Resource consumption of Federated Learning approach applied on edge IoT devices in the AGV environment

Bohdan Shubyn[1,2][0000−0002−3051−1544], Piotr Grzesik[1][0000−0001−8868−0765], Taras Maksymyuk[2][0000−0002−2739−9862], Daniel Kostrzewa[1][0000−0003−2781−3709], Paweł Benecki[1][0000−0003−4674−5393], Jia-Hao Syu[4][0000−0002−3875−9317], Jerry Chun-Wei Lin[5][0000−0001−8768−9709], Vaidy Sunderam[3][0000−0002−5128−7852], and Dariusz Mrozek[1][0000−0001−6764−6656]

[1] Silesian University of Technology, Department of Applied Informatics, Gliwice, Poland `Bohdan.Shubyn@polsl.pl`

[2] Lviv Polytechnic National University, Department of Telecommunications, Lviv, Ukraine

[3] Department of Computer Science, Emory University, Atlanta, GA 30322, USA `vss@emory.edu`

[4] Department of Computer Science and Information Engineering, National Taiwan University, Taipei, Taiwan

[5] Department of Computer Science, Electrical Engineering and Mathematical Sciences, Western Norway University of Applied Sciences, Bergen, Norway

Abstract. Federated learning is a distributed machine learning method that is well-suited for the Industrial Internet of Things (IIoT) as it enables the training of machine learning models on distributed datasets. One of the most important advantages of using Federated Learning for Automated Guided Vehicles (AGVs) is its capability to optimize resource consumption. AGVs are typically resource-constrained systems and must operate within tight power and computational limits. By using Federated Learning, AGVs can perform model training and updating on-board, which reduces the amount of data that needs to be transmitted. This paper presents experiments to assess the consumption of resources of the Jetson Nano edge IoT device while training the Federated Learning model, and compares it with referential machine learning approaches.

Keywords: Federated Learning · predictive maintenance · smart production · Artificial Intelligence · resource consumption · recurrent neural networks

1 Introduction

Federated Learning (FL) is a cooperative Machine Learning (ML) technique that relies on the idea of gaining experience in local environments by many distributed, locally built ML models and sharing the experience to build the global

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inference model [16]. Local models can be trained on edge IoT devices that usually have limited storage and computing capabilities compared to typical workstations. This approach reduces communications needs and energy consumptions, since after training local models on locally available data, only the local experience (e.g., ML model parameters) is shared, not the data itself. Therefore, Federated Learning is well suited to Industrial Internet of Things (IIoT) systems and IIoT-based monitoring of AGV-enabled production lines thus contributing to smart and agile manufacturing.

Automated Guided Vehicles (AGVs) and collaborative robots (cobots) play an important role in computer-integrated smart manufacturing as they support assembly tasks in an autonomous manner [23]. They can independently analyze signals from a variety of sensors to complete their operational tasks without human intervention. This requires accumulating a wealth of local data and making decisions in the context of the current environmental conditions, monitored by sensors and transportation commands acquired from external systems, such as the Transportation Management System (TMS) [17].

The inherent properties of FL make it also a suitable approach for monitoring the health of the intelligent machines working in smart production lines, like the AGVs or cobots (Fig. 1). Since smart factories employ many such autonomous units, they all can gather their experience based on operational cycles implemented in the factory. All these devices are equipped with local, edge IoT devices capable of collecting data and building local ML models for various purposes, e.g., predicting the inability to complete specific operational cycles due to low battery levels or predicting necessary maintenance tasks by finding anomalies in analyzed signals [22].

