Vol. 06, No. 02, pp. 290 –300 (2025)
ISSN: 2708-0757

JOURNAL OF APPLIED SCIENCE AND TECHNOLOGY TRENDS

www.jastt.org

Adaptive Federated Learning Empowered Wireless Localization Framework Using Vehicle Sensors

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Abstract

Currently, wireless localization plays a vital role in supporting a wide range of tasks within smart cities. For example, vehicle tracking services are increasingly used in tunnels and bridges to detect objects and prevent collisions. Both indoor and outdoor localization are equally important for applications such as traffic management and vehicle positioning. However, existing localization techniques still face significant challenges, particularly with respect to accuracy, latency, and resource consumption. Addressing these limitations is therefore essential to ensure reliable and efficient operation in smart city environments. This study proposes an Adaptive Federated Learning–Enabled Wireless Localization Framework (ALFLS) designed specifically for mobility-based vehicle tasks. The novelty of ALFLS lies in its ability to apply pattern learning for both indoor and outdoor localization, leveraging federated learning to execute tasks while maintaining high quality of service. The framework also incorporates an optimized placement strategy for edge and cloud node resources, supported by a training algorithm that enhances real-time localization accuracy. To evaluate performance, experimental localization datasets were tested on a benchmark testbed, highlighting the practical benefits of ALFLS. The simulation results demonstrate that the framework improves localization accuracy by up to 98%, reduces latency by approximately 30%, and achieves significantly higher resource utilization compared to existing methods. These results confirm that ALFLS provides a robust, efficient, and scalable solution for addressing the persistent challenges of wireless localization in smart city environments.

Keywords: *Wireless Localization, Adaptive Federated Learning,* *Indoor Localization, Outdoor Localization, Vehicle Tasks, Edge, Cloud, Traffic, Tunnel, Accuracy*

Received: August 05th, 2025 / Revised: September 21st, 2025 / Accepted: September 29th, 2025 / Online: October 02nd, 2025

I. INTRODUCTION

Wireless localization has become an integral part of modern smart city systems, supporting essential services such as vehicle tracking, traffic coordination, and collision avoidance. In critical environments like tunnels, bridges, and densely populated urban areas, the ability to locate moving vehicles with precision is vital for maintaining safety and efficiency. Both indoor and outdoor localization play equally important roles in these contexts, yet current methods often fall short. Existing techniques continue to struggle with issues of accuracy, response delays, and heavy resource demands, which limit their reliability for large-scale, real-time applications[1]. Localization for vehicle applications is crucial for maintaining road safety and various mechanisms in smart cities [1]. Road safety, which is compromised by the inaccuracy of

doi: 10.38094/jastt62464

localization, is an essential issue. Localization is the process of tracking the exact location of vehicles and any other objects; if it is inaccurate, it leads to numerous challenges [2]. Therefore, it is a crucial mechanism for utilizing wireless localization in smart cities [3]. Wireless localization is typically embedded in every vehicle and mobility device to track location in both outdoor and indoor environments, enabling various tasks [4].

Traditional localization methods, such as GPS, time-of-arrival (ToA), angle-of-arrival (AoA), and received signal strength (RSS)–based techniques, have been widely deployed in both indoor and outdoor settings [3-5]. While these methods provide a baseline for tracking and positioning, they often suffer from significant drawbacks when applied in complex smart city environments. GPS signals, for example, are easily obstructed in tunnels, urban canyons, and indoor spaces, leading to severe accuracy degradation. RSS and ToA methods are susceptible to noise, multipath fading, and interference, which are common in dense urban networks. Moreover, these approaches typically rely on centralized architectures, which can be resource-intensive and prone to latency when handling large volumes of data. As mobility patterns in smart cities become increasingly dynamic and data-driven, the limitations of traditional localization systems—in terms of accuracy, latency, scalability, and adaptability—highlight the need for more intelligent and resilient solutions [4].

Numerous studies have proposed various architectures, frameworks, and methodologies to enhance localization using different machine learning algorithms. For example, numerous studies suggest that localization pattern learning can be accomplished through supervised learning approaches that utilize labeled data. Although it has a limitation, supervised learning cannot label new patterns that occur at runtime due to ambiguity in the data. Therefore, with the dynamic methods of supervised and unsupervised learning, real-time localization pattern handling is introduced to improve localization. This approach utilizes different sensors, such as LIDAR, camera, and global positioning system (GPS), which generate data for localization tracking and train them at runtime into distinct clusters [5-7].

The primary objective of this study is to develop an Adaptive Federated Learning Edge-Enabled Localization Framework utilizing wearable sensors to optimize indoor and outdoor vehicle localization, reduce error rates, minimize latency, and enhance security and accuracy in traffic, accident, and vehicle detection tasks, with improved communication efficiency. To address these challenges, this study contributes by proposing an Adaptive Federated Learning Edge-Enabled Localization Framework that leverages distributed learning across wearable devices and edge nodes, thereby reducing dependence on centralized servers and enhancing real-time decision-making. The framework integrates GPS, IMU, and wearable sensor data with adaptive learning models to optimize hybrid indoor and outdoor localization, thereby overcoming the limitations of existing HIOLS and ILS systems, which struggle with accuracy and resource efficiency. By shifting computation to the edge and employing federated aggregation, the framework effectively reduces communication overhead, minimizes latency, and ensures timely responsiveness for critical tasks such as traffic monitoring, route optimization, and accident management. Furthermore, the system incorporates energy-aware scheduling mechanisms that balance localization accuracy with sustainable operation, extending the lifespan of resource-constrained wearable devices [8-10]. To safeguard against emerging threats, the framework embeds secure model aggregation and privacy-preserving techniques within the federated learning process, ensuring that sensitive vehicular and user mobility data remain protected from adversarial manipulation or leakage. Finally, through adaptive model updates and robust error-handling strategies, the framework significantly improves localization accuracy and resilience in noisy, heterogeneous, and dynamic ITS environments, thereby advancing the state of the art in intelligent transportation systems and enabling safer, more efficient, and more reliable vehicle localization. The paper makes the following contributions.

