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Proximity-Aware Federated Learning for Symbiotic Task Offloading in Vehicular Edge Intelligence

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Abstract*—Vehicular Edge Computing (VEC) is a key enabler of real-time intelligence in next-generation transportation systems. However, conventional Federated Learning (FL) in VEC typically depends on static edge-server aggregation, resulting in high communication overhead, increased latency, and poor responsiveness under dynamic mobility. To overcome these challenges, we propose Proximity-Aware Federated Learning (PA-FL), a decentralized framework that integrates vehicle-to-vehicle (V2V) collaboration and edge-assisted synchronization to enhance learning efficiency, scalability, and robustness. PA-FL introduces three core innovations: (i) *Collaborative Local Aggregation*, where vehicles perform proximity-based model fusion before forwarding updates to the edge, reducing uplink traffic and accelerating convergence; (ii) *Adaptive Neighbor Selection*, which dynamically filters peers based on spatiotemporal proximity and link stability to ensure context-relevant learning; and (iii) *Context-Aware Synchronization*, which adjusts aggregation frequency based on vehicular density and mobility to improve energy efficiency and learning consistency. Extensive experiments demonstrate that PA-FL achieves an average accuracy of 87.08% ± 0.49, surpassing state-of-the-art FL baselines by over 13% in accuracy and 11% in F1 score. It reduces task failure rates across all proximity ranges and lowers per-round energy consumption to 0.038 J, achieving a 6× improvement in communication efficiency. Delay per communication round is also reduced to 0.85 seconds, supporting real-time responsiveness. These results validate PA-FL as a resilient and scalable framework for symbiotic FL where vehicles collaboratively learn from local context while contributing to global intelligence in AI-integrated, 6G-enabled vehicular edge environments.

***Index Terms*—Symbiotic Internet of Things, Federated Learning, Vehicular Edge Computing, Task Offloading, Vehicle-to-Vehicle Communication, Distributed Machine learning, 6G**

I. INTRODUCTION

Symbiotic-IoT-powered vehicular applications [1] where vehicles, edge servers, and infrastructure operate cooperatively in real-time, such as autonomous navigation [2], [3], cooperative perception [4], and real-time traffic analytics demand ultra-reliable and low-latency computational support [5], [6]. Vehicular Edge Computing (VEC) has emerged as a promising paradigm by bringing computation closer to the data source [7], allowing vehicles to offload tasks such as object detection, trajectory planning, and sensor fusion to nearby edge servers or peers [8]. However, the highly dynamic nature of vehicular networks marked by mobility, heterogeneous connectivity, and fluctuating resource availability continues to challenge the reliability and efficiency of such systems [9], [10].

This work lays the foundation for real-time collaborative intelligence across next-generation autonomous fleets. Federated Learning (FL) has become a cornerstone for privacy-preserving and bandwidth-efficient model training in distributed vehicular environments [11], [12]. FL-TD3 [11], for instance, leverages actor-critic deep reinforcement learning to optimize task offloading, while FedDQL [12] minimizes energy and delay jointly through deep Q-learning. In parallel, DRL-based [13] and GAN-enhanced [14] FL frameworks have improved adaptability and decision-making under dynamic conditions.

Despite these advances, most FL-based vehicular solutions remain dependent on centralized edge aggregation, which undermines scalability and resilience in sparse or unstable networks. Hierarchical schemes like HFEL [15] and asynchronous FL via Lyapunov optimization [16] attempt partial decentralization, yet overlook the potential of direct vehicle-to-vehicle (V2V) collaboration. Moreover, advanced aggregation strategies such as attention-based FL [17] and DDPG-FL [13] often incur high computational costs, limiting their suitability for real-time, resource-constrained environments.

Emerging trends call for more adaptive and proximity-aware intelligence. Recent works ranging from multi-armed bandits [18] and input-aware offloading [19] to mobility-aware scheduling [20], [21] emphasize context-driven decision-making under uncertainty. Intent and trajectory-aware strategies [10], [22] further support collaboration shaped by vehicular context.

Decentralized learning frameworks based on multi-agent reinforcement learning [23] and contextual clustering [24] have shown that peer-to-peer coordination reduces latency and improves energy efficiency. Additionally, V2V and multi-hop routing mechanisms [25] have enabled localized model exchange even in sparse regions. Complementary strategies such as edge-cloud coordination [26], traffic-aware optimization [27], and NOMA-based resource allocation [28] further highlight the importance of flexibility in large-scale vehicular

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networks. However, none of these efforts explicitly enable real-time peer-to-peer model aggregation prior to edge fusion.

Problem Statement: Despite substantial progress, current FL frameworks underutilize the potential of direct, real-time, proximity-based interactions among vehicles. This results in limited learning convergence, increased communication overhead, and poor scalability in high-mobility environments. There is a clear need for decentralized, proximity-aware learning that leverages direct vehicle collaboration.

To address this gap, we propose a novel 5G-enabled Vehicular Edge Computing (VEC) architecture that supports large-scale AI models through proximity-based task offloading and Federated Learning (FL) in Symbiotic-IoT environments. Leveraging Cellular-V2X (C-V2X) communication, our framework enables vehicles to exchange model updates directly with nearby peers in real-time, thereby reducing edge-server dependency and enhancing collaborative efficiency.

We validate our framework using a realistic dataset generated through the integration of SUMO and EdgeCloudSim, simulating 28 edge devices geographically aligned with Vodafone base station coordinates in Cosenza, Italy. This setup accurately reflects urban vehicular dynamics and communication conditions, offering a robust and reproducible evaluation environment.

We introduce Proximity-Aware Federated Learning (PA-FL), a decentralized, multi-layer learning framework that enables vehicles to pre-aggregate model updates with proximate peers before forwarding to the edge. PA-FL prioritizes *spatial locality*, *task similarity*, and *temporal stability* to ensure relevant, low-latency, and consistent learning. To the best of our knowledge, this is the first FL framework that explicitly exploits real-time peer-to-peer collaboration via C-V2X to improve scalability and efficiency in Symbiotic-IoT vehicular systems. Our key contributions are:

- We generate a synthetic dataset using realistic vehicular and edge device positions using SUMO and EdgeCloudSim.
- We propose **PA-FL**, a novel decentralized FL framework for Symbiotic-IoT, enabling real-time model exchange and aggregation among nearby vehicles using C-V2X communication, thereby minimizing edge reliance and increasing robustness.
- We develop an adaptive peer selection strategy based on spatial proximity, task similarity, and node stability, fostering efficient, context-aware collaboration.