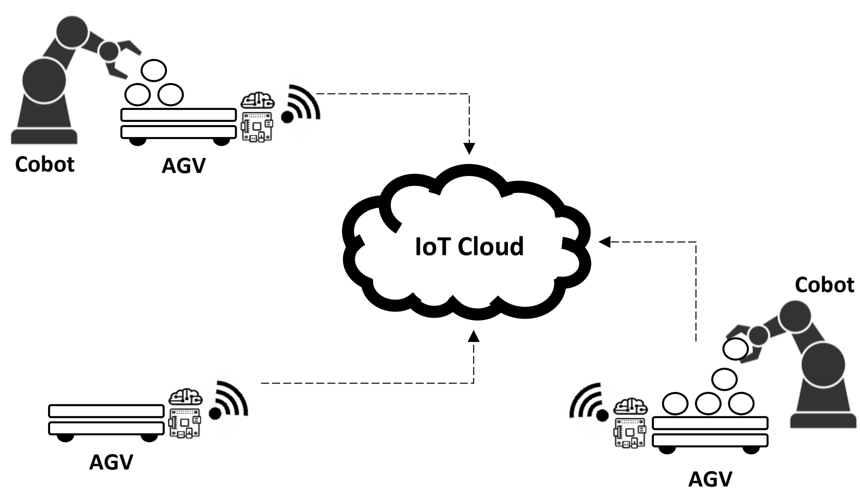

Fig. 1. AGVs performing edge IoT-based local inference and sending local models to the IoT cloud to build a global inference model.

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These predictive tasks can be performed locally, but blending the experience of other AGVs with the local knowledge may bring additional improvements in the quality of inference, and opens the vehicles for the broader spectrum of operational conditions and abnormalities. However, a perfect inference model would require ideal datasets and an excellent algorithm for predictive tasks. This is not easy to achieve. The first factor depends on the existing working conditions and can evolve over time. The second factor is constrained by the capabilities of the IoT device hosting the local ML model. In this paper, we focus on the second factor. We investigate the resource and power cost of performing the predictive tasks with FL/ML algorithms on the NVidia Jetson Nano edge device mounted on the AGV. By performing predictive tasks for momentary energy consumption (MEC) of the AGV as a whole, we compare the energy cost of FL and referential ML.

The rest of the paper is organized as follows. In Section 2, we review the works related to Autonomous Guided Vehicles and Federated Learning. Section 3 explains the concept of the Federated Learning approach we rely on and the inference algorithm we implemented on edge IoT devices mounted on AGVs. Section 4 shows the results of experiments concerning the resource costs while performing the inference with Federated Learning. Finally, Section 5 discusses the obtained results and summarizes the paper.

2 Related Works

2.1 Automated Guided Vehicles

Since Automated Guided Vehicles (AGVs) operate as portable robots that transport objects with autonomous navigation, they are widely used in industrial facilities such as manufacturing plants, assembly lines, and warehouses [6]. Some AGVs consist of trailers or plates to transport materials in factories and support the development of smart factories [3, 10].

Literature shows that navigation is an essential task for AGVs and aims to reduce manual work and increase onboard autonomy to control the AGV [7]. Traditional AGVs are guided and navigated by cables, and the next generation of AGVs consists of wireless guidance systems without physical guidance paths [18]. The wireless guidance systems require environmental information for AGV navigation, such as the arrangement of AGVs, the destination, and the paths. The environment information can either be provided by the central management system or acquired by AGV sensors such as radar, lidar, ultrasound, and an optical camera [15]. Furthermore, with the basic function of navigation, the AGV system could perform route planning, which makes path decisions for AGV navigation with multiple constraints or optimized destinations [1]. Apart from individual AGV routes, the AGV management system also handles traffic management and load transfer to avoid collisions and optimize AGV resource consumption [11].

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2.2 Federated Learning

Federated learning has attracted researchers' attention since 2017 [8] with federated averaging (FedAvg) as a typical model [9] outperforming Federated Stochastic Variance Reduced Gradient (FSVRG) [5] and asynchronous Cooperative Learning (CO-OP) on most real-world datasets [13]. Federated learning is widely used in various research areas, such as healthcare [19], Internet of Things [12], and smart factory [4]. It is known for privacy and has a distributed nature [20], which contrasts with centralized learning algorithms (collecting and training based on all data at a powerful machine). In [2], Cho et al. studied the convergence analysis of FL for biased scheduling methods and investigated the convergence speed of FL. In [21], the authors reported a framework for federated edge learning that can adaptively schedule users to reduce total energy consumption. However, none of these works considered the power costs of the FL approach. Meanwhile, Nishio et al. noted the importance of resource consumption and designed a new FL protocol to perform the scheduling process according to computational resources channel conditions [14]. In [16], we also analyzed various training scenarios to improve the performance of the FL-based prediction model. However, in [16], we didn't focus on the consumption of resources and power efficiency. In this paper, we investigate these fields for the NVidia Jetson Nano edge device that we use in the AGV environment.

3 Federated Learning in the Distributed AGV Environment

In the AGV environment, Federated Learning (FL) is accomplished by training local models on edge IoT devices residing on the AGVs. The learning process is performed in so-called *rounds*.

