

Federated Learning with AMR-Assisted Few-Shot Calibration for Cross-Facility BLE Indoor Localization

Azin Moradbeikie
Università degli Studi di Trieste
Trieste, Italy
azin.moradbeikie@dia.units.it

David Beserra
*École Pour l'Informatique et les
Techniques Avancées (EPITA)*
14-16 Rue Voltaire 94270
Le Kremlin-Bicêtre – France
david.beserra@epita.fr

Abstract—Bluetooth Low Energy (BLE) fingerprinting provides accurate indoor localization in industrial facilities, but deployment across multiple facilities remains costly because each site requires extensive data collection and model training. In addition, raw Received Signal Strength Indicator (RSSI) measurements are often not sharable across facilities due to privacy and operational constraints. This paper presents a federated learning framework with autonomous mobile robot (AMR)-assisted few-shot calibration for cross-facility Bluetooth Low Energy (BLE) localization. Facilities collaboratively train a shared localization model while exchanging only model parameters. At a new facility, an autonomous mobile robot (AMR) performs a short patrol to collect Received Signal Strength Indicator (RSSI) measurements with Simultaneous Localization and Mapping (SLAM)-based position labels. These samples are then used to fine-tune the global model, eliminating the need for manual site surveys. This procedure removes the need for manual site surveys, reducing per-site deployment cost from weeks of measurement to minutes of automated patrolling. The framework is evaluated on a synthetic multi-facility extension of a real industrial Bluetooth Low Energy (BLE)/autonomous mobile robot (AMR) testbed. On the held-out new facility, the federated model achieves 70.7% zero-shot accuracy; after a few short calibrations producing only 200 autonomous mobile robot (AMR)-labeled samples, accuracy rises to 83.5%, which is within 1.6 percentage points of the centralized reference model (85.1%) trained directly on that facility. Across a five-facility leave-one-facility-out evaluation, accuracy improves from 80.7% to 90.5% under the same calibration budget. On this testbed, the results show that AMR-assisted calibration improves adaptation to facility variants while preserving data privacy.

Index Terms—Indoor localization, Bluetooth Low Energy, federated learning, autonomous mobile robot, few-shot adaptation.

I. INTRODUCTION

Indoor localization is a key component of industrial automation, supporting asset tracking, autonomous navigation, predictive maintenance, and worker safety [1]. Since Global Navigation Satellite System (GNSS) signals are unavailable indoors, Received Signal Strength Indicator (RSSI)-based wireless localization has become a widely used solution [18]. Among available technologies, Bluetooth Low Energy (BLE)

is attractive due to its low cost, low power consumption, and compatibility with commercial devices [7].

BLE localization has been widely studied in individual facilities [17]. Fingerprinting methods build radio maps and use machine-learning models to estimate positions [2], [16]. Recent work has improved robustness through adaptive path-loss estimation [13], Wi-Fi/BLE fusion [15], [17], and collaborative architectures that combine Static Infrastructure Nodes (SIN) with Mobile Infrastructure Nodes (MIN) mounted on Autonomous Mobile Robots (AMR) [10], [14]. In these systems, AMR-based Simultaneous Localization and Mapping (SLAM) provides accurate position references for radio-map construction. Although these approaches achieve good localization accuracy, deployment across multiple facilities remains costly [8], [9].

The main deployment bottleneck is the effort required to calibrate each new site. Fingerprinting-based localization typically requires extensive data collection, model training, and environment-specific calibration [3]. Consequently, every facility is treated as an independent problem, even when multiple sites share similar layouts and operating conditions. For organizations managing fleets of warehouses, factories, or hospitals, this repeated calibration process limits scalability.

Sharing knowledge across facilities can reduce this cost. However, transferring raw RSSI measurements is impractical because they contain sensitive information about facility layouts, asset locations, and operational patterns. Federated learning (FL) enables collaborative model training while keeping data local [12]. Recent works have applied FL to fingerprinting-based localization in multi-building and multi-floor scenarios [4], [5], [11]. However, the global FL model is a compromise across participating facilities. In industrial deployments, facilities differ in layout, beacon placement, and propagation conditions. Therefore, deployment at a new site typically requires fine-tuning with a small labeled support set. Obtaining this support set usually requires a manual site survey, reintroducing a significant part of the deployment cost.

