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

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GreenDays - Lyon - March 2023

1 Thesis and Research keypoints

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

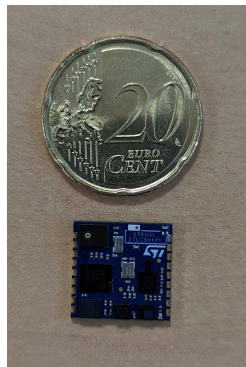
2 Bottom-up Approach

- 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	≤ 50 MHz	≤ 512 KB	≤ 64 KB	≤ 10 mA

Intermittent Learning : Duty cycling

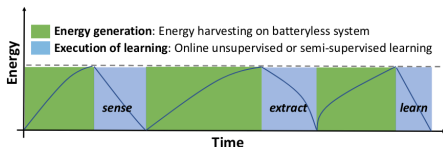
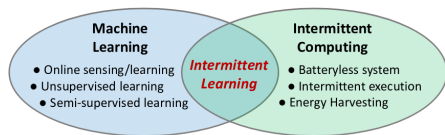


Figure 1: Intermittent Learner duty [Lee et al. 2019]

- ▶ 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

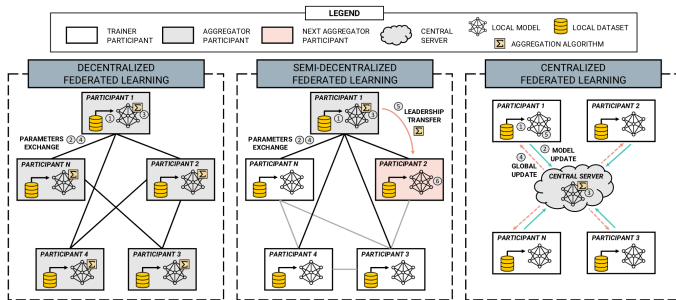


Figure 2: DFL architectures [Beltrán et al. 2022]

- ▶ 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

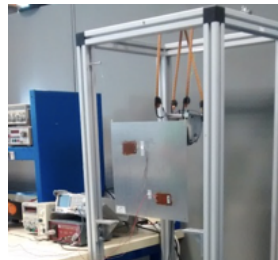
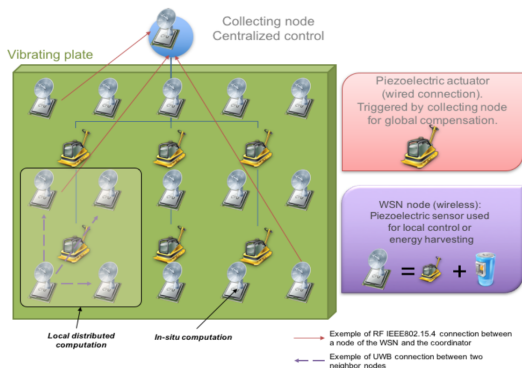


Figure 3: Ampere's vibrating rig [Zieliński 2015]

▶ Experimental Issues

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

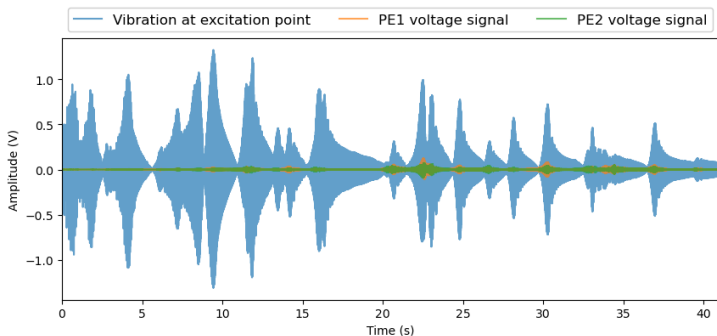


Figure 4: Dataset 1 / 30 ($f_{sampling} = 1.6$ kHz, $f_{exc} = 10$ Hz \rightarrow 500)

► Tools

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

Preliminary Results

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

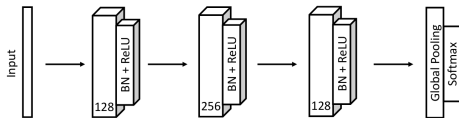


Figure 5: FCN [Wang et al. 2016]

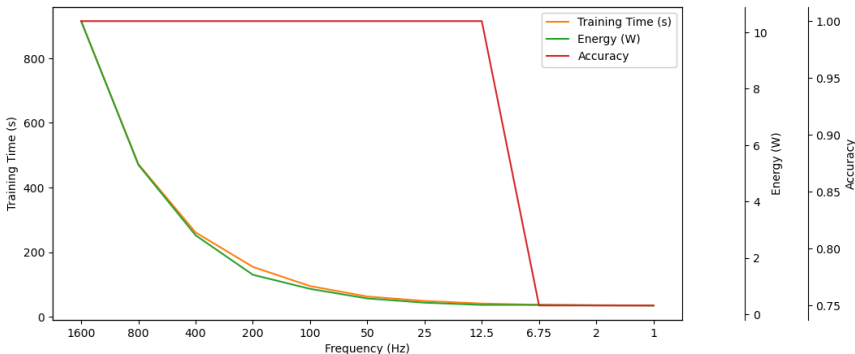
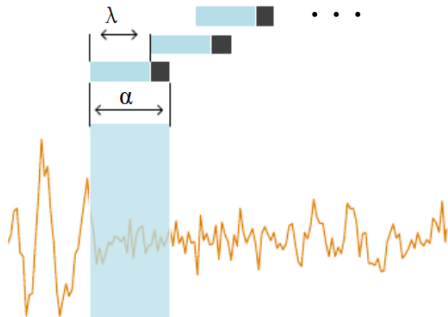


Figure 6: FCN subsampling comparisons

Evaluating Trade-offs

- ▶ Training carbon impact : 0.1 - 1 gCO₂e (total : 6.2 gCO₂e ; 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)

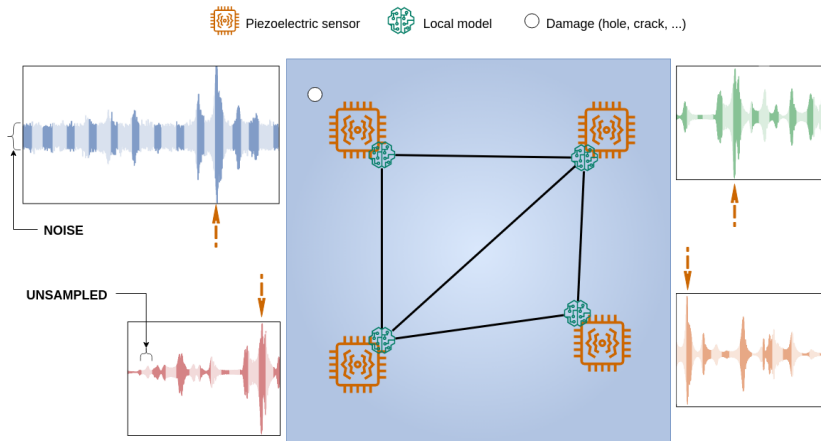


Figure 7: Federated Learning objectives

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

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