1) N**ovelty:** We proposed an Adaptive Federated Learning Edge-Enabled Wireless Localization Framework (ALFLS) that integrates heterogeneous sensor data, edge processing, secure federated learning, and adaptive GPS/IMU cooperation to provide robust, low-latency, and accurate localization for vehicles. The main novelty is that it handles the inaccuracy of localization in both indoor and outdoor environments, regardless of whether services are available or unavailable. We handle these situations and improve the overall performance of the localization. Federated learning is necessary because in localization, we have distributed resources with storage constraints, and we need huge amounts of data for training. Therefore, we trained the data on different aspects based on abstractions and insights. Federated learning only offloads the trained data to the aggregated node for learning, thereby improving localization and achieving both indoor and outdoor performance.
2) The main finding of the ALFLS is to improve the learning of localization at different nodes based on edge computing and aggregate to the cloud for the overall improvement.
3) We present the testbed simulation environment to conduct the experiments on the experimental testbed's dataset.
4) We have global and localization schemes to minimize the errors from localization during access to vehicle tasks in applications.

The paper is organized in the following way. Section II is about related work. Section III is the proposed method. Section IV is the evaluation and section V is conclusion.

II. Related Work

Localization and positioning have been extensively studied across various application domains, including healthcare, construction monitoring, and intelligent transportation systems. Wearable sensor-based localization has emerged as an important direction, particularly for tracking human movement in dynamic environments. Gracey-McMinn et al. [1]

demonstrated the effectiveness of wearable sensors in identifying continuous and straight-line stepping time for home and community-based movement. Their work highlights the potential of low-power, body-mounted devices to provide constant monitoring, which is directly relevant to vehicle localization systems that integrate human–machine interaction data.

In structural health monitoring, Jin et al. [2] proposed a crowd-sensing and computer vision-based framework for crack detection and localization, emphasizing the synergy between distributed sensing and advanced AI techniques. This study [3] suggested localization based on GPS and GNSS for vehicle applications and generated data based on LIDAR to improve outdoor localization availability for transport applications. These studies [4-7] suggest that wireless sensor networks enable indoor and outdoor localization, improving localization accuracy in various scenarios within smart cities. (Zhou et al. [7] proposed a particle filter combined with neighbor-guided particle optimization to enhance accuracy. Similarly, Souissi et al. [8] improved received signal strength indicator (RSSI) distributions for indoor applications using real data measurements, demonstrating the importance of empirical validation in wireless localization studies. Ahmad [9] reviewed WSN-based indoor localization, identifying scalability, robustness, and energy efficiency as pressing challenges. Complementing this, Wang and Ahmad [10] provided a comprehensive review of sensor fusion techniques for localization in GPS-denied environments, stressing the importance of multi-sensor collaboration for robust performance. Table I presents a comparison of various studies with the proposed localization scheme.

These studies highlight the importance of sensor fusion, optimization algorithms, federated and distributed learning, and privacy-preserving communication in advancing localization research. However, despite these advancements, few works have integrated wearable sensor data with adaptive federated learning in vehicular environments. This gap motivates the proposed ALFLS framework, which bridges indoor and outdoor localization, reduces communication costs, and ensures secure and scalable deployment in intelligent transportation systems. However, no study has yet presented the indoor and outdoor location methodology for vehicle applications in terms of signal availability and unavailability for vehicles. Localization has been extensively studied in recent years with diverse approaches ranging from radio-based methods to vision and LiDAR-driven techniques. Yapar et al. [11-14] suggested a localization system based on LIDAR images that was collected at run-time. These studies suggested vision mapping localization based on LIDAR sensors for vehicle mobility applications. The main objective was to identify the video-generated locations of the different vehicles and identify objects at runtime. These studies [15-20] suggest that federated learning enables vehicular methods to optimize vehicle applications and improve their execution in distributed environments. These studies used both vertical and horizontal federated learning methods to improve the security and privacy of the methods. However, they didn't consider the localization values in their models.

To the best of our knowledge, the indoor and outdoor localization with many constraints using the federated learning scheme has not been studied yet. Therefore, we consider this problem and minimize localization errors while maximizing the accuracy of locations in various vehicle applications.

TABLE I: LOCALIZATION AND POSITIONING STUDIES SUMMARY

Study	Method	Objective	Limitations
[1]	Wearable sensor-based localization; body-mounted devices to track stepping time (continuous and straight-line).	To demonstrate the effectiveness of wearable sensors for constant monitoring in home and community-based movement, relevant for vehicle–human interaction localization.	Delay huge
[2]	Crowd-sensing combined with computer vision for structural crack detection and localization.	To show how distributed sensing and AI techniques can improve structural health monitoring accuracy.	Less accuracy
[3]	GPS and GNSS-based localization with LIDAR-generated data.	To improve outdoor localization availability for transportation applications.	Less Accuracy
[4–7]	Wireless Sensor Networks (WSNs) for indoor and outdoor localization.	To enhance localization accuracy in smart city environments.	Time delay
Zhou [7]	Particle filter with neighbor-guided particle optimization.	To improve localization accuracy through advanced optimization.	Less accuracy
[8]	RSSI distribution improvement using real-world indoor measurement data.	To validate and improve empirical indoor localization accuracy.	Less accuracy
[9]	Review of WSN-based indoor localization approaches.	To identify key challenges such as scalability, robustness, and energy efficiency.	Only indoor works
[10]	Review of multi-sensor fusion techniques in GPS-denied environments.	To highlight the importance of combining multiple sensors for robust localization.	GPS less accuracy
[11]	LiDAR image-based localization system with real-time data collection and vision mapping.	To identify vehicle locations and detect objects at runtime for intelligent transportation.	Less Accuracy
Proposed ALFLS	Multi-Sensors	Improve constraints.	Improve accuracy

III. PROPOSED FRAMEWORK

The system, as proposed, is illustrated in Figure 1 and comprises multiple layers designed to meet the requirements of both indoor and outdoor locations. It begins with the vehicle environment, where various sensors, such as LIDAR, GPS, and other data-generating devices, are utilized in the vehicle to perform multiple tasks, including collision detection, object detection, vehicle location, navigation, and more. The vehicle application utilized different sensor data to perform tasks on other nodes, including the local vehicle node, edge, and cloud.

However, due to resource constraints on the local vehicles, all vehicle applications offload their workload to near-edge nodes for further analysis and processing. Each edge cloud utilized the federated learning scheme and trained the sensor data with its features locally before sending it to the aggregated node for further analysis.