The remainder of this manuscript is structured as follows. Section II reviews related work and foundational concepts. Section III presents the proposed PA-FL framework in detail. Section IV outlines the experimental setup and reports empirical results. Section V discusses key findings and limitations. Finally, Section VI concludes the paper and suggests directions for future work.

II. Background and Related Work

In the symbiotic era of 6G, where vehicles, edge servers, and networks collaborate and learn in a mutually beneficial way, Federated Learning (FL) plays a crucial role in enabling privacy-preserving, low-latency, and context-aware intelligence. In addition, FL enables decentralized model training with privacy preservation and has been widely applied in VEC. However, vehicular environments present unique challenges, including high mobility, intermittent connectivity, and rapidly changing network topology. This section reviews relevant literature across architectural, hierarchical, and communication-aware FL approaches and highlights their limitations in dynamic vehicular scenarios.

In the context of the 6G era, the emergence of the Symbiotic Internet-of-Things (S-IoT) envisions a tightly integrated cyber-physical–social system, where massive interconnected devices collaborate seamlessly with Giant AI models to deliver hyper-intelligent, real-time services. Within such a paradigm, FL in VEC becomes a foundational enabler for distributed intelligence, allowing vehicles and edge nodes to collaboratively train models while maintaining data privacy. Nevertheless, realizing this vision requires overcoming fundamental limitations of current FL strategies in VEC, particularly their adaptability to the highly dynamic and heterogeneous nature of symbiotic IoT environments.

A. *FL Architectures for Vehicular Networks*

Zhang et al. [3] proposed a foundational FL architecture integrating mobile edge computing with vehicular networks. While effective for general VEC settings, it assumes relatively static topologies and lacks mechanisms for local V2V collaboration. Xu et al. [29] developed a semi-decentralized FL approach using SDN to coordinate multi-task model updates. Despite improved edge coordination, it does not exploit spatial proximity or peer-to-peer interactions, limiting its responsiveness in fast-moving clusters.

B. *Clustered and Hierarchical FL*

Clustered aggregation has been used to reduce communication costs in the symbiotic IoT-driven vehicular edge networks. Taïk et al. [30] and Puppala et al. [31] proposed cluster-based and decentralized FL schemes, respectively, which reduce dependency on central servers. However, they assume stable group formation and are sensitive to mobility-induced disruptions. Ganguly et al. [32] introduced floating edge aggregation to adapt to topology changes, yet its infrastructure dependency introduces synchronization delays in real-time traffic.

C. *Communication-Aware FL Enhancements*

Several studies introduce V2V and D2D communication for improved efficiency. Yan et al. [33], [34] formulated V2V scheduling using reinforcement learning, reducing latency but overlooking model reliability and stability. Li et al. [35] proposed D2D-assisted FL under energy constraints, yet ignored model staleness and heterogeneous reliability. Lin et al. [24] and Xue et al. [36] employed over-the-air computation for fast aggregation, which assumes synchronized device availability and suffers from amplified channel noise unsuitable for dynamic vehicular conditions.

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D. Client Selection and Edge Caching

Dynamic client selection has been explored to optimize participation. Bao et al. [37] used fuzzy logic based on vehicular velocity and connectivity, and Su et al. [38] adopted multi-armed bandit algorithms. These works improve adaptability but do not account for communication or mobility stability during learning. Wang et al. [39] proposed FL-enhanced edge caching for V2X systems, but focused on content delivery rather than collaborative model training.

This hybrid strategy significantly enhances scalability, adaptability, and robustness in dynamic vehicular networks.

III. Proposed Method

To address the challenges of high mobility, intermittent connectivity, and dynamic topology for the symbiotic task offloading at Vehicular edge networks, we propose Proximity-Aware Federated Learning (PA-FL). The proposed PA-FL enables decentralized model training through intelligent peer-to-peer interactions complemented by periodic synchronization with edge servers. This section presents a comprehensive mathematical formulation of PA-FL, detailing its three major components: (1) V2V model exchange, (2) adaptive proximity-based model aggregation, and (3) edge-assisted global synchronization.

Positioned within the broader vision of the symbiotic IoT for giant AI/ML in the 6G era to task offloading in vehicular edge, PA-FL represents a step toward achieving scalable, collaborative intelligence across heterogeneous vehicular edge environments. In this symbiotic ecosystem, vehicles act as intelligent agents capable of mutual learning, model sharing, and dynamic cooperation, laying the groundwork for the deployment of large-scale AI services. PA-FL leverages the distributed intelligence of Symbiotic IoT and the ubiquitous connectivity promised by 6G to enable resilient and adaptive learning architectures aligned with the demands of future autonomous and hyper-connected transportation systems. Figure 1 illustrates the proposed proximity-aware FL framework.

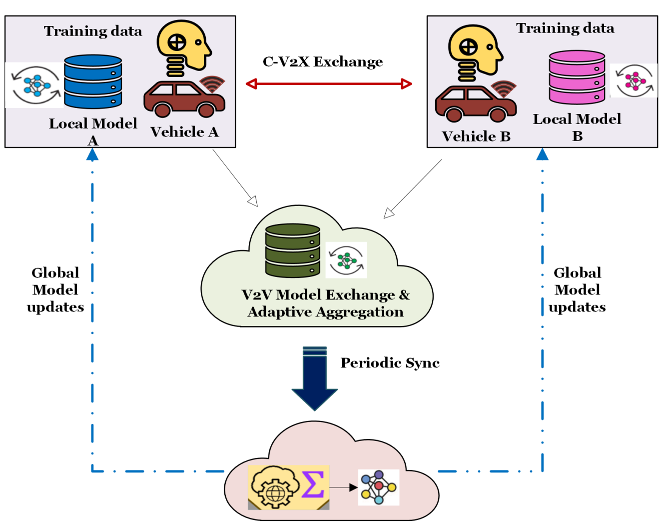

Fig. 1: Conceptual scheme of the proposed proximity-Aware Federated Learning (PA-FL) framework.

A. V2V Model Exchange via C-V2X

Let $\mathcal{V} = \{1, 2, \ldots, V\}$ denote the set of vehicles in the environment. At any time t, each vehicle $v \in \mathcal{V}$ holds a local model $\mathbf{w}_v^t \in \mathbb{R}^d$, where d is the model parameter dimension.

