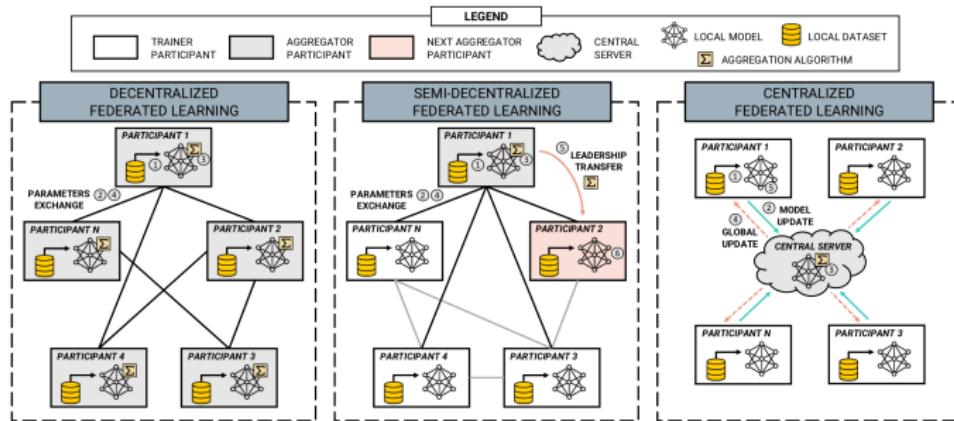


Figure 2: DFL architectures [Beltrán et al. 2022]

- ▶ 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)

# Outline

## 1 Thesis and Research keypoints

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

## 2 Bottom-up Approach

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

# Ampere's active control platform

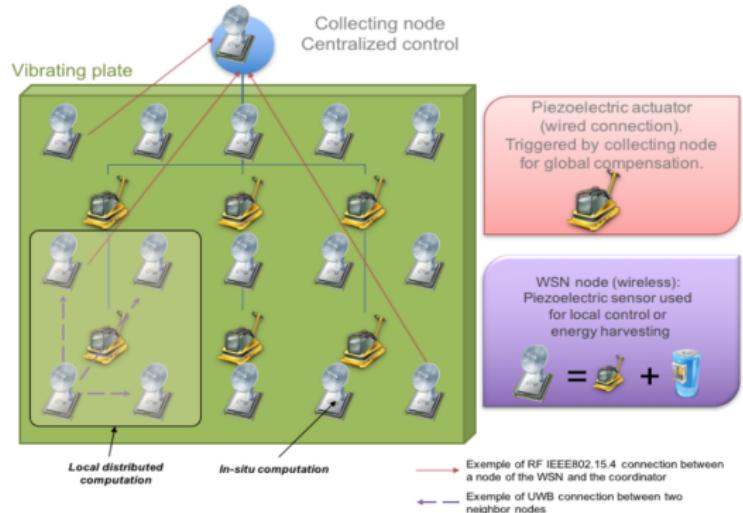


Figure 3: Ampere's vibrating rig [Zieliński 2015]

## ► Experimental Issues

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

# Data and tools

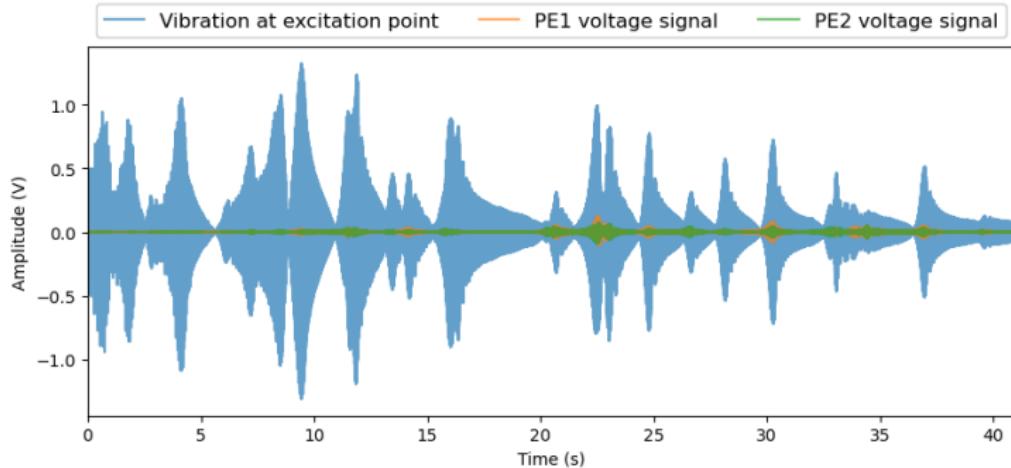


Figure 4: Dataset 1 / 30 ( $f_{sampling} = 1.6 \text{ kHz}$ ,  $f_{exc} = 10 \text{ Hz} \rightarrow 500$ )

## ► Tools

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

# Preliminary Results

- ▶ Anomaly detection
- ▶ Regression
- ▶ Classification

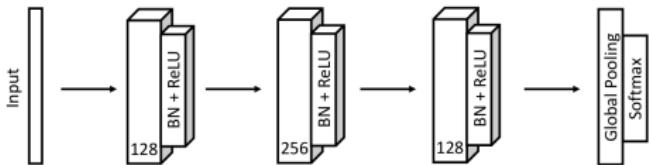


Figure 5: FCN [Wang et al. 2016]