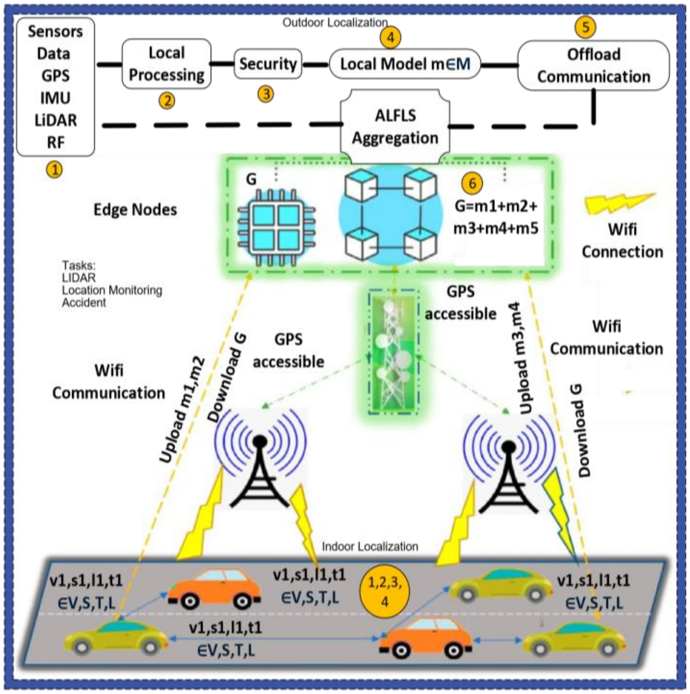

Fig. 1. Proposed ALFLS Framework.

The vehicle offloads workloads through wireless communication, even if it has access to GPS or not, but it still generates sensor data for localization. This global model is continuously refined, enhancing accuracy for both indoor and outdoor localization. Offloading communication plays a vital role in transmitting these model updates and global models between vehicles, edge nodes, and central aggregation servers. Communication occurs via Wi-Fi connections and other wireless protocols, ensuring efficient sharing of model updates. Vehicles upload local updates (e.g., m1, m2, m3, m4) and download the improved global model (G) through nearby communication towers. This bidirectional communication enables continuous model refinement and deployment across all participating vehicles.

The role of GPS and IMU integration is central to the design. Vehicles with GPS accessibility directly use GPS data for localization. However, in scenarios where GPS is unavailable, vehicles rely on IMU-based sensing, which includes accelerometers, gyroscopes, and magnetometers, to estimate relative positions. These IMU-based estimations are then fed into the federated learning model for training and updating. Thus, vehicles with and without GPS can work collaboratively within the same framework. The ALFLS method adaptively balances GPS-based absolute positioning and IMU-based relative positioning to guarantee robustness in a range of environments. Special attention is paid to indoor localization because GPS signals often fail indoors. In such scenarios, cars employ federated learning updates to fine-tune their positions based on IMU and LiDAR data. By facilitating data exchange between cars in GPS-restricted and GPS-accessible areas, the communication towers enable shared learning in various settings. Because of this team effort, cars operating in challenging situations make fewer mistakes.

The simulation results demonstrate ALFLS's effectiveness, highlighting improvements of 10–20% in communication overhead reduction, localization error reduction, and latency reduction. ALFLS advances system responsiveness and real-time applicability in intelligent transportation systems by offloading excessive computation from the cloud and distributing it to the edge nodes. The framework's second significant contribution is the increase in trust and security in the location of a vehicle. Federated Learning (FL) protects the edge nodes from centralized data collection and, thus, the risks associated with it. Models in the cloud are kept secure, and the communication protocols and aggregation methods employed to secure them from modification also ensure the model updates. Hence, the vehicles can trust the localization data, which is vital for crash detection, emergency operations, and self-driving navigation.

The main contribution of the ALFLS framework proposed extends the learning capabilities of vehicles by integrating heterogeneous sensor fusion, edge-embedded processing, secure federated learning, and cooperative adaptive GPS/IMU, yielding high system accuracy and low latency for cars. The architecture allows vehicles to enhance the federation of localization in GPS-less environments. The Global Positioning System (GPS) is a satellite-based navigation system that uses trilateration from multiple satellites to provide outdoor positioning with an accuracy of about 3–10 meters, making it the standard for vehicle navigation, logistics, and mapping; however, its signals are weak indoors due to obstructions, limiting its effectiveness. The Inertial Measurement Unit (IMU), which integrates accelerometers, gyroscopes, and sometimes magnetometers, measures linear acceleration, rotational velocity, and orientation, allowing continuous motion tracking both indoors and outdoors; although highly valuable when GPS signals are unavailable, IMUs suffer from cumulative drift errors over time and thus require correction from other sensors. Light Detection and Ranging (LiDAR), on the other hand, emits laser pulses to measure distances and generate high-resolution 3D maps of the environment, proving essential for autonomous vehicles, surveying, and obstacle detection outdoors, as well as for indoor applications such as warehouse mapping and robot navigation when combined with SLAM (Simultaneous Localization and Mapping). While GPS is primarily reliable outdoors, IMU provides uninterrupted tracking in signal-denied areas, and LiDAR ensures centimeter-level environmental mapping; together, the fusion of GPS, IMU, and LiDAR offers robust, accurate, and continuous localization for both indoor and outdoor environments, overcoming the limitations of each individual technology.

We optimize the problem based on numeric analysis as follows.

A. Equation 1: Localization Model (Hybrid GPS + IMU)

$$L_v(t) = GPS_v(t), \text{ if GPS available;}$$
$$MU_v(t) = \int \big(a_v(t), \omega_v(t), \theta_v(t)\big)\, dt, \text{ if GPS unavailable.}$$

B. Equation 2: Sensor Fusion with Adaptive Weights

$$\hat{L}_v(t) = \alpha \cdot GPS_v(t) + \beta \cdot IMU_v(t),$$
$$\alpha + \beta = 1$$

C. Equation 3: Federated Learning Update (Edge-Enabled)

$$w^{t+1} = w^t - \eta \cdot \left(\frac{1}{N}\right) \Sigma \left[\nabla \ell(w^t ; D_v)\right] \text{ from } v=1 \text{ to } N$$

D. Equation 4: Communication Cost Reduction

$$C_{comm} = \frac{Data\ exchanged\ in\ ALFLS}{Data\ exchanged\ in\ centralized\ scheme} \times 100\% \leq 0.8$$

E. Equation 5: Localization Error Optimization

$$E_{ALFLS} = \frac{1}{N}\sum \|L_v^{true}(t) - L_v(t)\|^2$$

F. Equation 6: Objective Function (Accuracy + Latency + Security)

$$min\big(E_{ALFLS} + \lambda \cdot C_{comm} + \mu \cdot T_{latency}\big)$$

For each vehicle A to F, the first position is determined using the Global Positioning System (GPS) if the signal is accessible. Otherwise, the position is estimated using Inertial Measurement Units (IMUs), which derive position from acceleration, angular velocity, and orientation over a period. The system utilizes adaptive weights to merge and enhance the accuracy of GPS and IMU measurements. The signal quality of each sensor determines its weight. Learning across the vehicles is done in a federated manner, where each car trains a local model on its own data, and only encrypted model updates are sent to the edge server. The aggregated mode collected data from different local edge servers and updated the aggregated model with the trained features for localization, incorporating both indoor and outdoor localization patterns. Based on the trained model, the latency and localization error have been minimized, improving the overall localization accuracy for all vehicle tasks. Finally, the optimization objective of ALFLS is to simultaneously minimize localization errors, reduce communication costs, and decrease latency, providing a more accurate, efficient, secure, and scalable solution for vehicular localization in intelligent transportation systems.