Each vehicle v broadcasts its model request $\mathcal{R}_v^t$ to all vehicles within a communication radius R, forming a neighbor set:

$$\mathcal{N}_v^t = \left\{ i \in \mathcal{V} \setminus \{v\} \,\middle|\, \left\|\mathbf{p}_v^t - \mathbf{p}_i^t\right\|_2 \leq R \right\} \tag{1}$$

where $\mathbf{p}_v^t \in \mathbb{R}^2$ is the spatial position of vehicle v at time t.

Each responding vehicle $i \in \mathcal{N}_v^t$ transmits its current model $\mathbf{w}_i^t$ along with metadata for stability estimation. A consensus filter $\phi(\cdot)$ is applied to received models to reject outdated or redundant updates:

$$\mathcal{M}_v^t = \left\{ \phi(\mathbf{w}_i^t, \tau_i^t) \,\middle|\, i \in \mathcal{N}_v^t \right\} \tag{2}$$

where τ_i^t encodes model age and metadata such as transmission success history.

B. Adaptive Proximity-based Model Aggregation

Given models from neighboring vehicles, each node v aggregates them based on a relevance score η_{vi}^t that captures both spatial and temporal dynamics:

$$\eta_{vi}^t = \lambda_1 \cdot \frac{1}{\|\mathbf{p}_v^t - \mathbf{p}_i^t\|_2} + \lambda_2 \cdot \frac{\mathcal{S}_i^t}{\max_{j \in \mathcal{N}_v^t} \mathcal{S}_j^t} \tag{3}$$

where $\lambda_1, \lambda_2 \in \mathbb{R}^+$ are trade-off parameters, and $\mathcal{S}_i^t$ is a composite stability score for neighbor i defined as:

$$\mathcal{S}_i^t = \frac{\gamma_1}{1 + \mathrm{Var}(\mathbf{v}_i^{[t-k,t]})} + \gamma_2 \cdot \hat{q}_i^t \tag{4}$$

Here,

- $\mathrm{Var}(\mathbf{v}_i^{[t-k,t]})$ is the temporal velocity variance of vehicle i over a sliding window of size k, representing motion consistency.
- $\hat{q}_i^t \in [0, 1]$ is the exponentially-weighted moving average of packet delivery success rate.
- γ_1 and γ_2 weigh the motion and communication components, respectively.

The normalized weights for aggregation are obtained via softmax:

$$\alpha_{vi}^t = \frac{\exp(\beta \eta_{vi}^t)}{\sum_{j \in \mathcal{N}_v^t} \exp(\beta \eta_{vj}^t)} \tag{5}$$

where $\beta \geq 0$ controls the sharpness of attention.

The updated local model at time $t+1$ is given by:

$$\mathbf{w}_v^{t+1} = \sum_{i \in \mathcal{N}_v^t} \alpha_{vi}^t \cdot \mathbf{w}_i^t \tag{6}$$

To ensure convergence properties, the aggregation can optionally incorporate a momentum term $\mu \in [0, 1]$:

$$\mathbf{w}_v^{t+1} = (1 - \mu) \cdot \mathbf{w}_v^t + \mu \cdot \sum_{i \in \mathcal{N}_v^t} \alpha_{vi}^t \cdot \mathbf{w}_i^t \tag{7}$$

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TABLE I: Comparison of PA-FL with related Federated Learning approaches in vehicular networks.

Paper	Core Contribution	V2V	Prox.-Agg.	Dyn. Sched.	Unique Strength
Zhang et al. (2023) [3]	General FL architecture for VEC	✗	✗	✗	Foundational overview
Xu et al. (2024) [29]	Task-incentive optimization	✗	✗	✓	Incentive design
Ganguly et al. (2022) [32]	Floating aggregation points	✗	✓	✓	Dynamic adaptation
Yan et al. (2023) [33]	V2V link scheduling	✓	✗	✓	GNN+RL latency model
Li et al. (2024) [35]	D2D for energy efficiency	✓	✗	✓	Energy-aware FL
Lin et al. (2021) [24]	Over-the-air aggregation	✗	✗	✗	Wireless robustness
Yan et al. (2024) [34]	V2V scheduling + FL	✓	✗	✓	Drift-plus-penalty scheduling
Taïk et al. (2022) [30]	Clustered aggregation	✓	✓	✗	Multi-task FL support
Bao et al. (2021) [37]	Client selection via fuzzy logic	✗	✓	✓	Velocity-based selection
Wang et al. (2024) [39]	FL for edge caching	✗	✗	✗	FL-based cache filtering
Su et al. (2024) [38]	Client selection in HFL	✗	✗	✓	Bandit-based CS
Li et al. (2021) [21]	FL + DQN for data sharing	✗	✗	✓	Collaborative learning
Xue et al. (2022) [36]	AirComp-based HFL	✗	✗	✓	Air-based aggregation
Our PA-FL	V2V proximity-aware FL	✓	✓	✓	Softmax-stable local aggregation

C. Edge-Assisted Global Synchronization

Let T_s be a global synchronization interval. At every t such that $t \mod T_s = 0$, vehicles transmit their current model $\mathbf{w}_v^t$ to the edge server. The edge aggregates the models using a weighted average:

$$\mathbf{w}_g^{t+1} = \sum_{v \in \mathcal{V}} \omega_v^t \cdot \mathbf{w}_v^t \tag{8}$$

where $\omega_v^t = \frac{n_v}{\sum_{u \in \mathcal{V}} n_u}$ reflects the data volume n_v used by each client.

The global model $\mathbf{w}_g^{t+1}$ is then disseminated back to all vehicles:

$$\mathbf{w}_v^{t+1} \leftarrow \mathbf{w}_g^{t+1}, \quad \forall v \in \mathcal{V} \tag{9}$$

Vehicles with unstable connections may defer participation in a given global round and resume in the next eligible round, ensuring resilience without stalling system-wide progress.

D. Convergence and Stability Considerations

Assuming convex loss functions and bounded gradient norms, the local model update with proximity-aware weights satisfies:

$$\mathbb{E}\left[\|\mathbf{w}_v^{t+1} - \mathbf{w}^*\|^2\right] \leq (1-\xi)\mathbb{E}\left[\|\mathbf{w}_v^{t} - \mathbf{w}^*\|^2\right] + \delta \tag{10}$$

where $\mathbf{w}^*$ is the optimal model, $\xi > 0$ is the contraction rate dependent on μ, β, and λ_i, and δ accounts for gradient noise and asynchronism.