This work eliminates that residual cost by exploiting the AMRs already deployed in many industrial environments. The

AMR’s onboard SLAM provides accurate position estimates, while its BLE receiver collects RSSI measurements along its trajectory. A short autonomous patrol of a newly onboarded facility therefore produces the labeled support set required for fine-tuning, without manual intervention. The AMR thus takes on a second role beyond its operational use as a Mobile Infrastructure Node: it acts as an on-demand calibrator that bootstraps the localization model at each new site.

This paper proposes a federated learning framework with AMR-assisted few-shot calibration for BLE indoor localization across multiple industrial facilities. Each facility trains locally and exchanges only model parameters. A shared global model is learned through federated training and then adapted to a new facility using a small AMR-generated support set. This approach reduces deployment effort while preserving data privacy.

Evaluation of multi-facility BLE localization is difficult because public datasets containing multiple industrial environments are not available. Existing BLE datasets are largely limited to single buildings [16]. To address this limitation, this work introduces a synthetic facility generation procedure based on measurements collected from a real industrial BLE/AMR testbed [14]. Synthetic facilities are generated by varying propagation parameters while preserving the statistical characteristics of the original measurements. These facilities are then used as independent clients during federated training.

The contributions of this paper are:

- A federated learning framework for BLE indoor localization across multiple facilities without sharing raw RSSI measurements.
- An AMR-assisted few-shot calibration strategy that automatically generates adaptation data using SLAM-based position estimates, removing the need for manual site surveys.
- A synthetic multi-facility dataset generation procedure based on real BLE measurements for reproducible evaluation under industrial conditions.

The remainder of this paper is organized as follows. Section II reviews related work on BLE indoor localization, federated learning, and few-shot adaptation. Section III presents the problem formulation and the proposed federated learning framework with AMR-assisted calibration. Section IV describes the industrial BLE/AMR testbed, the construction of the multi-facility dataset, the synthetic facility generation procedure, and the evaluation protocol. Section V reports the experimental results and analyzes the impact of AMR-assisted few-shot adaptation on cross-facility localization performance. Finally, Section VI concludes the paper and outlines directions for future work.

II. RELATED WORK

BLE indoor localization methods are primarily divided into path-loss model-based and fingerprinting approaches [7], [18]. Sciacaluga *et al.* proposed a low-complexity BLE positioning algorithm for large industrial areas with limited anchor

density; the approach is single-site and assumes stable propagation, which limits its applicability in dynamic industrial settings [17]. Moradbeikie *et al.* introduced an adaptive path-loss estimation procedure using a location-aware AMR [13]; the calibration is local to one facility, and the resulting parameters do not transfer to other deployments. Faragher and Harle characterized BLE location fingerprinting and demonstrated hybrid Wi-Fi/BLE fusion, but their evaluation is restricted to a single building and does not address cross-site deployment [7]. Ramezanpour *et al.* surveyed BLE accuracy across environment-specific propagation models and concluded that recalibration over time and across deployments remains an open problem [16].

McMahan *et al.* [12] introduced FedAvg, the standard aggregation protocol for federated learning. While FedAvg enables collaborative training without sharing raw data, it is task-agnostic and does not provide mechanisms for client-specific adaptation after deployment.

Several studies have applied federated learning to indoor localization. Çiftler *et al.* [5] proposed a privacy-preserving RSS fingerprinting framework based on federated learning, although evaluation was limited to a single building with homogeneous receivers. Liu *et al.* [11] developed FLoc, an edge-fog-cloud architecture for multi-building radio-map updating, assuming that participating sites already possess operational fingerprint databases. Cheng *et al.* [4] addressed heterogeneous fingerprint databases through FedLoc, focusing on database heterogeneity rather than variations in radio propagation across facilities. Etiabi *et al.* [6] investigated communication-efficient localization through federated distillation, while DAPFedLoc [19] introduced personalized federated learning for non-IID fingerprint distributions using client-side data augmentation.

Despite these advances, the federated model remains a compromise across participating clients, and facility-specific adaptation is typically required to achieve deployment-grade accuracy. Existing FL-based localization approaches assume that the labeled data needed for this adaptation are already available [4], [5], [11], [19]. Consequently, they do not address how such calibration data can be obtained in industrial environments, where manual site surveys remain a major deployment cost.