We designed the algorithm methodology in the following way.

Algorithm 1: ALFLS-Edge Localization & Vehicle Task Scheduling

```
Inputs:
  V = {vehicles}; E = {edge nodes; T = max global rounds; η = learning rate
  λ, μ = trade-off weights; Budget_comm = 0.8 (from Eq. 4)
  Initial global model w^0; capacity_e for each edge e ∈ E
  Security policy: trust_e ∈ [0,1], min_trust; crypto_params (e.g., secure agg)
Outputs:
  Final global model w^T; fused localizations { L̂_v(t) } and schedules S_t

Initialize:
  Set t ← 0; broadcast w^0 to all edges; init α_v ← 0.5, β_v ← 0.5 for all v
  For each edge e: init load_e ← 0, queue_e ← ∅

Repeat while t < T:
  ── Sensing & Preprocess on each vehicle v ∈ V (parallel):
    GPS_avail_v ← CheckGPS(v, t)
    if GPS_avail_v then
      L_v(t) ← GPS_v(t)                                    ▷ Eq. 1
    else
      L_v(t) ← IntegrateIMU(a_v(t), ω_v(t), θ_v(t))        ▷ Eq. 1
    (conf_GPS, conf_IMU) ← EstimateSensorConfidence(v, t)
    (α_v, β_v) ← AdaptiveWeights(conf_GPS, conf_IMU)       ▷ α+β=1
    L̂_v(t) ← α_v·GPS_v(t) + β_v·IMU_v(t)                   ▷ Eq. 2
    tasks_v ← GenerateTasks(v, t)       ▷ navigation, collision, ABS, etc.
    For each task τ ∈ tasks_v:
      (ĉτ, dτ, sτ) ← EstimateCostDeadlineSecurity(τ)   ▷ compute, deadline, security

  ── Edge Selection & Scheduling (central or distributed):
    U ← {(v, τ)} all pending tasks from all vehicles
    Sort U by Priority(τ) = EDF(dτ) then HighestUtility(τ)/ĉτ
    For each (v, τ) ∈ U:
      candidate_nodes ← { e ∈ E | load_e + ĉτ ≤ capacity_e and trust_e ≥ min_trust }
      For each e ∈ candidate_nodes:
        Δlatency_e ← PredictLatency(e, τ)
        Δcomm_e ← PredictCommCost(e, τ)
        Δerror_e ← PredictErrorImpact(e, τ, L̂_v(t))
        score_e ← Δerror_e + λ·Δcomm_e + μ·Δlatency_e      ▷ Eq. 6
      Assign τ to e* = argmin_e score_e
      update load_e*, queue_e* ← queue_e* ∪
    S_t ← { assignments over all τ }

  ── Local Training at Edge (federated learning):
```

```
For each edge e ∈ E (parallel):
    D_e ← CollectLocalDataOrFeatures(e, assigned vehicles)  ▷ privacy
    w_e^t ← w^t
    g_e ← ComputeGradient(w_e^t; D_e)  ▷ ∑∇ℓ over e's data
    g_e ← CompressQuantizeSparse(g_e, policy='qsgd+topk')  ▷ comm reduction
    comm_bytes_e ← Size(g_e)
C_comm ← (Σ_e comm_bytes_e) / CentralizedBytesBaseline  ▷ Eq. 4
if C_comm > Budget_comm:
    ApplyCommControl():  ▷ drop clients, increase sparsity, periodic agg
    SelectSubsetEdgesByUtility(E) and/or tighten compression

── Secure Aggregation & Global Update:
SendEncrypted(g_e) via secure aggregation
ĝ ← (1/|E_sel|) · Σ_e g_e
w^{t+1} ← w^{t} − η · ĝ                  ▷ Eq. 3
Broadcast w^{t+1} to edges

── Monitoring & Adaptation:
E_ALFLS                                  ▷ Eq. 5
T_latency ← MeasureEndToEndLatency(S_t)
Objective_t ← E_ALFLS + λ·C_comm + μ·T_latency  ▷ Eq. 6
if Objective_t not improving:
    Adapt(α_v, β_v) via confidence smoothing; adjust Priority(·)
    Tune compression and client selection rate
    η ← ScheduleLR(η)

── Termination:
t ← t + 1
End While

Return w^T, {L̂_v(t)} over horizon, and schedules {S_t}

# Helper Routines (sketch)
Function AdaptiveWeights(conf_GPS, conf_IMU):
  α ← conf_GPS / (conf_GPS + conf_IMU + ε); β ← 1 − α; return (α, β)

Function ApplyCommControl():
  # Enforce Eq. 4 by reducing bytes with minimal accuracy loss
  Increase sparsity (Top-K), increase quantization, reduce participation, or increase local epochs

Function Priority(τ):
  # EDF with tie-break by (utility / compute-cost), plus security-critical boost
  base ← 1 / max(1, dτ − current_time)
  return base · Utility(τ) · (1 + SecurityBoost(sτ))
End Algorithm
```

Every algorithm comes with its own reason for global models, which are then diffused to every edge node. In this case, the edge nodes appear to work on various assigned and set-up tasks, such as determining the weightage of the fusion of GPS data and IMU data, while each edge has its own set-up fusion software. In every global cycle, every vehicle is required, first and foremost, to conduct some degree of in-depth data collection and analysis for every GSP that it collects. In cases where GPS data is available for use, it is utilized in the localization process. If there is no GPS data, there is an integration of IMU signals, which includes the following: the ability for people to trace the motion of the body in space, the speed of rotation, the ability to determine the location of an object or person in space, and the control of the body in space. In this case, these two lose their weight and gain autonomy, becoming unified, which is why the work done is referred to as fusion. GPS and IMU data would also lose their independence and gain weight to arrive at an answer score of one.