Definition 1. *A round is a single iteration of distributed training of local models, sharing experience, building the global model, and updating local models with global wisdom.*

A single round consists of the steps that are presented in Fig. 2. This process is iterative, and we should repeat the course of the round periodically or when we get the needed amount of new data.

The first step of a round covers training many local models M_i on AGVs with locally acquired and collected data. Local models may rely on various algorithms, e.g., different architectures of recurrent neural networks (RNNs), but once chosen, the architecture is homogeneous for all AGVs. Next, local models are sent to the data center in the IoT cloud (step 2). In the next step (step 3), we build the global model M by averaging the weights of local models (local RNNs):

$$M = \sum_{i=1}^{N} M_i * \mathbb{I}_{M_i} \tag{1}$$

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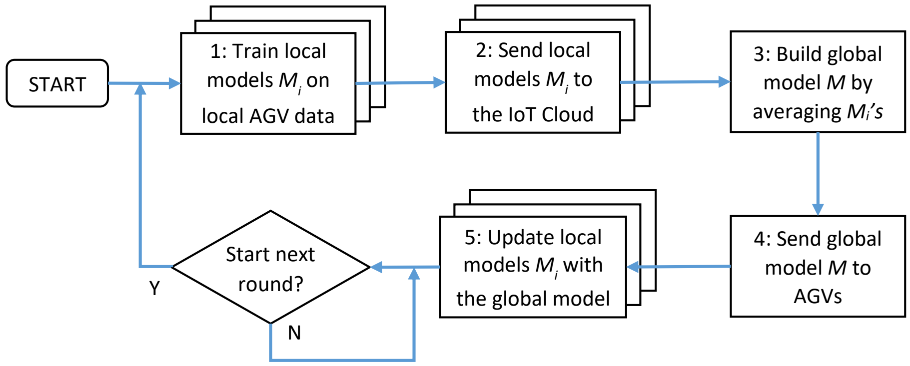

Fig. 2. Federated Learning performed in the distributed AGV environment.

where M_i is the local model built on the i-th AGV, $\mathbb{I}_{M_i}$ is the *influence* of a specific local model M_i when creating the global model, N is the number of AGVs, and $*$ is point-wise multiplication.

Definition 2. *The influence of the local model is the average relative complement of the contribution of the partial loss generated by the local model to the total loss produced by all local models.*

The influence $\mathbb{I}_{M_i}$ of a local model M_i can be calculated according to the following formula:

$$\mathbb{I}_{M_i} = \frac{1}{N-1} \frac{\sum_{j=1}^{N} L_{M_j} - L_{M_i}}{\sum_{j=1}^{N} L_{M_j}}, \tag{2}$$

where L_{M_i} is the loss calculated for the i-th AGV (MSE or Validation loss).

The global model is built specifically for the inference task performed, and its architecture should be appropriate. Within this work, we focus on predicting momentary energy consumption (MEC). We decided to predict MEC, as this parameter is important in the operation of AGVs. Any deviation of this value may indicate a particular malfunction of the vehicle or its parts. We plan to use this value to detect anomalies reflected in the significant difference between the value received by the device and the one predicted by our neural network. Our previous work [16] proved that LSTM networks for building the inference model and Mean Square Error (MSE) as a metric for verifying the influence of local models perform well when predicting MEC.

Once the global model is built centrally, it is sent back to the AGVs (step 4) and overwrites the local models M_i on each AGV (step 5). This way, global wisdom updates local knowledge, and the round completes. After acquiring another portion of data by each AGV, training local models can start in the next round.

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4 Determining Jetson Nano's Resource Consumption in Federated Learning

For the experiments, we used NVidia Jetson Nano acting as an edge device on the AGVs. The edge device mounted on the AGV collects data by itself. Then, it uses the data to train a prediction model for the *Momentary energy consumption* (MEC) value over time, which is one of the indicators for faults or improper use of the AGV. During this process, we observed the resource consumption on the edge device with and without Federated Learning.

As the prediction model was implemented on edge Jetson Nano device, all the data collected by the device were used to train and build the prediction model locally without directly sending the data anywhere. Since we predicted the value of the MEC in time, we decided to use a recurrent neural network (RNN) based on the LSTM cell since this type of architecture copes quite well with time series.

