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

Antoine Bonneau[1,2] Frédéric Le Mouël[1] Fabien Mieyeville[2]

Contact : antoine.bonneau@insa-lyon.fr

[1]Univ Lyon, INSA Lyon, Inria, CITI, EA3720, 69621 Villeurbanne, France
[2]Univ Lyon, Université Claude Bernard Lyon 1, INSA Lyon, Ecole Centrale de Lyon, CNRS, Ampère, UMR5005, 69622 Villeurbanne, France

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Outline

1. Thesis and Research keypoints
   - Research keypoints
   - On-Device Learning
   - Intermittent Learning
   - Federated Learning

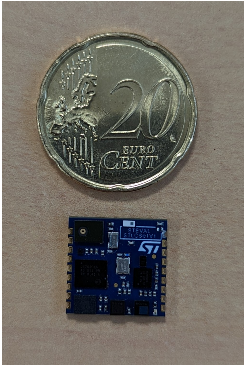
2. Bottom-up Approach
   - Use case : Ampere's active control platform
   - Data and tools
   - Preliminary Results
   - Evaluating Trade-offs
   - Constrained hardware and Distributed Solutions

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	$\leq 50\ MHz$	$\leq 512\ KB$	$\leq 64\ KB$	$\leq 10\ mA$

Intermittent Learning : Duty cycling

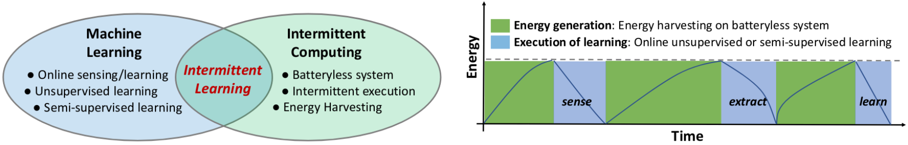


Figure 1: Intermittent Learner duty [Lee et al. 2019]

- 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

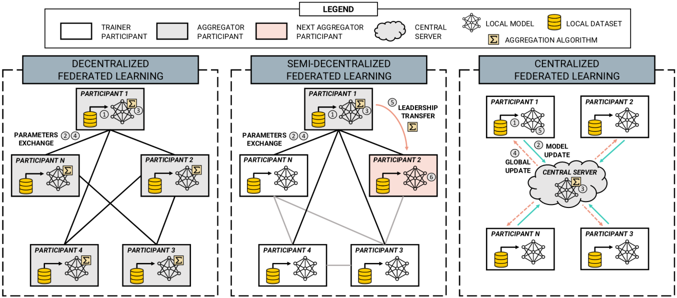


Figure 2: DFL architectures [Beltrán et al. 2022]

- 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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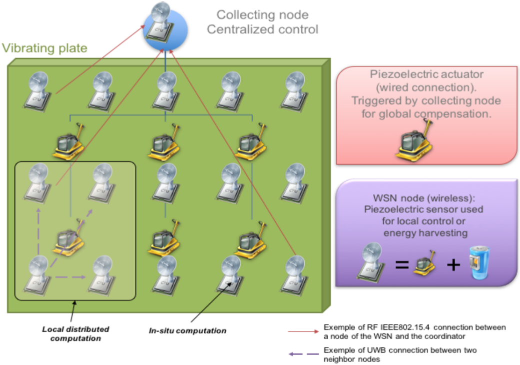
Ampere's active control platform



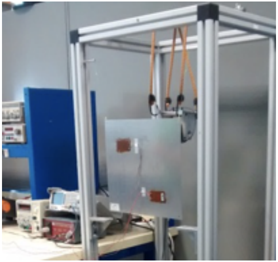


Figure 3: Ampere's vibrating rig [Zieliński 2015]

