HEAT EMISSION AND BATTERY EFFICIENCY MODELLING FOR MOBILE DEVICES IN FEDERATED MACHINE LEARNING

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Keywords: **federated machine learning, mobile devices, heat and battery performance**

The dynamic development of 5G and future 6G networks poses new challenges for telecommunications related to low latency, radio resource saving, and adaptation to unstable transmission conditions. Traditional, centralized approaches to training artificial intelligence models require transferring massive amounts of data to cloud servers, which generates significant delays and overloads network links. A solution to this problem is Federated Machine Learning (FML), which allows models to be trained locally on end-user mobile devices, such as smartphones, by sending only updated neural network weights to the main aggregator [3].

However, local training of advanced AI algorithms leads to extreme loads on CPU units of mobile devices, resulting in significant heating and battery drain [2] [4]. The aim of this work is to present a physical and mathematical model describing these phenomena and to propose a mechanism (thermal guard) that dynamically interrupts the learning process based on thermal readings.

The research environment was built using the Flower framework [1] and the TensorFlow Lite library, employing five Samsung smartphones as edge clients and a laptop acting as an aggregator. The base model was a lightweight Multi-Layer Perceptron (MLP) trained on distributed and uncorrelated input data from various network operators, simulating a Non-IID environment.

The impact of the aggregation process and local training on the device was defined by observing the system temperature. The heat emission Q(t) during training can be described by a reduced thermal balance model of the device:

$$C_p \frac{dT}{dt} = P_{CPU}(\eta, \omega) - h \cdot S \cdot (T - T_{env}) \tag{1}$$

Where: Cp is the heat capacity of the device, T is the current processor temperature, P_{CPU} is the power dissipated by the computing unit (dependent on the learning rate η and batch size ω), h is the heat transfer coefficient of the device's cooling system, S is the surface area of exchange, and T_{env} is the ambient temperature. Based on the above, an original client suitability index was derived, which reduces the priority of a given smartphone in the federated cycle when temperature T exceeds a critical threshold (45°C in the study), preventing thermal throttling and protecting the device's battery [5].

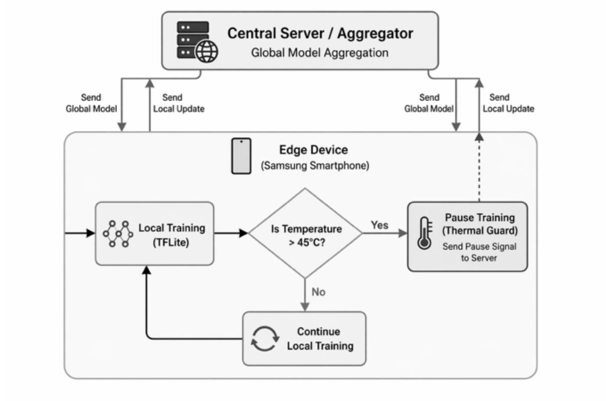

Fig. 1. Experimental run: impact of asynchronous thermal compensation on mobile device processor temperature in consecutive FML rounds.

The proposed architecture and the thermal guard mechanism are currently undergoing experimental evaluation. Theoretical analysis of the thermal model and preliminary proof-of-concept tests indicate significant potential for optimizing energy consumption and preventing hardware degradation. Some empirical results, covering correlations between 5G network conditions and the energy efficiency of edge devices, will be presented during the speech. The described approach may serve as a basis for future resource management solutions in Massive Internet of Things (mIoT) systems and satellite Non-Terrestrial Networks (NTN).

References

[1] Beutel D. J., Topal T., Mathur A., Qiu X., Parcollet T., de Gusmão P. P. B., Lane N. D., Flower: A Friendly Federated Learning Research Framework, arXiv preprint 2020, arXiv:2007.14390.

[2] Zhang Q., Zhu Z., Zhou A., Sun Q., Dustdar S., Wang S., Energy-Efficient Federated Training on Mobile Device, TU Wien / IEEE 2023.

[3] Taik A., Cherkaoui S., Federated Learning for Energy Constrained IoT devices: A systematic mapping study, arXiv preprint 2023, arXiv:2301.03720.

[4] Gu Y., Zhao L., Deng B., Wu S., Evaluation of Thermal Stress on IoT-based Federated Learning, Kennesaw State University Symposium 2024.

[5] Chen R., Wan Q., Zhang X., Qin X., Hou Y., Wang D., Fu X., Pan M., Wireless Aware Energy Efficient Federated Learning over Mobile Devices via Algorithm and Hardware Co-Design, IEEE/ACM Transactions on Networking 2026, 34, 4283-4298.