In order to assess the effectiveness of Federated Learning in predicting AGV energy consumption, we collected data from nine test runs of Formica-1, one of the AGVs developed by AIUT Ltd., for which our group provides AI-based solutions. The entire data set contained roughly 12,500 samples collected with a frequency of 1 Hz.

During the test drives, we executed various scenarios, including repeated circular and counterclockwise paths, driving forward and backward at a speed of 0.2 m/s, repeated emergency braking, fast acceleration in both directions, and moving the lifting plate up and down. We performed each scenario with an empty vehicle and a half-loaded payload compartment (weighing 425 kg).

In order to see how Federated Learning affects the resource consumption of edge devices at the time of training, we decided to test the following three situations:

1. Using the LSTM-based MEC prediction model without FL model trained on the entire data set (12,000 training samples).
2. Using the LSTM-based MEC prediction model trained in 4-round FL (4-R FL) on three Jetson Nano edge devices. We used three edge devices, and each of them collected 4,000 samples in 4 rounds of training (1,000 training samples per round).
3. Using the LSTM-based MEC prediction model trained in 8-round FL (8-R FL) on three Jetson Nano. We used three edge devices, and each of them collected 4,000 samples in 8 rounds of training (500 training samples per round).

In summary, we analyzed how many Jetson Nano resources are required for training the prediction model without FL, for one round of 4-R FL and one round of 8-R FL. To see how many resources are used when training the recurrent neural network, we used the *jetson stats* Python library. For all considered experiments, we were using Jetson Nano in the highest performance mode.

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4.1 Using LSTM without Federated Learning on the entire data set

In the first series of experiments, we decided to check how many resources the edge device consumed without the use of Federated Learning. In this case, we trained our neural network on the entire training data set (12,000 samples). Fig. 3 shows average resource consumption during training on this data set.

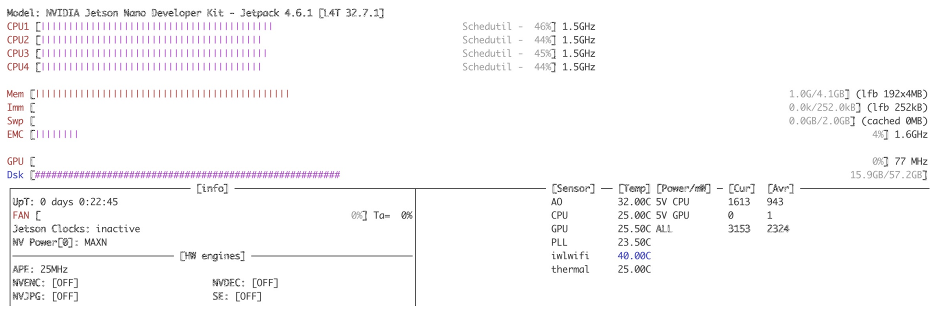

Fig. 3. Resource consumption on the edge device while training the MEC prediction model on the whole data set.

The training took 1,472 seconds, and from Fig. 3, we can observe that all four processors of the Jetson Nano were 45 percent loaded. Additionally, 1.0 GB of RAM and observed momentary power consumption of 3,153 mW during the experiment, equate to 4,641 J of total energy consumption on this device while training.

The results of the MEC prediction with the LSTM model without FL are presented in Fig. 4. We tested our model on 500 samples that were not part of the training data, resulting in an MSE value of 924.23. This figure shows two signal values, real (represented in blue) and predicted by our neural network (represented in orange). The greater the difference between these signals, the worse our neural network model performs. In this case, we see that the signal values are similar, indicating that our model performs well.

4.2 Using LSTM with 4-round Federated Learning

In this series of experiments, we launched Federated Learning on three devices. Moreover, we used 4-R FL on each device to execute four learning rounds, build a global MEC prediction model, and share weights between these devices. This means each edge device collected 1,000 samples per round (12,000 samples in total for four training rounds). In this case, we recorded how many resources were consumed by the edge device when we trained the MEC prediction model with 1,000 samples (in one round). The average resource consumption during training on this dataset is shown in Fig. 5.