This work combines mobile-anchor BLE localization with federated fingerprinting. It builds upon the SIN/MIN architecture and the use of AMR-based SLAM positioning to generate labeled localization data, while leveraging federated learning for privacy-preserving knowledge transfer across facilities. The key distinction from existing work is that the AMR is also used as an automated calibration agent, generating the support set required for few-shot adaptation at a new facility. This transforms calibration from a manual fingerprinting process into a short autonomous robotic procedure, reducing deployment effort while preserving data privacy.

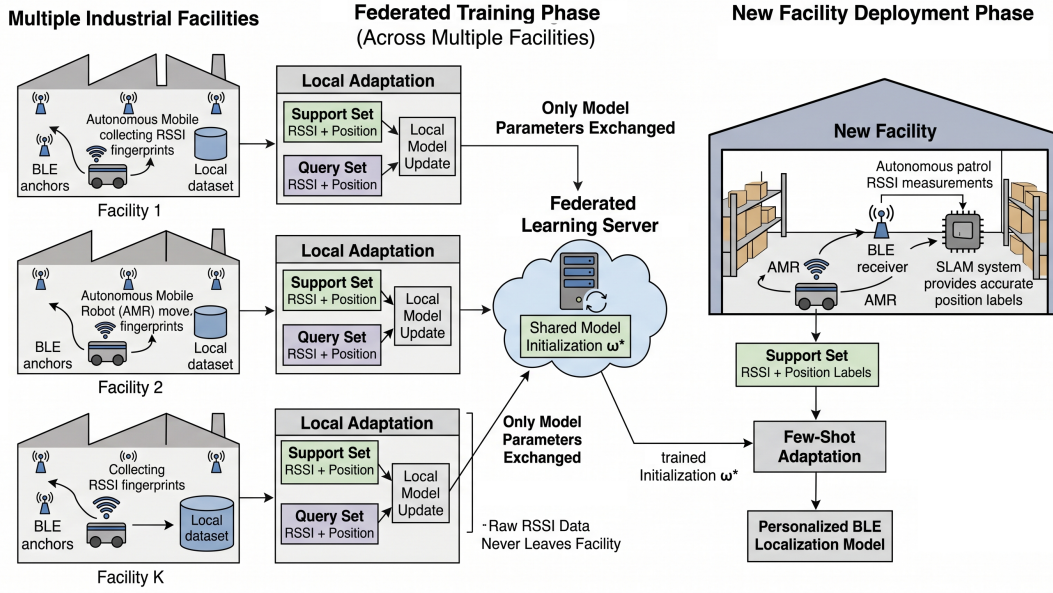


Fig. 1. Workflow of the proposed federated learning framework.

III. PROPOSED METHOD

The proposed framework enables BLE localization knowledge transfer across multiple industrial facilities without sharing raw measurements. Each facility is considered an independent learning client with its own BLE deployment, propagation characteristics, and local fingerprint database.

The system operates in two phases: *federated training*, in which facilities collaboratively learn a shared global model while exchanging only model parameters; and *AMR-assisted few-shot calibration*, in which a newly onboarded facility uses an AMR to automatically generate a small labeled support set on which the global model is fine-tuned into a facility-specific deployment. The complete workflow is illustrated in Figure 1. First, each facility collects RSSI fingerprints from its BLE infrastructure, with the AMR providing position labels through SLAM. Second, facilities collaboratively train a shared global model without exchanging raw fingerprint data. Third, when a new facility is deployed, a short AMR patrol automatically generates labeled calibration data. Finally, the global model is fine-tuned on these samples and deployed for localization.

A. Problem Setting

Consider a fleet of K facilities. Facility k holds a local dataset $\mathcal{D}_k = \{(x_i, y_i)\}_{i=1}^{N_k}$. The input is shown in Equation 1.

$$x = [r^{\text{norm}}; m; u] \in \mathbb{R}^{2P+R}, \quad (1)$$

where $r^{\text{norm}} \in \mathbb{R}^P$ is the locally normalized RSSI vector from P receivers, $m \in \{0, 1\}^P$ is a packet-reception mask, and $u \in \{0, 1\}^R$ one-hot encodes the AMR zone. The label $y \in \{1, \dots, C\}$ is the room of the broadcasting beacon. The objective is to learn parameters ω^* from the federation that generalize across the fleet and that admit efficient fine-tuning at any unseen facility k^* using a small labeled support set $\mathcal{S}_{k^*}$.