This guarantees sublinear convergence under standard assumptions, enhanced by localized model exchange to improve empirical convergence speed in dynamic vehicular environments.

Algorithm 1 Proximity-Aware Federated Learning (PA-FL)

Initialize: Each vehicle $v \in \mathcal{V}$ initializes local model $\mathbf{w}_v^0$, defines communication radius R, synchronization interval T_s, and learning rate η.
for each communication round $t = 0, 1, 2, \dots$ **do**
  for each vehicle $v \in \mathcal{V}$ **in parallel do**
    Train model $\mathbf{w}_v^t$ using local data $\mathcal{D}_v$:
$$\mathbf{w}_v^t \leftarrow \mathbf{w}_v^t - \eta \nabla \ell(\mathbf{w}_v^t; \mathcal{D}_v)$$
    Identify neighbor set $\mathcal{N}_v^t = \{i \mid \|\mathbf{p}_v^t - \mathbf{p}_i^t\| \leq R\}$
    for each $i \in \mathcal{N}_v^t$ **do**
      Compute stability score $\mathcal{S}_i^t = \frac{\gamma_1}{1+\mathrm{Var}(\mathbf{v}_i)} + \gamma_2 \cdot \hat{q}_i^t$
      Compute relevance score:
$$\eta_{vi}^t = \lambda_1 \cdot \frac{1}{\|\mathbf{p}_v^t - \mathbf{p}_i^t\|} + \lambda_2 \cdot \frac{\mathcal{S}_i^t}{\max_j \mathcal{S}_j^t}$$
    end for
    Compute softmax weights $\alpha_{vi}^t = \frac{e^{\beta \eta_{vi}^t}}{\sum_{j \in \mathcal{N}_v^t} e^{\beta \eta_{vj}^t}}$
    Aggregate neighbor models:
$$\mathbf{w}_v^{t+1} = \sum_{i \in \mathcal{N}_v^t} \alpha_{vi}^t \cdot \mathbf{w}_i^t$$
    Optional momentum update:
$$\mathbf{w}_v^{t+1} \leftarrow (1-\mu) \cdot \mathbf{w}_v^t + \mu \cdot \mathbf{w}_v^{t+1}$$
  end for
  if $t \mod T_s = 0$ **then**
    Each vehicle v uploads $\mathbf{w}_v^{t+1}$ to edge server
    Edge server performs global aggregation:
$$\mathbf{w}_g^{t+1} = \sum_{v \in \mathcal{V}} \omega_v^t \cdot \mathbf{w}_v^{t+1}$$
    Broadcast $\mathbf{w}_g^{t+1}$ to all vehicles
    Each vehicle updates: $\mathbf{w}_v^{t+1} \leftarrow \mathbf{w}_g^{t+1}$
  end if
end for

IV. Experimental Setup and Results

In this section, we explained our experimental setup, data generation process based on 5G communication, and the baseline methods.

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TABLE II: Summary of mathematical symbols used in the PA-FL framework.

Symbol	Description
$\mathcal{V}$	Set of vehicles participating in the PA-FL system
V	Total number of vehicles
$\mathbf{w}_v^t$	Local model of vehicle v at communication round t
$\mathbf{w}_g^t$	Global model aggregated by the edge server at round t
d	Dimension of the model parameter vector
$\mathbf{p}_v^t$	2D spatial position of vehicle v at time t
R	Communication radius for V2V model exchange
$\mathcal{N}_v^t$	Set of neighboring vehicles within radius R of vehicle v at time t
$\phi(\cdot)$	Filter function to reject stale or redundant model updates
τ_i^t	Metadata (e.g., age, quality) of model received from neighbor i
$\mathcal{M}_v^t$	Set of filtered models received by vehicle v at time t
η_{vi}^t	Relevance score of neighbor i from the perspective of vehicle v at time t
λ_1, λ_2	Weights controlling influence of spatial proximity and stability
$\mathcal{S}_i^t$	Stability score of neighbor vehicle i at time t
γ_1, γ_2	Weights for motion and communication stability in $\mathcal{S}_i^t$
$\mathrm{Var}(\mathbf{v}_i^{[t-k,t]})$	Velocity variance of vehicle i over time window $[t-k, t]$
$\hat{q}_i^t$	Exponentially weighted average of packet delivery ratio for vehicle i
α_{vi}^t	Normalized weight assigned to neighbor i for model aggregation by v
β	Sharpness parameter for softmax weighting
μ	Momentum term controlling local model update smoothing
n_v	Local data sample size at vehicle v
ω_v^t	Aggregation weight based on n_v for edge server
T_s	Interval between global aggregation rounds
$F(\cdot)$	Global loss function
$f_v(\cdot)$	Local loss function of vehicle v
σ^2	Upper bound on variance of stochastic gradients
L	Smoothness constant for loss functions
$\mathbf{w}^*$	Optimal model that minimizes the global loss $F(\mathbf{w})$
δ	Convergence error term accounting for gradient noise/divergence
ξ	Learning contraction coefficient under convexity
k	Window size used to compute temporal velocity variance

A. Experimental Setup

To evaluate the proposed Proximity-Aware Federated Learning (PA-FL) method, we design a comprehensive simulation-based experiment using a real-time mobility-aware vehicular dataset. The simulation involves ten vehicular clients collaborating through proximity-driven V2V communication, periodically synchronized by an edge server.

We employ a lightweight feed-forward neural network (FFN), denoted as `SmallFFN`, implemented using the PyTorch deep learning framework[1]. The model is designed to reflect real-world vehicular constraints, providing an optimal trade-off between performance and computational efficiency. The architecture consists of three fully connected layers with batch normalization and dropout regularization.

The choice of small local epochs (2) reflects realistic constraints in vehicular edge learning, where rapid adaptation is needed with minimal compute. A communication radius of 2.0 units effectively models local interactions, and periodic synchronization ($T = 2$) with the edge server mitigates isolated learning issues. The λ and γ weights are set to emphasize proximity while considering temporal stability, which is crucial in mobile client scenarios. The softmax sharpness factor $\beta = 2.0$ enables controlled neighbor influence during aggregation, preventing overfitting to a single peer. A low learning rate ensures stable convergence over the 100-round simulation.