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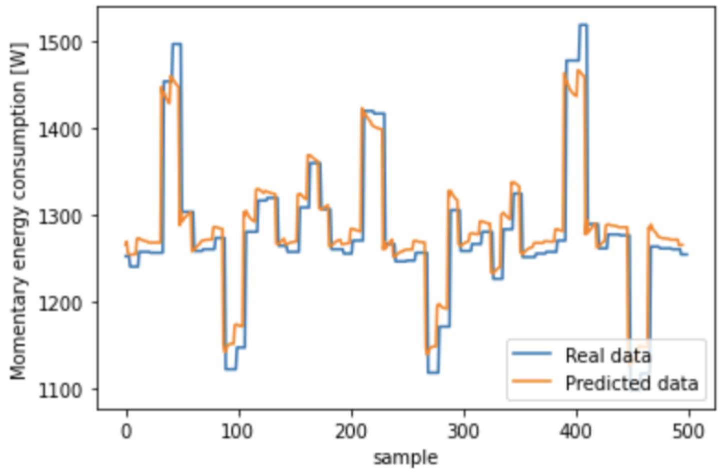

Fig. 4. Prediction performance of the LSTM model trained on the entire training data set.

The training took 133 seconds per round, and from Fig. 5, we can observe that all four processors of the Jetson Nano were 46 percent loaded. Additionally, 1 GB of RAM and observed momentary power consumption of 3,232 mW during the experiment, equates to 5,158 J of total energy consumption while training. Generally, we consumed almost the same resources as in the case without Federated Learning. However, we split this resource consumption between three devices.

The MEC prediction results obtained with the LSTM model trained in 4-R FL are presented in Fig. 6. We tested our model on 500 samples that were not part of the training data, which resulted in an MSE value of 948.28.

4.3 Using LSTM with 8-round Federated Learning

In this series of experiments, three edge devices collected 500 samples per round (12,000 samples for 8 training rounds). The average resource consumption during the training round on this data set is shown in Fig. 7.

The training time took 66 seconds, and from Fig. 7, we can observe that all four Jetson Nano processors are, on average, 44 percent loaded. Additionally, 1GB of RAM and observed momentary power consumption of 2,570 mW during the experiment, equates to 4,070 J of total energy consumption while training.

The MEC prediction results obtained with the LSTM model trained in 8-R FL are presented in Fig. 8. We tested our model on 500 samples that were not part of the training data, resulting in an MSE value of 849.39.

In this training scenario, we observed lower power consumption and noticed that the processor works at lower frequencies, which, in our opinion, is related

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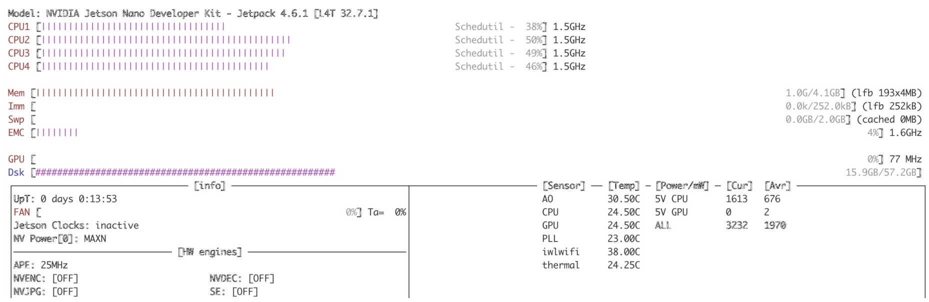

Fig. 5. Resource consumption on the edge device while training the MEC prediction model in 4 rounds of Federated Learning.

to the lower consumption of power. Such results indicate that the 8-round Federated Learning option consumed the least edge device resources. Moreover, this approach allowed us to obtain the best prediction accuracy, which converges with the observations presented in [16].

5 Discussion and Conclusions

Time, CPU utilization, RAM usage, and IoT device power consumption are all critical performance indicators for building the prediction models working onboard Autonomous Guided Vehicles. They all directly impact the consumption of energy (MEC) from the batteries of the AGVs, and, ultimately, their capabilities to function effectively and efficiently. For these reasons, we investigated how these resources were consumed during the training of a neural network locally on them.

This study demonstrates that the most effective and resource-saving way to train neural networks locally on Autonomous Guided Vehicles is by using a larger number of Federated Learning (FL) rounds. Table 1 summarizes the results of the different stages of the experiment. As we can observe, using 8-round training allowed for significant resource savings, reduced the overall load on the device, and improved the MEC signal prediction effectiveness, which is crucial for detecting anomalies in AGVs. Also, obtained results of Total Energy Consumption show that by using 8 rounds of Federated Training, we consume 12% less energy, not taking into account that this consumption will be additionally distributed between edge IoT devices. Furthermore, using FL provides better security for industrial data by processing data locally on the devices, reducing communication needs and the amount of data transferred. These findings can help develop more efficient and secure neural network training methods for AGVs. In future work, we plan to compare the prediction effectiveness and resource consumption of several different types of neural networks using Federated Learning. Since any neural network can be applied in FL, we have a large selection of models as an alternative to LSTM, which we used in this work.