B. Model

A neural network with parameters $\omega = (\theta, \phi)$ produces class scores by composing an encoder f_θ and a classifier g_ϕ :

$$p(y | x; \omega) = \text{softmax}(g_\phi(f_\theta(x)))_y. \quad (2)$$

Training minimizes the cross-entropy loss by using equation 3.

$$L(\omega; \mathcal{D}) = -\frac{1}{|\mathcal{D}|} \sum_{(x, y) \in \mathcal{D}} \log p(y | x; \omega). \quad (3)$$

C. Federated Training

The fleet trains the global model over T communication rounds. At round r , the server broadcasts the current parameters $\omega^{(r)}$ to all participating clients. Each client k initializes $\omega_k \leftarrow \omega^{(r)}$ and performs E local epochs of stochastic gradient descent on its training data with learning rate η :

$$\omega_k \leftarrow \omega_k - \eta \nabla_{\omega} L(\omega_k; \mathcal{B}), \quad (4)$$

for mini-batches $\mathcal{B} \subset \mathcal{D}_k$. Each client then returns its updated parameters to the server, which aggregates them through sample-weighted averaging [12]:

$$\omega^{(r+1)} = \sum_{k=1}^K \frac{|\mathcal{D}_k|}{\sum_{k'} |\mathcal{D}_{k'}|} \omega_k. \quad (5)$$

Over T rounds, this procedure minimizes the federated objective

$$\omega^* = \arg \min_{\omega} \sum_{k=1}^K \frac{|\mathcal{D}_k|}{\sum_{k'} |\mathcal{D}_{k'}|} L(\omega; \mathcal{D}_k). \quad (6)$$

Raw data never leaves any client. Each client fits its RSSI normalization statistics locally on its own training data; only the model parameters ω are exchanged.

D. AMR-Assisted Few-Shot Calibration

When the system is deployed at a previously unseen facility k^* , the AMR performs an autonomous patrol of duration τ . The mounted BLE receiver records measurements while the AMR's SLAM provides ground-truth positions, yielding a labeled support set

$$\mathcal{S}_{k^*} = \{(x_i, y_i)\}_{i=1}^{K_{k^*}}, \quad K_{k^*} = \lfloor \tau / \Delta_t \rfloor, \quad (7)$$

where Δ_t is the BLE sampling interval. Starting from the federated global model $\omega_{k^*} = \omega^*$, the model is fine-tuned for n_{ft} gradient steps on this support set:

$$\omega_{k^*} \leftarrow \omega_{k^*} - \alpha \nabla_{\omega} L(\omega_{k^*}; \mathcal{S}_{k^*}). \quad (8)$$

The deployed model is the result after n_{ft} updates. Because the global model has already encoded the structure shared across the fleet, K_{k^*} remains in the tens-to-hundreds range and n_{ft} in the tens of steps, corresponding to minutes of AMR patrolling, in contrast to the hours to days of manual fingerprinting required by per-site training from scratch.

IV. DATASET AND EVALUATION PROTOCOL

Figure 2 illustrates the architecture of the original BLE/AMR industrial localization testbed and the construction of the multi-facility federated dataset used in this study. A detailed description of the real facility, hardware, SIN placement, and data collection protocol is provided in [14]. BLE beacons are deployed across facility zones and are observed by seven Static Infrastructure Nodes (SINs) and one Mobile Infrastructure Node (MIN) mounted on an Autonomous Mobile Robot (AMR). The AMR provides SLAM-based position information while collecting RSSI measurements, producing labeled fingerprint records consisting of beacon identifiers, room information, and RSSI values from all receivers. The real facility dataset is subsequently extended through synthetic facility generation, resulting in five independent facilities used as federated learning clients.

Facility $k = 0$ is the real Method C deployment; facilities $k = 1, \dots, 4$ are synthetic. Each contributes $N_k \approx 10,570$ records of the form $\{\text{timestamp, beacon ID, AMR room, beacon zone, RSSI}_1, \dots, \text{RSSI}_8\}$, with RSSI_1 – RSSI_7 from the SINs and RSSI_8 from the AMR-mounted MIN. The target is the beacon zone $y \in \{1, 2, 3\}$.