[1]https://pytorch.org

B. Dataset Generation Process

To simulate realistic vehicular edge computing (VEC) environments, we integrate the traffic simulator SUMO with EdgeCloudSim. This integration enables the modeling of multi-tier VEC systems where moving vehicles generate tasks that are offloaded to nearby edge data centers or to a central cloud. Our environment simulates vehicles running diverse applications while moving through an urban map of Cosenza, Italy. Vehicle mobility traces are generated using SUMO, guided by real-world road layouts extracted with `OSMWebWizard.py`. The Vodafone 5G base station configuration is used to enhance realism. EdgeCloudSim is responsible for simulating both computational and network aspects, while SUMO handles mobility traces.

Each vehicle is equipped with a load generator that initiates tasks characterized by:

- `VehicleID`, `TaskType`, `TaskLength`
- `UploadDelay`, `DownloadDelay` (5G channel)

Task types vary by complexity and inter-arrival rate:

- **Short Tasks** (e.g., navigation): High frequency
- **Medium Tasks** (e.g., infotainment): Moderate frequency
- **Long Tasks** (e.g., hazard detection): Low frequency

This variation captures realistic vehicular workloads and their impact on network and compute resources.

To generate the training dataset for machine learning models, a random orchestration policy is executed under diverse load conditions. The resulting synthetic dataset includes:

- `DeviceID`, `Timestamp`, `PathLoss`, `DistanceToEdge`, `SignalStrength`
- `GearboxPower`, `CPUUsage`, `Workload`, `TaskID`, `ExecutionLocation`
- `Upload/DownloadDelay (5G)`, `TaskStatus`

Additional metadata such as `HostID` helps assess resource allocation across edge nodes, while `TaskInputType` and `TaskLength` reflect data volume and computational demand, respectively.

To simulate wireless signal propagation realistically, we employ the 5G Closed-In (CI) path loss model. It accounts for both frequency and distance, yielding accurate latency and channel estimation critical for informed task offloading decisions.

$$PL_{\text{CI}}(f, d)\,[\text{dB}] = FSPL(f, 1\,\text{m})\,[\text{dB}] + 10n\log_{10}(d) + \chi_{\text{CI},\sigma} \tag{11}$$

$$FSPL(f, 1\,\text{m})\,[\text{dB}] = 20\log_{10}\left(\frac{4\pi f}{c}\right) \tag{12}$$

Here:

- $PL_{\text{CI}}(f, d)$ is the total path loss in dB.

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- $FSPL(f, 1\,\mathrm{m})$ is the free space path loss at 1 meter.
- n is the path loss exponent (PLE).
- $\chi_{\mathrm{CI},\sigma}$ represents the shadow fading with standard deviation σ.
- d is the transmitter-receiver distance, and f is the carrier frequency.

We simulate an Urban Micro-Cellular (UMi) Street Canyon (SC) scenario to represent dense metropolitan conditions. This enables robust modeling of non-line-of-sight (NLOS) instances, environmental obstructions, and high-mobility dynamics common in vehicular edge infrastructures.

By combining SUMO's mobility precision with EdgeCloudSim's compute-network modeling, we construct a comprehensive dataset reflecting dynamic vehicular edge environments. The dataset enables proximity-aware learning and supports evaluation of task offloading strategies under realistic 5G connectivity conditions.

TABLE III: Simulation Parameters

Parameter	Value
Task arrival time	3 / 5 / 15 sec
Task length	3 / 10 / 20
Type of application	Navigation / Danger / Infotainment
Upload/Download data size (KB)	20 / 20, 40 / 20, 20 / 80
Network delay model	MMPP/M/1 queue model

C. Baseline

To evaluate the effectiveness of PA-FL, we compare it with two baseline methods that capture different ends of the centralized-decentralized federated learning spectrum in vehicular environments.

1) DFL-DDS: Decentralized Federated Learning with Diversified Data Sources: The DFL-DDS algorithm [40] represents a fully decentralized FL paradigm where vehicles exchange model parameters directly with neighbors via V2V communication. To overcome the problem of limited data source diversity due to mobility constraints, each vehicle maintains a *state vector* $\mathbf{s}_k^t$ reflecting the contribution of each data source. The aggregation weights $\boldsymbol{\alpha}_k^t$ are optimized by minimizing the Kullback-Leibler (KL) divergence between the state vector and a uniform target distribution $\mathbf{g}$:

$$\min_{\boldsymbol{\alpha}_k^t} \mathrm{KL}(\mathbf{s}_k^t \| \mathbf{g}) = \sum_{i=1}^{K} s_{k,i}^t \log\left(\frac{s_{k,i}^t}{g_i}\right). \tag{13}$$

Although DFL-DDS improves model accuracy by diversifying the data sources, it does not consider vehicle proximity, dynamic mobility patterns, or edge server synchronization. PA-FL extends this approach with proximity-aware model exchange and stability-based aggregation, improving both robustness and convergence.

2) VEDS: V2V-Enhanced Dynamic Scheduling: VEDS [34] addresses FL in vehicular networks by introducing selective participation and relayed model transmission via opportunistic vehicles (OPVs). Each vehicle m performs local model updates using stochastic gradient descent (SGD) as:

$$\mathbf{w}_{m,k} = \mathbf{w}_{k-1} - \frac{\eta_k}{B_k} \sum_{\mathbf{x} \in \mathcal{B}_{m,k}} \nabla f(\mathbf{w}_{k-1}; \mathbf{x}), \tag{14}$$

where η_k is the learning rate and $\mathcal{B}_{m,k}$ is the local batch. After training, the edge server aggregates models as:

$$\mathbf{w}_k = \frac{\sum_{m \in \hat{\mathcal{S}}_k} |\mathcal{D}_m| \mathbf{w}_{m,k}}{\sum_{m \in \hat{\mathcal{S}}_k} |\mathcal{D}_m|}. \tag{15}$$

Although VEDS enables model transmission through relays, it lacks a direct mechanism to adaptively account for mobility or proximity in aggregation. PA-FL builds on this by integrating stability-aware V2V selection and periodic edge-assisted synchronization to mitigate such issues.

These baselines cover both centralized (edge-assisted) and decentralized (V2V-based) FL paradigms. By outperforming DFL-DDS (decentralized, proximity-agnostic) and VEDS (centralized with relaying).