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

Data and tools

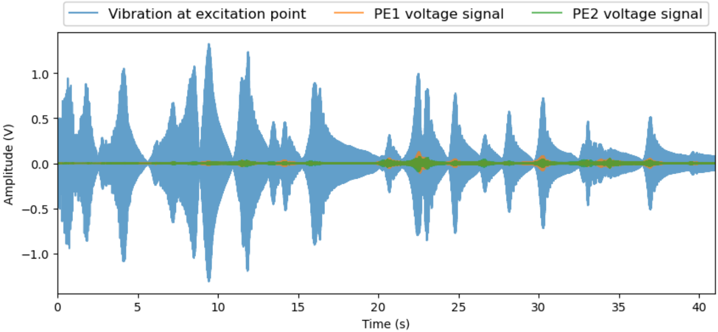


Figure 4: Dataset 1 / 30 ($f_{sampling} = 1.6$ kHz, $f_{exc} = 10$ Hz $\rightarrow$ 500)

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

Preliminary Results

- Anomaly detection
- Regression
- **Classification**

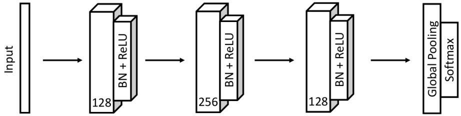


Figure 5: FCN [Wang et al. 2016]

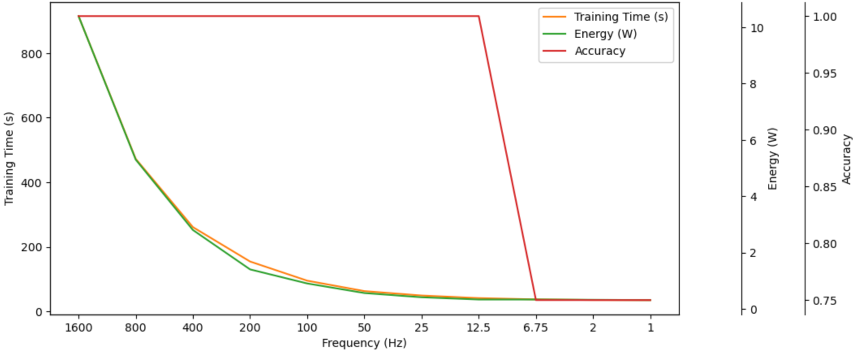
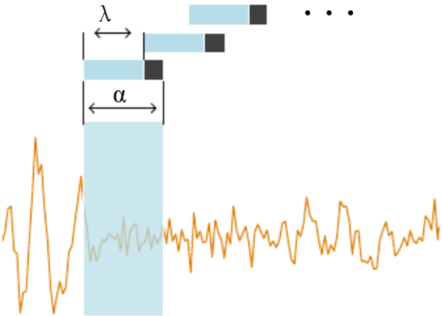


Figure 6: FCN subsampling comparisons

Evaluating Trade-offs

- Training carbon impact : 0.1 - 1 gCO_2e (total : 6.2 gCO_2e ; 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)

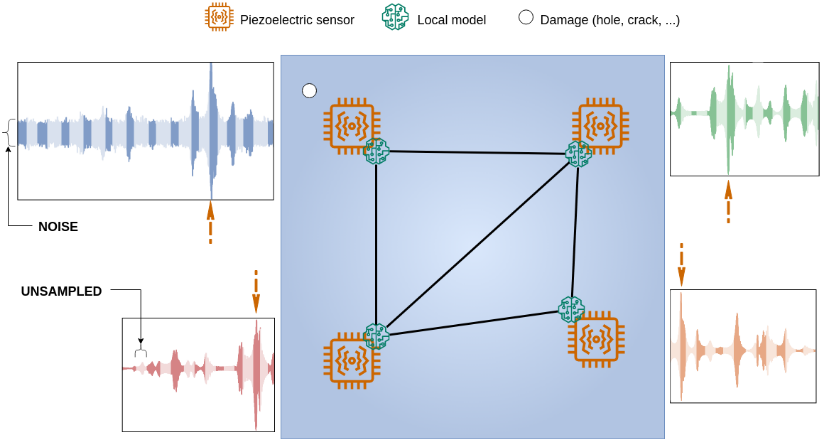


Figure 7: Federated Learning objectives

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

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