Synthetic facility generation. For every (beacon, room, receiver) cell, the empirical mean $\mu^{(b,r,i)}$, standard deviation $\sigma^{(b,r,i)}$, and packet-loss rate $p_{\text{loss}}^{(b,r,i)}$ are estimated from the real data, yielding a table of 288 cells. Synthetic RSSI samples are drawn as Equation 9.

$$\text{RSSI}_i^{(k)} \sim \mathcal{N}\left(\mu^{(b,r,i)} + \delta^{(k)}, \sigma^{(b,r,i)}\right) + \eta_{i,t}^{(k)}, \quad (9)$$

with packet loss applied at probability $p_{\text{loss}}^{(b,r,i)}$. The per-facility offset $\delta^{(k)} \sim \mathcal{N}(0, \sigma_{\text{bldg}}^2)$ with $\sigma_{\text{bldg}} = 3$ dB models wall-material, transmit-power, and receiver-gain differences between distinct deployments, consistent with empirically reported industrial BLE variation [17]. The per-row noise $\eta_{i,t}^{(k)} \sim \mathcal{N}(0, 1 \text{ dB}^2)$ captures short-time-scale interference within a

facility. The AMR trajectory and broadcast schedule of the real deployment are reused, preserving the (beacon, room, receiver) structure.

Validation. Three diagnostics confirm that the synthetic facilities are realistic and distinct. (i) *Cell-statistic preservation*: the Pearson correlation between real and synthetic cell statistics is $\rho_{\mu} \in [0.992, 0.998]$ and $\rho_{\sigma} \in [0.960, 0.968]$ across all 288 cells and four facilities. (ii) *Realism*: the 1-Wasserstein distance between each synthetic facility and the real one, averaged over the eight receiver marginals, lies in $[0.88, 5.03]$ dB, consistent with $\sigma_{\text{bldg}} = 3$ dB. (iii) *Inter-facility divergence*: pairwise W_1 distances among synthetic facilities span $[1.56, 8.24]$ dB (mean 4.38 dB), against a within-facility sampling-noise baseline (first vs. second half) of only $[0.13, 0.35]$ dB. Synthetic facilities are therefore plausible perturbations of the real testbed and distinct from one another by more than an order of magnitude above the sampling noise.

Evaluation protocol. Each facility's records are stratified by y into 65% for training, 15% for validation, and 20% for test. Validation is used for early stopping; the test split is held out for final reporting. A leave-one-facility-out (LOFO) protocol is used: for each $k^* \in \{0, \dots, 4\}$, the other four facilities form the federated training set. The trained initialization is evaluated on k^* (i) zero-shot on its test split, and (ii) K -shot adapted, where K samples from k^* 's training split form the support set, n_{ft} fine-tuning steps are applied per Section III-D, and the personalized model is tested. The support set is drawn as a contiguous time window to reflect an AMR patrol; the i.i.d. case is reported separately. All experiments use seeds $\{0, 1, 2\}$ and report means with 95% Student- t confidence intervals. Three seeds were used as a compromise between statistical characterization and the computational cost of the full LOFO protocol; the reported 95% confidence intervals remain non-overlapping across the operating points that support the paper's claims.

V. RESULTS

All experiments follow the architecture and hyperparameters of Section III, with inner steps $n = 5$, batch size 64, and a maximum of $T = 200$ rounds with early stopping on the federation-weighted validation loss. Each experiment is repeated across three seeds; reported figures are means with 95% Student- t confidence intervals.

A. Centralized Baseline

A single MLP is trained directly on facility $k = 0$ to establish the upper bound for that facility's localization accuracy. The model reaches $85.13 \pm 1.19\%$ test accuracy with macro-F1 0.849 and Expected Calibration Error 0.012, indicating a well-calibrated classifier. This number serves as the reference ceiling against which the proposed framework is compared.