D. Performance Evaluation

We evaluate the performance of our proposed PA-FL framework against state-of-the-art distributed federated learning approaches, including DFL-DDS by Su et al. [40], DynSched-FL by Zhang et al. [3], and the adaptive aggregation method by Yan et al. [34]. The evaluation covers core metrics such as classification accuracy, precision, recall, F1 score, communication delay, average neighbors per round, and energy consumption — all critical for symbiotic task offloading in Vehicular Edge Intelligence.

Table V presents the overall performance comparison. PA-FL achieves the highest classification accuracy at **87.08%** with a notably low standard deviation of **±0.49**, highlighting its consistency across communication rounds. This represents a relative improvement of over **13% in accuracy** and **11% in F1 score** compared to DFL-DDS, demonstrating PA-FL's strong generalization and robustness in dynamic vehicular scenarios.

These gains stem from PA-FL's core architectural strength: its proximity-aware, stability-sensitive aggregation mechanism. By dynamically adjusting aggregation weights based on vehicular movement and peer stability, PA-FL adapts more effectively than baselines that rely on static or overly reactive communication schedules.

Figure 2 shows that PA-FL maintains superior accuracy over 100 communication rounds. The baselines suffer from fluctuating trends due to limited neighborhood awareness or fixed update intervals. In contrast, PA-FL sustains high accuracy by selectively prioritizing meaningful V2V interactions.

Figure 3 illustrates the average number of neighbors participating in aggregation. With a consistent engagement of **0.98** $\pm$ **0.44**, PA-FL leverages diverse and timely neighbor inputs, accelerating convergence and enhancing learning diversity without introducing communication bottlenecks. Higher average neighbors (approximately one peer per round) indicate that most vehicles are engaged in collaborative updates rather than isolated learning. This stable and efficient peer connectivity is critical in highly dynamic vehicular environments where link quality and peer presence can vary significantly.

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TABLE IV: Summary of Dataset Generation in VEC Simulation

Field	Source Component	Purpose / Description
VehicleID, DeviceID	SUMO, EdgeCloudSim	Unique identifiers for each mobile client (vehicle)
TaskType, TaskLength, TaskID	Load Generator	Defines computational load and ID for each task
UploadDelay, DownloadDelay	5G Channel Model	Captures network latency for each transmission
SignalStrength, PathLoss, DistanceToEdge	Propagation Model (5G CI)	Reflects wireless signal quality and location-specific effects
CPUUsage, GearboxPower, Workload	EdgeCloudSim	Describes resource state and energy usage of client
ExecutionLocation, TaskStatus	Orchestration Policy	Indicates whether the task was executed locally or offloaded; tracks success/failure
Timestamp	SUMO, EdgeCloudSim	Synchronizes events and mobility context
HostID	EdgeCloudSim	Identifies the edge node handling the task
TaskInputType	Task Generator	Specifies input format (e.g., video, sensor) to infer data volume

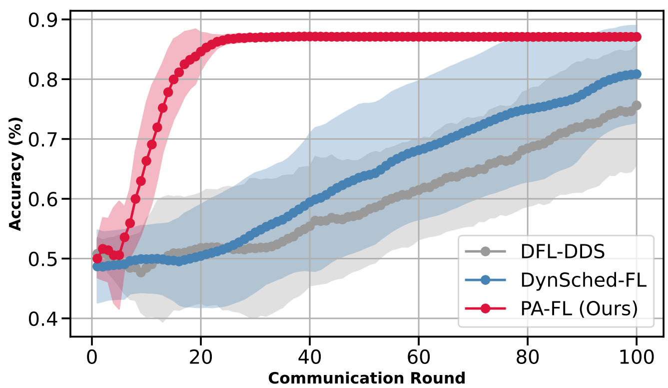

Fig. 2: Accuracy trend over 100 communication rounds for PA-FL and the DFL-DDS.

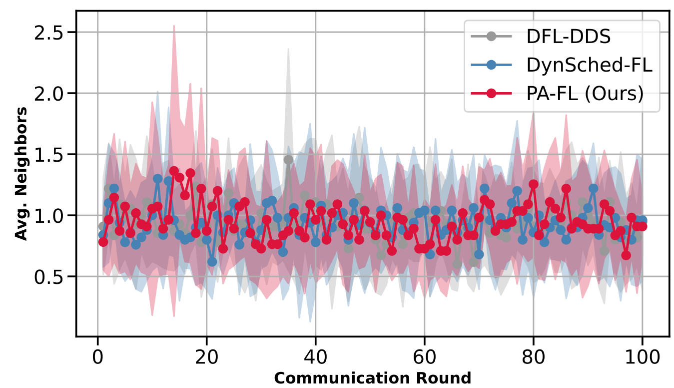

Fig. 3: Average number of neighbors per round.

To examine classification reliability, we compare confusion matrices averaged over 10 runs in **Figure 4**. PA-FL shows superior classification on both classes. Particularly for the minority class (True = 1), PA-FL achieves a recognition rate of **71.69% ± 0.56** versus only **62.03%** in the DFL-DDS baseline. This boost confirms the advantage of our V2V aggregation, which captures richer contextual patterns and reduces bias toward majority classes.

Figure 5 examines the impact of communication proximity on task offloading outcomes. PA-FL shows lower task failure rates across all six proximity bins–especially beyond 200 meters–while DFL-DDS and DynSched-FL degrade rapidly. These results highlight PA-FL's ability to intelligently avoid weak links, ensuring high task success in variable topologies.

Figure 6 confirms PA-FL's runtime efficiency. It maintains an average per-round delay of only **0.85 seconds**, well below real-time thresholds, and achieves the lowest energy footprint of **0.038J**, nearly **6× more efficient** than other methods. Such minimal energy cost ensures that PA-FL is viable for deployment even in constrained edge devices or electric vehicles with limited power budgets.

These combined results confirm that PA-FL is not only a high-performing learning framework but also a lightweight and scalable solution tailored for real-time, resource-constrained vehicular edge intelligence.

E. Ablation Studies

To better understand the contribution of our proximity-aware optimization strategy, we conduct an ablation study under identical experimental settings. In this setting, we disable the proximity-based V2V filtering mechanism and use only a basic weighted averaging scheme as proposed in Zhang et al. (2023) [3]. This allows us to isolate the effect of our selective, stability-sensitive aggregation method.