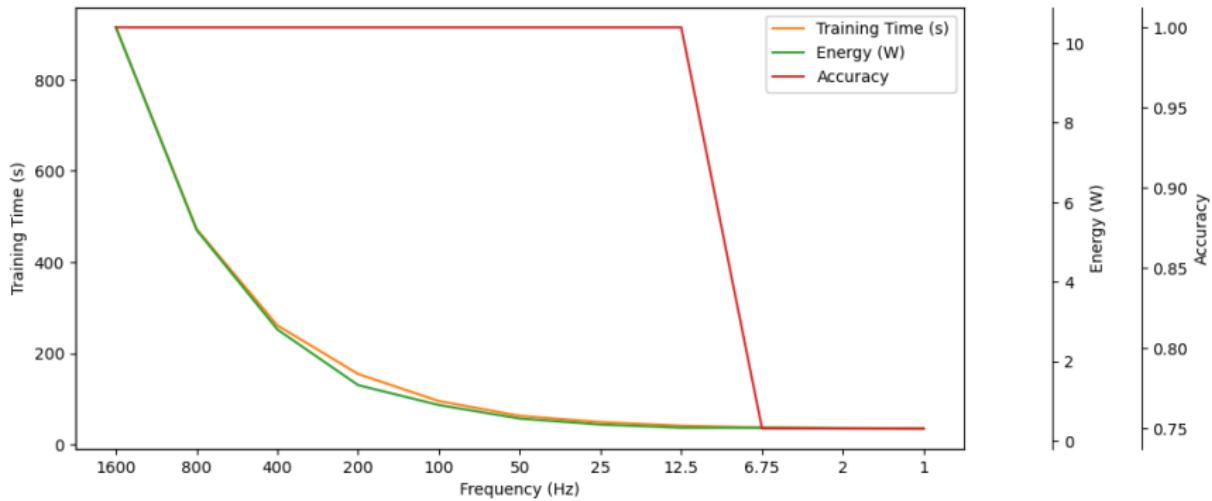
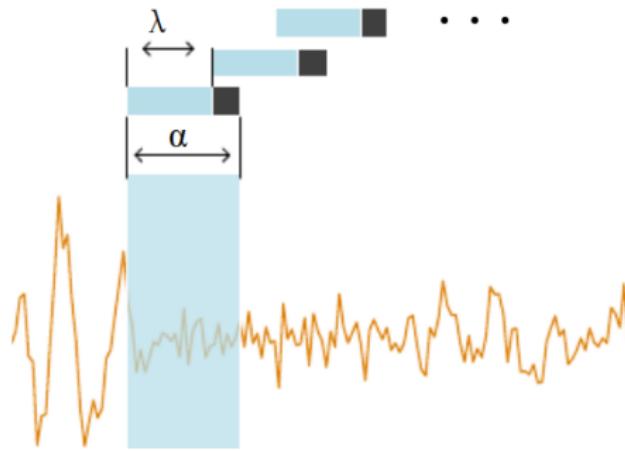


Figure 6: FCN subsampling comparisons

# 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 ( $\frac{1}{2}, \frac{1}{4}, \dots$ )
  - ▶ 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)

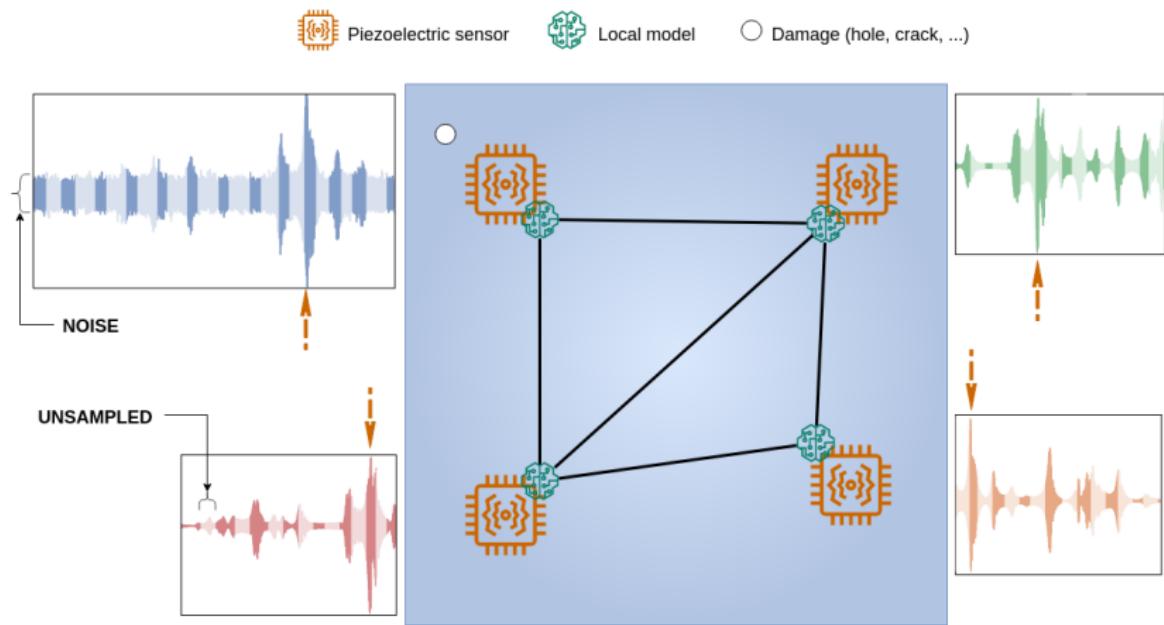


Figure 7: Federated Learning objectives

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

# 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

# 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](https://doi.org/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](https://doi.org/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](https://doi.org/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](https://doi.org/10.1109/JIOT.2021.3073112).
-  Lin, Ji et al. (July 2022). "On-Device Training Under 256KB Memory". In: DOI: [10.48550/arXiv.2206.15472](https://doi.org/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>.