B. Federated Averaging Baseline

The shared global model is trained on the four-client federation $\mathcal{K} \setminus \{0\}$, with facility $k^* = 0$ held out for final evaluation. Training converges after 96 rounds (best round and

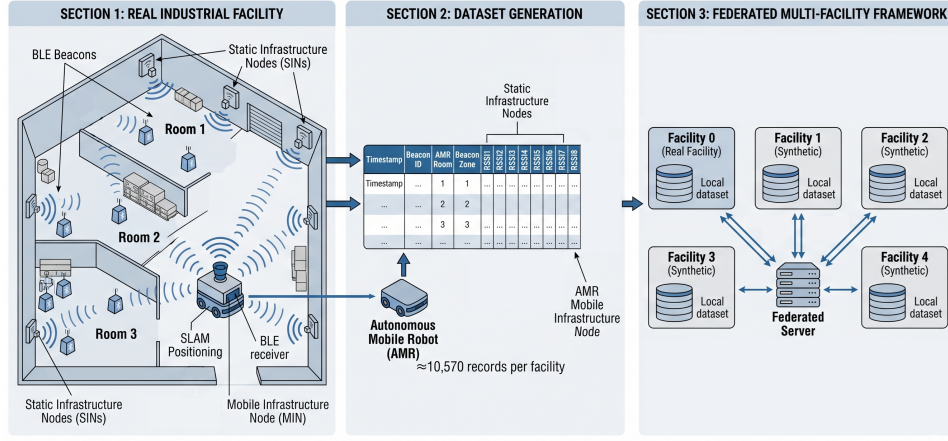


Fig. 2. Architecture of the industrial BLE localization testbed and construction of the multi-facility federated dataset.

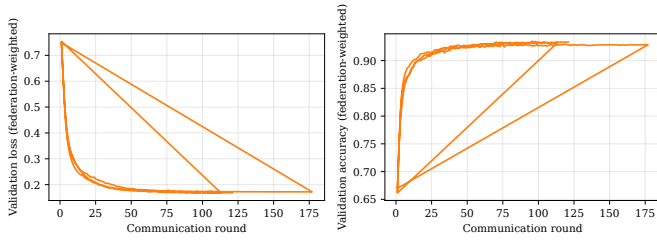


Fig. 3. An illustration of FedAvg convergence.

TABLE I
ACCURACY ON HELD-OUT FACILITY $k^* = 0$.

Method	Accuracy
Centralized (oracle, trained on k^*)	0.8513 ± 0.0119
FedAvg, zero-shot	0.7070 ± 0.0275
FedAvg + fine-tune, $K=10$	0.7375 ± 0.0247
FedAvg + fine-tune, $K=50$	0.8070 ± 0.0377
FedAvg + fine-tune, $K=200$	0.8354 ± 0.0189

early stopping triggered at round 121), reaching a federation-weighted validation accuracy of 0.92 (Fig. 3).

C. AMR-Assisted Few-Shot Calibration

When the converged global model is applied to the held-out facility without adaptation, accuracy drops to $70.70 \pm 2.75\%$, a 14.4 pp gap from the centralized ceiling, which reflects the mismatch between the federation-averaged initialization and the specific propagation profile of the facility. Fine-tuning on a contiguous AMR-derived support set closes most of this gap. Accuracy improves monotonically with the support-set size K , reaching $73.75 \pm 2.47\%$ at $K=10$, $80.70 \pm 3.77\%$ at $K=50$, and $83.54 \pm 1.89\%$ at $K=200$ — within 1.6 pp of the centralized oracle (Fig. 4, Table I). With a typical BLE sampling interval, $K=200$ corresponds to a few minutes of autonomous AMR patrolling, in contrast to the hours-to-days of manual fingerprinting required by per-site training from scratch. The full per-method comparison is shown in Fig. 5.

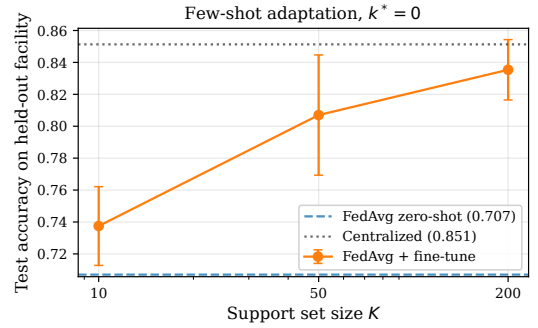


Fig. 4. Few-shot adaptation on held-out facility $k^* = 0$.