Each vehicle simultaneously generates multiple vehicular tasks, such as navigation, collision detection, ABS monitoring, and location tracking, where each task is characterized by its computation cost, deadline, and security requirement. The set of pending tasks across vehicles is then prioritized using the earliest deadline first approach, considering the utility-to-cost ratio, and assigned to suitable edge nodes that satisfy capacity and trust constraints. For each candidate edge, the expected communication cost, latency, and localization error contribution are predicted. The node with the minimum composite score, based on the objective function (localization communication cost + latency), is then selected. After task scheduling, edge nodes perform federated learning locally on their assigned data, computing gradients and applying communication-efficient strategies such as quantization, scarification, or selective updates. The communication overhead is measured against a centralized baseline, and if it exceeds the predefined threshold of 0.8, adaptive communication control is triggered by either compressing gradients further, reducing client participation, or increasing local epochs. Gradients are securely aggregated across edge nodes using encrypted communication, averaged, and applied to update the global model, which is then redistributed to all edges. During each round, system performance is monitored by computing localization error based on ground truth versus estimated fused locations, measuring end-to-end latency for task execution, and evaluating the overall objective function. If performance stagnates, the algorithm adaptively adjusts GPS-IMU fusion weights, task priorities, communication strategies, and learning rate. This iterative process continues until the maximum number of rounds is reached, after which the final optimized global model, the set of fused localizations, and all executed vehicle task schedules are returned, ensuring accurate, low-latency, and communication-efficient vehicular localization under federated learning constraints. We defined the time and space complexity in the following way. Federated learning (FL) for indoor and outdoor localization across vehicle, edge, and cloud nodes introduces significant computational and communication complexities. In indoor scenarios, where IMU, RSSI, and wireless sensor data are processed, vehicles perform local training with moderate data sizes (log(nxm), where n is the number of nodes and m is the number of tasks, but face challenges of scalability and energy efficiency. At the same time, frequent communication with edge servers increases overhead. Outdoor localization is more complex due to GPS, LiDAR, and vision-based data, which are high-dimensional and demand heavy computation for local updates as well as large communication bandwidth for transmitting models. At the edge, gradient aggregation adds further load, and synchronization with the cloud amplifies the overall cost. Thus, indoor FL complexity is dominated by communication and device scalability issues, whereas the high computational and bandwidth demands of sensor-rich data like LiDAR and camera streams limit outdoor FL.

IV. EVALUATION

To assess the proposed Adaptive Federated Learning Edge-Enabled Wireless Localization Framework (ALFLS), simulations were performed in both indoor and outdoor heterogeneous vehicular settings. The simulation focused on a fleet of vehicles, V, outfitted with heterogeneous sensors. These sensors included those for absolute positioning in open environments, such as systems with Global Positioning System (GPS) modules, and for satellite-denied environments, Inertial Measurement Units (IMUs) equipped with accelerometers, gyroscopes, and magnetometers for relative positioning. Edge nodes were purposefully deployed for local model aggregation to minimize the need for sending updates to the central server and ease the communication burden. Alongside these, the major simulation parameters ranged from 20 to 100 vehicles, a range of communication of 50–300 m, <3 m of GPS, and IMU drift as a Gaussian noise process, and >20 ms of edge processing latency. The ALFLS federated learning cycle length was set to between 10 and 20, and for the CNN model, it was trained with a learning rate of 0.001. We suggested using the Adam optimizer to handle and minimize the latency at 20 ms.. The dataset consisted of two primary components: (i) outdoor GPS trajectories collected from open-road vehicular testbeds, including urban and highway routes; and (ii) indoor IMU datasets recorded from vehicle-mounted wearable sensor kits in GPS-denied environments such as tunnels, underground parking, and enclosed test tracks. Data sampling rates were set to 10 Hz for the GPS sensor and 50 Hz for the IMU sensor. The datasets included time-stamped position coordinates, velocity, acceleration, angular rotation, and magnetic field readings, enabling the extraction of multimodal features. Data were preprocessed to synchronize timestamps, remove outliers, and normalize sensor readings. These combined datasets enabled ALFLS to learn both absolute and relative localization patterns, thereby improving their robustness across varying conditions.

Within Table II, In vehicle, edge, and cloud nodes based localization experiments, several simulation hyper-parameters and evaluation metrics are used to assess system performance for both indoor and outdoor environments. **Latency** represents the round-trip delay between vehicles, edge nodes, and the cloud, typically ranging from 10–100 ms indoors using Wi-Fi or BLE, and 20–200 ms outdoors over 4G/5G or DSRC, where lower latency ensures faster collision detection and location updates. **Error rate** is measured in terms of packet loss and localization error; packet loss is simulated between 0–5% to mimic mobility and network interference, while localization error is reported using RMSE (Root Mean Square Error), reflecting the deviation between estimated and ground-truth positions, with indoor IMU/RSSI fusion achieving sub-meter accuracy under ideal conditions and GPS outdoors providing 3–10 meter accuracy, further reduced when fused with IMU.