As shown in the results, the simplified version still achieves competitive performance: **81.00** $\pm$ **2.72** (Accuracy), **79.03** $\pm$ **3.35** (Precision), **78.46** $\pm$ **3.58** (Recall), and **78.31** $\pm$ **3.63** (F1 Score). However, the variance is notably higher across all metrics compared to PA-FL, indicating reduced stability in learning convergence.

Moreover, the simplified version incurs higher average latency (**1.07** $\pm$ **0.31 s**) and greater energy consumption (**0.217** $\pm$ **0.030 J**), similar to traditional methods. These observations reinforce the significance of proximity-guided selection, which not only enhances predictive performance but also improves efficiency and communication reliability.

This ablation confirms that the core strength of PA-FL lies in its ability to adaptively exploit V2V dynamics for stable, energy-efficient, and high-quality model training.

V. Discussion and Limitations

The experimental results demonstrate that PA-FL consistently outperforms baseline approaches across multiple performance dimensions, including predictive accuracy, communication efficiency, and task offloading reliability. These gains

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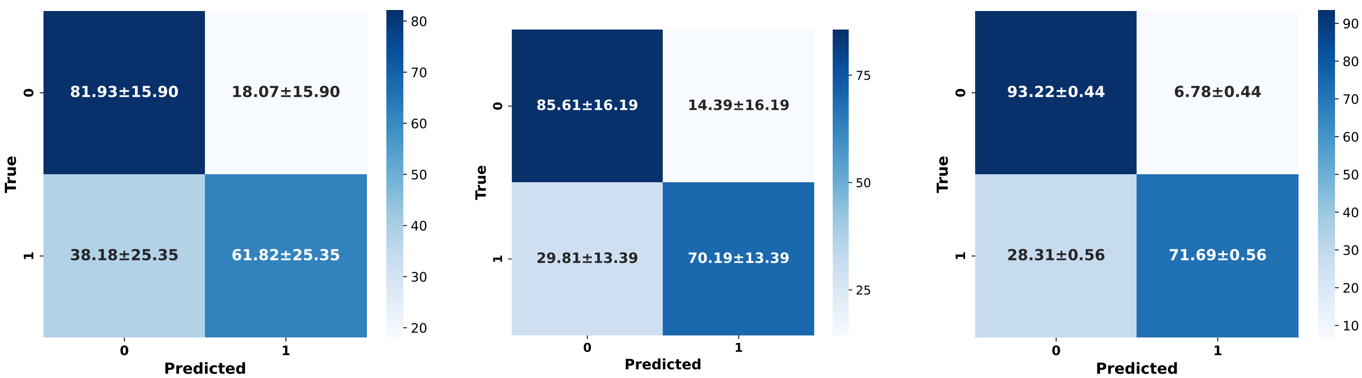
TABLE V: Performance Comparison.

Method	Accuracy (%)	Precision	Recall	F1 Score	Avg. Neighbors	Delay (s)	Avg. Energy (J)
Su et al (2022) [40]	73.81 ± 8.50	73.21 ± 15.74	72.87 ± 9.23	71.17 ± 12.97	0.87 ± 0.40	1.03 ± 0.28	0.220 ± 0.028
Yan et al (2024) [34]	80.85 ± 8.11	81.59 ± 4.24	77.38 ± 5.72	77.47 ± 7.04	0.95 ± 0.45	1.01 ± 0.30	0.220 ± 0.031
PA-FL (Ours)	**87.08 ± 0.49**	**84.86 ± 0.36**	**82.47 ± 0.34**	**82.92 ± 0.35**	**0.98 ± 0.44**	**0.85 ± 0.020**	**0.038 ± 0.003**



(a) DFL-DDS (b) DynSched-FL (c) PA-FL (ours)

Fig. 4: Confusion matrices showing the mean ± standard deviation of classification results over 10 experimental runs. Each cell is the averaged prediction percentage ± variability across rounds. PA-FL demonstrates stronger consistency and higher classification reliability, especially on the minority class (True = 1), compared to the DFL-DDS and DynSched-FL baselines. These results highlight the robustness and stability of our proximity-aware aggregation mechanism under vehicular mobility.

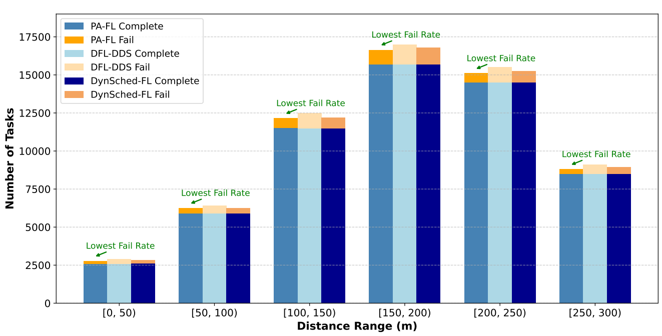


Fig. 5: Task offloading outcomes across varying proximity ranges for PA-FL (ours) and the DFL-DDS baseline. Each stacked bar represents the number of successfully completed and failed tasks within a specific distance bin. PA-FL consistently achieves lower failure rates highlighted with green annotations compared to DFL-DDS, particularly in longer distance intervals.

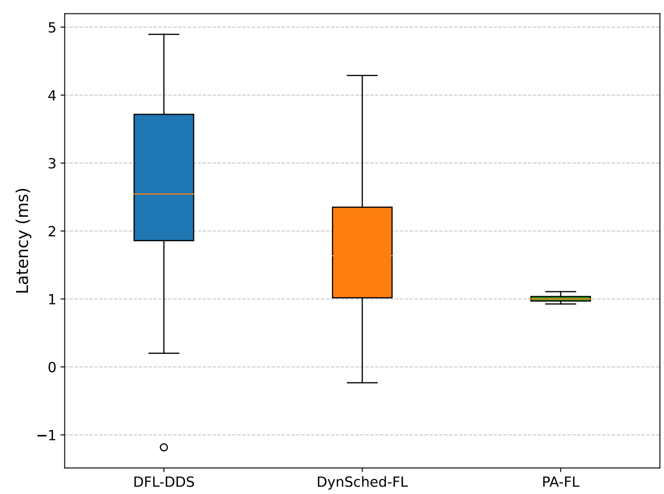


Fig. 6: Average communication delay per round. PA-FL consistently achieves sub-second latency, validating its suitability for real-time 5G-based vehicular edge applications.

are directly attributable to the integration of V2V-based model aggregation, adaptive neighbor scoring, and periodic edge synchronization. Together, these components allow PA-FL to make context-aware learning and offloading decisions, even under the constraints of high vehicular mobility.