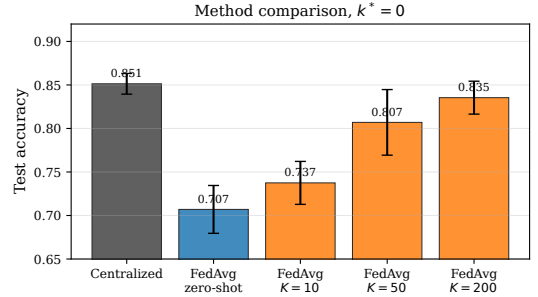


Fig. 5. Per-method test accuracy on held-out facility $k^* = 0$.

D. Cross-Facility Generalization (LOFO)

To confirm that the conclusion does not depend on the specific held-out facility, the experiment is repeated for each $k^* \in \{0, 1, 2, 3, 4\}$. Table II reports the mean test accuracy across the five LOFO folds. Across the fleet, accuracy improves from a zero-shot mean of 0.807 ± 0.070 to 0.905 ± 0.049 at $K=200$, with monotonic gains at every fold. The largest improvement (12.8 pp) is observed on the real facility ($k^* = 0$), which is also the most difficult fold; the synthetic folds start from a higher zero-shot accuracy and still benefit from calibration.

TABLE II

TEST ACCURACY ON EACH HELD-OUT FACILITY, AND THE LOFO MEAN ACROSS THE FIVE FOLDS.

Method	$k^*=0$	$k^*=1$	$k^*=2$	$k^*=3$	$k^*=4$	LOFO mean
Zero-shot	0.707	0.833	0.836	0.839	0.821	0.807 ± 0.070
$K=10$	0.738	0.902	0.895	0.887	0.854	0.855 ± 0.085
$K=50$	0.807	0.904	0.904	0.911	0.895	0.884 ± 0.054
$K=200$	0.835	0.925	0.919	0.933	0.910	0.905 ± 0.049

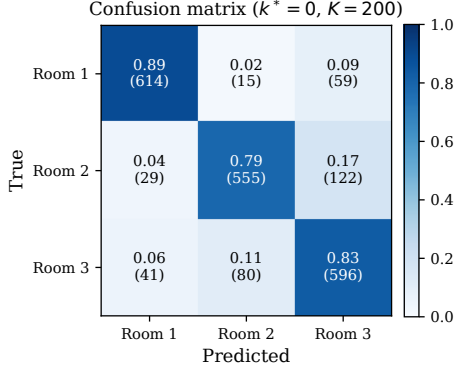


Fig. 6. Confusion matrix on held-out facility $k^* = 0$ at $K = 200$.

E. Per-Class Performance

Per-class metrics on the held-out facility at $K=200$ are shown in Fig. 6. The model achieves balanced precision and recall on rooms 1 and 2 but is weaker on room 3, where it is confused with room 2 in approximately 12% of cases. This asymmetry is consistent with the geometry of the testbed: rooms 2 and 3 share a wall, while room 1 is more spatially separated.

VI. CONCLUSION

This paper proposed a federated learning framework with AMR-assisted few-shot calibration for BLE indoor localization across fleets of facilities. The AMR already present at each site generates the labeled support set required for fine-tuning the federated model to the local environment, eliminating the manual site survey.

Two findings summarize the empirical behaviour. First, federated training alone transfers across the fleet with a LOFO mean zero-shot accuracy of 80.7%, providing initial evidence that fleet-scale collaboration is feasible without raw-data sharing, pending validation on a second physical site. Second, AMR-assisted few-shot calibration improves on the zero-shot value at every fold and at every support-set size: the LOFO mean rises from 80.7% to 90.5% at $K=200$, and on the most difficult fold (the real facility) accuracy rises from 70.7% to 83.5%, within 1.6 pp of the centralized oracle, using a number of samples corresponding to minutes of autonomous AMR patrolling.

Future work will validate the framework on a second physical testbed, incorporate AMR pose uncertainty into the support set, extend it to asynchronous federation, and transfer the AMR-assisted calibration concept to UWB and Wi-Fi CSI.