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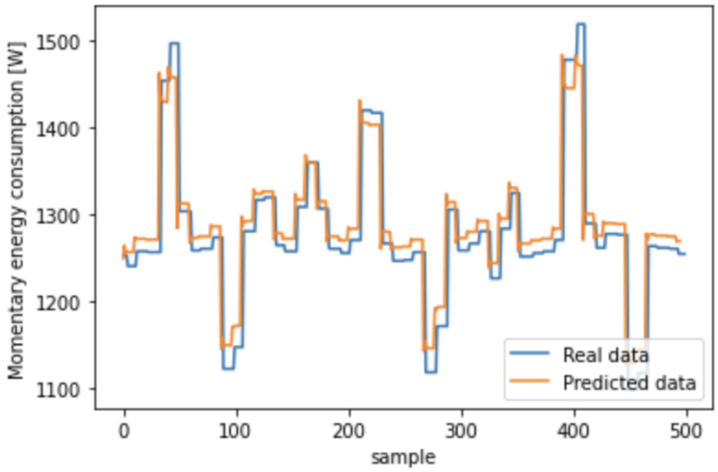

Fig. 6. Prediction performance of the LSTM model built in 4-round Federated Learning.

Table 1. Resource consumption for each of the tested scenarios for training the MEC prediction model.

Approach	Time per round	CPU	RAM	Momentary power consumption	Total energy consumption
LSTM without FL	1472 sec	45%	1 GB	3,153 mW	4,641 J
LSTM with 4-R FL	133 sec	46%	1 GB	3,232 mW	5,158 J
LSTM with 8-R FL	66 sec	44%	1 GB	2,570 mW	4,070 J

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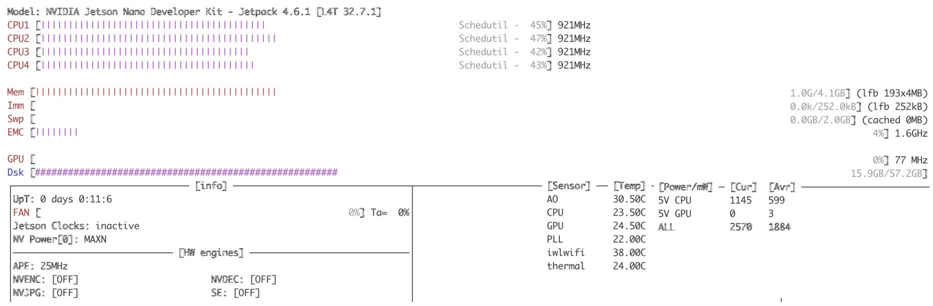

Fig. 7. Resource consumption on the edge device while training the MEC prediction model in 8 rounds of Federated Learning.

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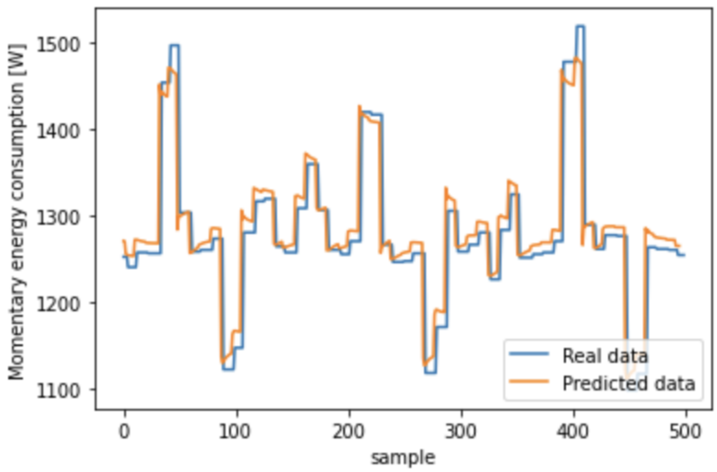

Fig. 8. Prediction performance of the LSTM model built in 8-round Federated Learning.

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