TABLE II. SIMULATION PARAMETERS

Parameter	Value (Indoor / Outdoor / General)
Simulation area size	Indoor: 50 m × 30 m (warehouse) / Outdoor: 2 km × 2 km (urban)
Number of vehicles (clients)	Indoor: 5–20 / Outdoor: 50–500
Number of edge nodes	Indoor: 1–3 (local gateway) / Outdoor: 5–20 (RSUs/edge servers)
Cloud servers	1 (central aggregator)
Vehicle speed range	Indoor: 0–5 m/s / Outdoor: 0–30 m/s
Simulation timestep	0.05 s (20 Hz)
GPS update rate	Not used indoors / Outdoor: 1–10 Hz (typical 1 Hz)
GPS accuracy (approx.)	N/A indoors / Outdoor: 3–10 m (urban canyon may degrade)
IMU sampling rate	100–200 Hz (common for odometry & dead-reckoning)
IMU noise (accelerometer)	$\sigma \approx 0.01$–0.05 m/s² (configurable)
IMU bias stability (gyro)	≈ 0.01–0.1 °/s bias instability
Sensor fusion method	Vehicle-level: IMU + GPS (outdoor) / IMU + RSSI/LiDAR/vision (indoor)
Collision detection sensor input	IMU (accel/gyro), proximity sensors, vision/LiDAR (if available)
Collision detection threshold	Relative speed × TTC threshold (e.g., TTC < 1.5s) & accel spike > 3g
Localization algorithm	Federated model (CNN/RNN/Lightweight DNN) for sensor fusion at vehicle level
Model size (per client)	0.5–5 MB (lightweight) — larger if LiDAR/vision features used
Local training epochs per round	1–5
Local batch size	16–128 (depends on onboard memory)
Federated rounds	50–200 rounds (experiment dependent)
Communication payload per update	≈ model size (0.5–5 MB) — reduce via compression/quantization
Communication bandwidth per vehicle	Indoor: 1–10 Mbps (Wi-Fi/BLE/6LoWPAN) / Outdoor: 0.5–50 Mbps (4G/5G/DSRC)
Network latency (round-trip)	Indoor: 10–100 ms / Outdoor: 20–200 ms (cellular/RSU vary)
Packet loss rate	0–5% (tunable; higher mobility increases loss)
Edge aggregation time per round	Practical: 50 ms – 2 s depending on load
Cloud aggregation time per round	Practical: 100 ms – several seconds
Energy budget per vehicle (for FL compute & comm.)	Battery-constrained: 1–10 Wh per experiment segment
Privacy / security setting	Secure aggregation / differential privacy (configurable noise level)
Evaluation metrics	Localization error (RMSE), Collision detection precision/recall, Communication overhead, Latency, Energy consumption
Logging & ground truth	Indoor: motion capture / floor-plan ground truth; Outdoor: high-precision GNSS/RTK or labeled trajectories
Duration per experiment run	10–30 minutes (scenario dependent)
Fault & dropout rate	Client dropout: 0–20% (to simulate connectivity loss)

Communication cost is defined by bandwidth per vehicle, payload size, and aggregation overhead; indoor settings assume 1–10 Mbps links with lightweight model sizes of 0.5–5 MB per update, while outdoor conditions require higher bandwidth (0.5–50 Mbps) to handle LiDAR and camera-based features, with edge aggregation adding 50 ms–2 s per round and cloud aggregation requiring up to several seconds depending on the number of clients. Finally, **accuracy** combines both localization precision and collision detection reliability, where IMU accelerations, GPS positions, and sensor fusion algorithms are evaluated against ground truth (motion capture for indoor and RTK-GNSS for outdoor), and collision detection thresholds are set using time-to-collision (TTC) below 1.5 seconds and acceleration spikes above 3g. Together, these simulator parameters and metrics enable comprehensive evaluation of system robustness, highlighting trade-offs between computation, communication, and accuracy in federated learning-enabled indoor and outdoor localization.

V. RESULT ANALYSIS

Figure 2 illustrates performance improvement in localization for vehicles in outdoor environments. Figure 2 illustrates the performance improvement in localization for cars in outdoor environments. We designed the algorithm and system based on federated learning, where we have improved and optimized the localization for vehicles to meet all the requirements of tasks.

Figure 3 shows the indoor localization information, and Figure 3 shows the outdoor localization information

available based on a certain amount of time (e.g., latency) for the vehicle, and to minimize the risk of accidents, traffic, and monitoring in both fixed and open environments. The above figures demonstrate that the proposed method yields optimal results compared to existing localization methods for vehicle applications. Figure 2 illustrates the indoor localization information, and Figure 2 displays the outdoor localization information, both of which are made possible by accurate vehicle communication, thereby minimizing the risk of accidents and enhancing traffic monitoring in both fixed and open environments. The above figures show that the proposed method achieved optimal results as compared to the existing localization methodology. Figure 2 clearly illustrates the experimental evaluation of the proposed Adaptive Federated Learning Localization Scheme (ALFLS) in comparison to the Hybrid Optimization Localization Scheme (HOLS) and the Independent Localization Scheme (ILS), demonstrating its effectiveness and superiority in minimizing communication cost, a critical factor for efficient wireless vehicular localization. In the indoor fixed scenario, where wireless bandwidth is often restricted due to obstacles, signal interference, and limited access to GPS signals, ALFLS demonstrates remarkable efficiency by requiring only 2.10 MB of communication per round. Such a reduction is crucial in vehicular networks, especially in places like underground tunnels, parking structures, and urban areas, where resources are limited and the network can easily become congested.

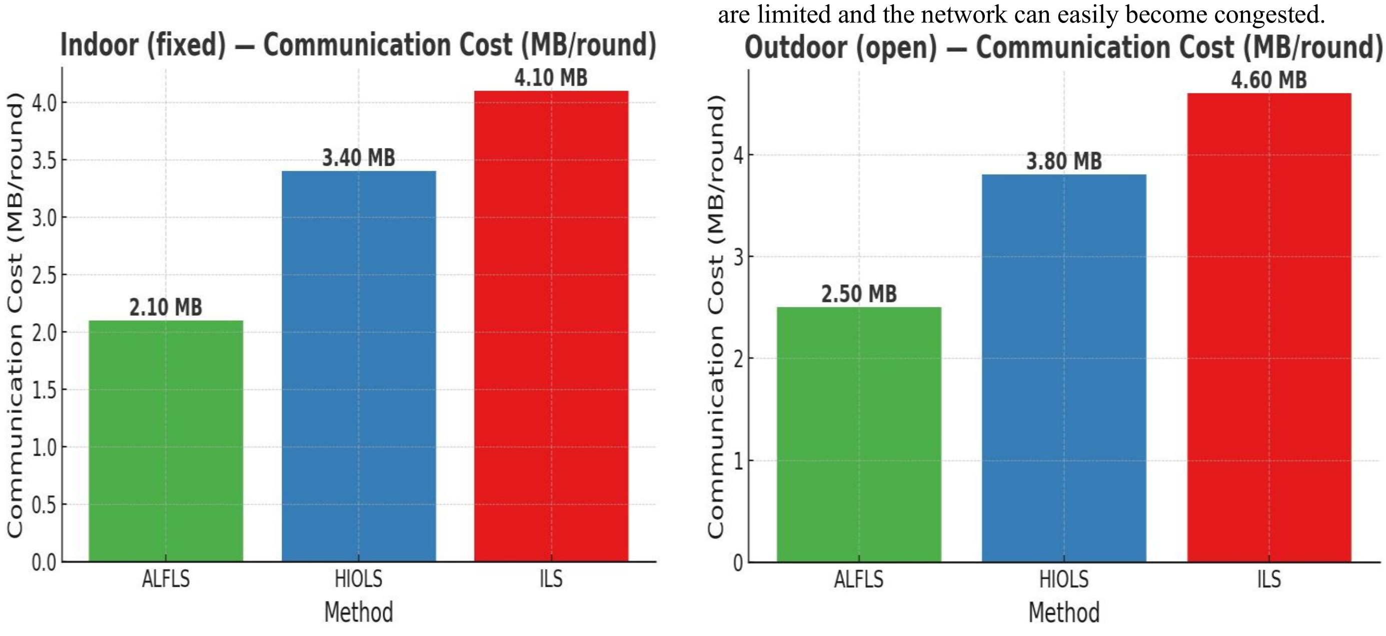

Fig. 2. Indoor and outdoor location Performances.