REFERENCES

- [1] Asaad, S.M., Maghdid, H.S.: A comprehensive review of indoor/outdoor localization solutions in iot era: Research challenges and future perspectives. *Computer Networks* **212**, 109041 (2022)
- [2] Bahl, P., Padmanabhan, V.N.: Radar: An in-building rf-based user location and tracking system. In: *Proceedings IEEE INFOCOM 2000. Conference on computer communications. Nineteenth annual joint conference of the IEEE computer and communications societies (Cat. No. 00CH37064)*. vol. 2, pp. 775–784. Ieee (2000)
- [3] Bi, J., Wang, Y., Cao, H., Qi, H., Liu, K., Xu, S.: A method of radio map construction based on crowdsourcing and interpolation for wi-fi positioning system. In: *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. pp. 1–6. IEEE (2018)
- [4] Cheng, X., Ma, C., Li, J., Song, H., Shu, F., Wang, J.: Federated learning-based localization with heterogeneous fingerprint database. *IEEE Wireless Communications Letters* **11**(7), 1364–1368 (2022)
- [5] Ciftler, B.S., Albaseer, A., Lasla, N., Abdallah, M.: Federated learning for rss fingerprint-based localization: A privacy-preserving crowdsourcing method. In: *2020 International Wireless Communications and Mobile Computing (IWCMC)*. pp. 2112–2117. IEEE (2020)
- [6] Etiabi, Y., Amhoud, E.M.: Federated distillation based indoor localization for iot networks. *IEEE Sensors Journal* **24**(7), 11678–11692 (2024)
- [7] Faragher, R., Harle, R.: Location fingerprinting with bluetooth low energy beacons. *IEEE journal on Selected Areas in Communications* **33**(11), 2418–2428 (2015)
- [8] Haghighat, A., Keshavarz, A., Moradbeikie, A., Lopes, S.I.: Improving rssi fingerprint localization in lorawan networks: An image-based approach. *IEEE Internet of Things Journal* (2026)
- [9] Haghighat, A., Sirous, Z., Moradbeikie, A., Keshavarz, A., Lopes, S.I.: Improving lorawan fingerprint-based localization by detecting and eliminating noisy rssi measurements. In: *2023 IEEE 9th World Forum on Internet of Things (WF-IoT)*. pp. 1–7. IEEE (2023)
- [10] Liu, Y., Wang, S., Xie, Y., Xiong, T., Wu, M.: A review of sensing technologies for indoor autonomous mobile robots. *Sensors* **24**(4), 1222 (2024)
- [11] Liu, Y., Li, H., Xiao, J., Jin, H.: Floc: Fingerprint-based indoor localization system under a federated learning updating framework. In: *2019 15th international conference on mobile ad-hoc and sensor networks (MSN)*. pp. 113–118. IEEE (2019)
- [12] McMahan, B., Moore, E., Ramage, D., Hampson, S., y Arcas, B.A.: Communication-efficient learning of deep networks from decentralized data. In: *Artificial intelligence and statistics*. pp. 1273–1282. Pmlr (2017)
- [13] Moradbeikie, A., Amorim, I., Azevedo, R., Jesus, C., Beserra, D., Lopes, S.I.: Collaborative indoor positioning: A machine learning approach for dynamic environments with autonomous mobile robots. In: *2025 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. pp. 6000–6005. IEEE (2025)
- [14] Moradbeikie, A., Azevedo, R., Jesus, C., Beserra, D., Lopes, S.I.: Indoor localization in a collaborative ble-based system through dynamic path loss estimation via location aware autonomous mobile robot. In: *2025 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. pp. 3542–3547. IEEE (2025)
- [15] Moradbeikie, A., Azevedo, R., Jesus, C., Lopes, S.I.: Rssi-based localization in industrial environments: a wi-fi/ble hybrid approach. In: *2024 IEEE International Conference on Industrial Technology (ICIT)*. pp. 1–6. IEEE (2024)
- [16] Morgan, A.A.: On the accuracy of ble indoor localization systems: An assessment survey. *Computers and Electrical Engineering* **118**, 109455 (2024)
- [17] Szyk, K., Nikodem, M., Zdunek, M.: Bluetooth low energy indoor localization for large industrial areas and limited infrastructure. *Ad Hoc Networks* **139**, 103024 (2023)
- [18] Zafari, F., Gkelias, A., Leung, K.K.: A survey of indoor localization systems and technologies. *IEEE communications surveys & tutorials* **21**(3), 2568–2599 (2019)
- [19] Zhang, X., Fan, Y., Liu, G., Chen, Z., Huang, H.: Data augmentation-based personalized federated learning for indoor localization with non-iid fingerprint data. *Journal of King Saud University Computer and Information Sciences* **37**(10), 338 (2025)