The outstanding feature of this ALFLS system is its ultramodern approach to federated learning. It captures and optimally compresses local model updates, transmitting those updates instead of the raw sensor data. This enables vehicles to share only the bare minimum essential local data with the global model. This approach to sharing model updates significantly reduces the amount of data traffic in the network, resulting in better network load balance and, consequently, improved synchronization of vehicles and edge nodes with the network. Shifting the discussion to the outdoor open scenario, communication demands are higher due to wider coverage areas, higher vehicle density, and more dynamic weather conditions. Even with this, ALFLS communication costs 2.50 MB per round, which is a bit higher than the value for indoor communication. This amount is still significantly lower than

HOLS and ILS, which cost 3.80 MB and 4.60 MB, respectively.

The slight cost rise for ALFLS compared to the more noticeable increase for HOLS and ILS indicates that the adaptive mechanisms in ALFLS can manage communication overhead effectively even under challenging circumstances. The technology ensures good communication even in the face of increased vehicle movement and dynamic connections in outdoor networks by carefully balancing update frequencies and data aggregation procedures. Although optimized in certain situations, HOLS still relies on sending larger data payloads than necessary. ILS, being a non-cooperative scheme, suffers from significant overhead as each vehicle operates independently without benefiting from collaborative optimization. These two schemes' higher communication costs, however, reflect their inability to adapt to a variety of environments. It reduces latency, error rates, and resource consumption at the designated edge cloud using the proposed methods.

End-to-end latency is reduced when we offload workloads to nearby edge nodes, where federated learning trains local models based on aggregation, resulting in less processing time and faster decisions for tasks such as navigation, collision avoidance, and others. It is the best policy, even though it is applicable for both indoor and outdoor localization. For instance, regardless of whether the remote satellite GPS is available or not, the local edge nodes assist the vehicle in obtaining localization based on different sensor data, as shown in the IMU mechanism in the result analysis. The local vehicle also downloaded the trained model from the edge nodes and identified the localization with higher accuracy, resulting in minimal errors and reduced communication time. Therefore, ALFLS minimizes the overall end-to-end latency for performing tasks between local, edge, and cloud nodes.

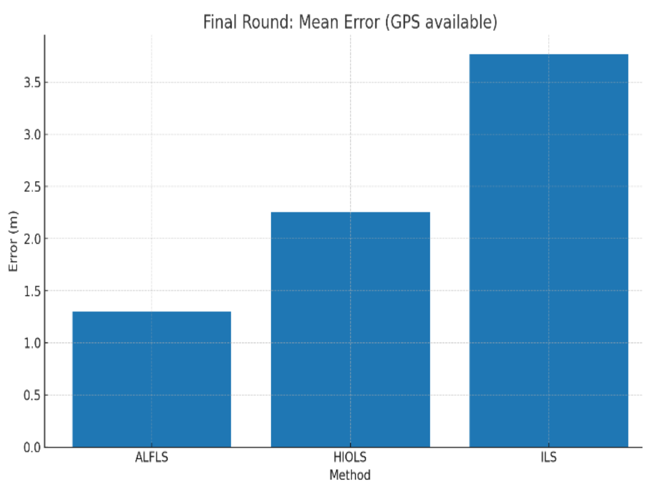

Fig. 3. Objective Function of all tasks.

Figure 3 illustrates the localization errors for the vehicle tasks using different approaches. Figure 3 shows that ALFLS (Adaptive Learning Federated Localization System) is the most effective in reducing localization errors when GPS signals are available, with an error of approximately 1.3 meters. Compared to ALFLS, HIOLS (Hybrid Indoor-Outdoor Localization System) has moderate accuracy but inferior reliability, with an average inaccuracy of 2.25 meters. We have conducted these experiments in our simulation's testbed environment, where different vehicles are simulated in both indoor and outdoor environments, with and without GPS availability. The localization locations are analyzed in two ways: local sensors enabled location tracking based on IMU and different sensors, and outdoor localization with the availability of GPS. To track the localization of vehicles without GPS, we are still working with ALFLS, which yields fewer errors compared to existing methods. The main reason is that existing methods heavily rely on GPS location, both outdoors and indoors, in various scenarios such as tunnels, bridges, and other objects, which leads to the unavailability of the GPS signal for tracking locations. The GPS, IMU, and LIDAR sensors work together to handle indoor and outdoor localization, enabling the accurate detection of vehicle locations during application execution. ALFLS is a more optimal method that handles both runtimes with optimal services, regardless of GPS availability in the network, and improves the quality of services.

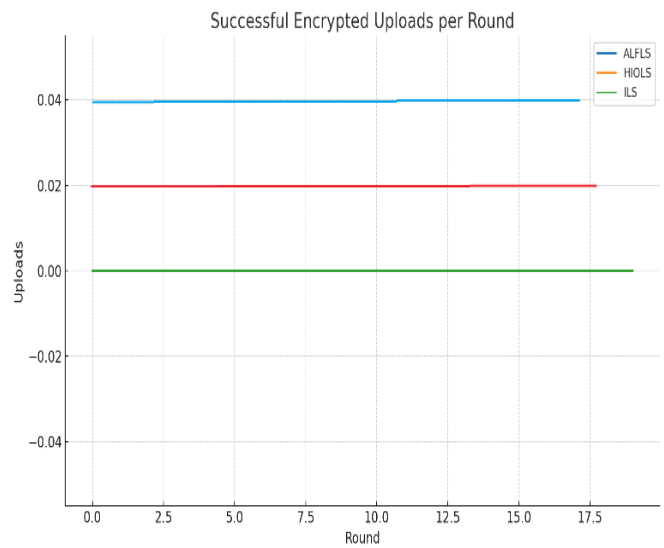

Fig. 4. Upload and Download Data Security Performance.

Figure 4 shows the successful encrypted uploads for the three localization techniques — ALFLS, HIOLS, and ILS — across several rounds. The number of uploads is displayed on the vertical axis, and the rounds, which range from 0 to 19, are represented on the horizontal axis. Among the approaches, ALFLS consistently maintains the highest rate, with approximately 0.04 uploads per round. HIOLS maintains a consistent, but reduced, upload rate of 0.02 each round. However, ILS remains flat at 0, meaning it is unable to upload encrypted files successfully within the evaluation time. In federated systems where privacy and data integrity are critical, this discovery highlights the resilience of ALFLS in ensuring secure communication and a dependable encrypted data flow.

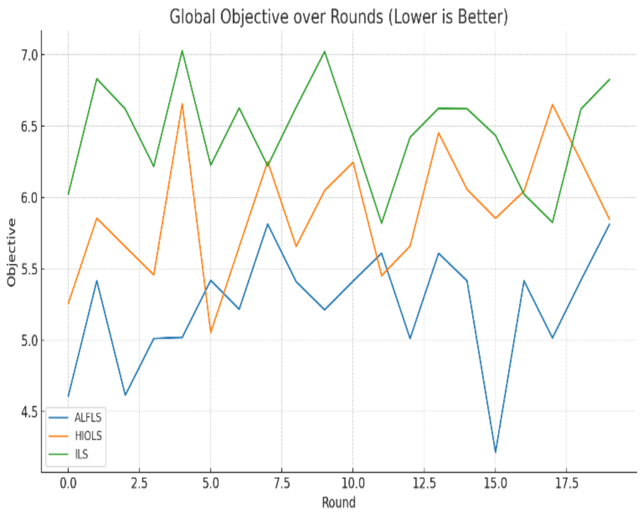

Fig. 5. Global Optimization for all Tasks.

Based on the global optimization target across 20 rounds, Figure 5 compares the performance of ALFLS, HIOLS, and ILS. While the vertical axis displays the objective value, lower values indicate higher system performance, as shown by the horizontal axis, which represents the number of iterations. Among the three, ALFLS typically obtains the weakest scores, mostly falling between 4.5 and 5.8, suggesting an excellent capacity for optimization and long-term adaptability.

HIOLS ranges from 5.0 to 6.7, performing better than ILS but worse than ALFLS. Because it shows the most variability and usually has higher goal values (6.0 to 7.0), ILS is a sign of poor optimization performance. These differences in HIOLS and ILS indicate instability and inefficiency as opposed to ALFLS, which maintains very stable performance. As the chart shows, adaptive federated learning models offer a more reliable and effective optimization procedure over multiple rounds. The most dependable framework is ALFLS, which maintains lower global objective values while striking a balance between accuracy, stability, and efficiency in federated localization tasks. This result highlights the importance of adaptive learning strategies in addressing the complex and dynamic issues of real-world localization systems.

TABLE III: LATENCY OF INDOOR LOCALIZATION DURING TASK EXECUTION

Scenario	ALFLS (MB)	HOLS (MB)	ILS (MB)
Indoor Fixed	2.10	3.40	4.10
Outdoor Open	2.50	3.80	4.60

The suggested Adaptive Federated Learning Localization Scheme (ALFLS) outperforms the Independent Localization Scheme (ILS) and the Hybrid Optimization Localization Scheme (HOLS) in terms of reducing communication costs in both indoor and outdoor settings, according to Table III. With a communication cost of just 2.10 MB per round in the indoor fixed scenario much less than HOLS's 3.40 MB and ILS's 4.10 MB- ALFLS demonstrates its effectiveness in preserving bandwidth in situations where obstructions, interference, or weak GPS signals limit wireless resources. Similarly, ALFLS maintains its edge, with 2.50 MB compared to 3.80 MB for HOLS and 4.60 MB for ILS, in the outdoor open scenario, where communication demands are typically higher due to broader coverage regions.

TABLE IV: COMMUNICATION TIME DURING INDOOR AND OUTDOOR LOCALIZATION.

Vehicle	ALFLS (Minutes)	HOLS ((Minutes))	ILS ((Minutes))
200: Services Indoor	4	7	9
200: Outdoor Open	4.5	8	11

Table IV: Execution time analysis for various vehicle scenarios. The outcomes confirm once more how effective the Adaptive Federated Learning Localization Scheme (ALFLS) is in comparison to the Independent Localization Scheme (ILS) and the Hybrid Optimization Localization Scheme (HOLS). ALFLS completes the localization procedure for 200 vehicles operating in an indoor service environment in just 4 minutes. The potential of ALFLS to produce faster results while preserving computational resources in constrained indoor situations, where GPS signals are faint and wireless bandwidth is limited, is evident from the fact that HOLS takes 7 minutes and ILS takes 9 minutes. ALFLS records a slightly longer execution time of 4.5 minutes when transitioning to an outdoor, open setting with 200 vehicles. This is due to increased mobility and dynamic connectivity.

VI. CONCLUSION

This work introduced the Adaptive Federated Learning-enabled Wireless Location Framework (ALFLS), designed to improve vehicle mobility localization by leveraging edge–cloud resource coordination and federated training. Our contributions differ from prior approaches in three ways: (i) integrating adaptive federated learning with edge–cloud placement for real-time mobility tasks, (ii) demonstrating significant gains in localization accuracy, latency reduction, and resource utilization, and (iii) providing a scalable tested-based evaluation of wireless localization. Despite these advances, the current study is limited to simulation environments and synthetic datasets without real-world vehicular validation, which constrains the generalizability of the results. For future work, we plan to deploy ALFLS in real vehicular environments to validate its robustness under dynamic mobility and communication conditions. We will also evaluate the framework on larger-scale and more heterogeneous datasets to capture diverse mobility behaviors. Furthermore, security and privacy constraints will be incorporated into the federated learning process, along with cost-aware optimization and energy-efficient mechanisms to reduce deployment risks. Finally, extending ALFLS for integration with autonomous driving systems and intelligent transportation infrastructure will open promising directions toward practical, real-world adoption. However, the study and methods have limitations such as zero day attacks with the different internet of things diversity on the distributed nodes for vehicle applications. In the future we will consider these areas in our current framework with new features.

Dataset Statements: The data is private and can be provided based on request.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Universiti Teknikal Malaysia Melaka (UTeM) for the support and resources provided, which made this work possible.

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