As shown in Table V, PA-FL achieves the highest accuracy and lowest variance across all evaluation metrics, underscoring its learning stability. Figure 4 further illustrates PA-FL's robustness in classification, especially in the identification of minority-class events. Compared to DFL-DDS and other baselines, PA-FL demonstrates improved model generalization across all classes. Additionally, Figure 5 highlights that PA-FL experiences significantly fewer task failures across proximity ranges, confirming its capacity to adapt aggregation decisions based on dynamic link stability and spatial context.

One key advantage of PA-FL is that it inherits the privacy-preserving nature of federated learning. Since raw data never leaves the client vehicles, privacy-sensitive information such as location traces and sensor logs remains secure. However, like all FL systems, PA-FL still relies on periodic model exchanges, which may introduce indirect risks such as model inversion or poisoning if adversaries manipulate the aggregation pro-

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cess. While our current method mitigates these risks through selective neighbor scoring, stronger defenses such as secure aggregation or differential privacy remain areas for future integration.

Despite these advantages, PA-FL has several limitations. First, it currently deploys a single global model across all vehicles, without any personalization. In highly heterogeneous environments–where preferences, data distributions, or hardware constraints differ this may lead to suboptimal local performance. Future extensions could incorporate local fine-tuning or meta-learning to address this challenge.

Second, the system uses a static communication radius (R) to determine V2V neighbors, which may not be optimal in dynamic traffic conditions. More adaptive strategies, such as energy-aware or mobility-aware peer selection, may offer improved efficiency and stability in real deployments. Third, PA-FL does not include topology-aware communication or model compression techniques. As a result, it may experience unnecessary communication overhead in large-scale networks. Recent works have shown that integrating compression and dynamic peer graph formation can reduce overhead without compromising accuracy.

Additionally, while PA-FL achieves high overall accuracy, it does not explicitly address class imbalance, which is common in safety-critical applications such as anomaly or rare-event detection. Synthetic oversampling or localized rebalancing techniques could further enhance minority class recall. Finally, proximity alone does not fully explain optimal offloading decisions, especially when the edge and cloud options have overlapping distance profiles. This suggests that additional contextual information, such as queue lengths, compute availability, or energy cost, should be considered to refine offloading logic.

These limitations reveal key opportunities to enhance PA-FL's personalization, adaptability, and robustness in real-world vehicular edge intelligence systems.

VI. Conclusions and Future Work

This paper introduced **Proximity-Aware Federated Learning (PA-FL)**, a novel framework tailored for symbiotic task offloading in 6G-enabled vehicular edge networks. PA-FL adapts the model aggregation process by incorporating spatiotemporal proximity and link stability into client selection, thereby aligning collaborative learning more closely with real-world mobility dynamics. In contrast to conventional federated schemes that rely on static schedules or periodic synchronization, PA-FL leverages dynamic V2V interactions to enable more responsive and contextually relevant updates.

Extensive empirical evaluations demonstrate that PA-FL consistently outperforms state-of-the-art DFL approaches in terms of classification accuracy, energy efficiency, task success rate, latency, and convergence stability. Through both full-system experiments and controlled ablation studies, we show that these improvements stem not from peripheral enhancements but from the core proximity-aware design. By enabling localized, high-quality collaboration while maintaining global consistency via periodic edge synchronization, PA-FL balances scalability, reliability, and resource efficiency. As intelligent vehicular networks evolve toward decentralized and self-adaptive systems, PA-FL provides a critical foundation for collaborative AI at the edge. It supports the emergence of symbiotic IoT ecosystems in which autonomous agents can learn continuously, adapt to their surroundings, and share knowledge through communication-efficient federated learning.

Future work will focus on extending PA-FL to support heterogeneous model architectures, integrating privacy-preserving mechanisms such as secure aggregation and differential privacy, and validating its performance through large-scale real-world deployments across varied urban and rural mobility scenarios. We also envision incorporating cross-domain adaptation techniques to improve transferability in unseen environments and context-aware offloading policies for fine-grained execution control. Ultimately, PA-FL moves us closer to realizing the vision of distributed intelligence for next-generation transportation systems, where collaborative learning becomes a native capability of connected vehicles and edge infrastructure.

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APPENDIX

A. Proof of Model Aggregation Convergence

We aim to show that the proximity-aware local aggregation rule converges under convexity assumptions.

a) Assumptions:

- Each local loss function $f_v(\mathbf{w})$ is convex and L-smooth, i.e.,

$$\|\nabla f_v(\mathbf{w}_1) - \nabla f_v(\mathbf{w}_2)\| \leq L\|\mathbf{w}_1 - \mathbf{w}_2\| \quad (16)$$

- The variance of stochastic gradients is bounded: $\mathbb{E}\|\nabla f_v(\mathbf{w}) - \nabla F(\mathbf{w})\|^2 \leq \sigma^2$.
- The optimal solution $\mathbf{w}^*$ minimizes the global loss:

$$F(\mathbf{w}) = \sum_{v \in \mathcal{V}} \omega_v f_v(\mathbf{w}) \quad (17)$$

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b) Goal: Show that the proximity-aware update rule:

$$\mathbf{w}_v^{t+1} = (1-\mu)\cdot \mathbf{w}_v^t + \mu \cdot \sum_{i\in\mathcal{N}_v^t} \alpha_{vi}^t \cdot \mathbf{w}_i^t \tag{18}$$

converges in expectation to the optimal model $\mathbf{w}^*$.

c) Sketch of Proof: Let $\bar{\mathbf{w}}^t = \sum_{v\in\mathcal{V}} \omega_v \mathbf{w}_v^t$ be the weighted average of local models.

By convexity and Jensen's inequality:

$$F(\bar{\mathbf{w}}^t) \le \sum_{v\in\mathcal{V}} \omega_v f_v(\mathbf{w}_v^t) \tag{19}$$

Now, using the L-smoothness of each f_v, we expand the distance to optimality:

$$\begin{aligned}\mathbb{E}\left[\|\bar{\mathbf{w}}^{t+1} - \mathbf{w}^*\|^2\right] &= \mathbb{E}\left[\left\|\bar{\mathbf{w}}^t - \mathbf{w}^* + (\bar{\mathbf{w}}^{t+1} - \bar{\mathbf{w}}^t)\right\|^2\right] \\ &\le \mathbb{E}\left[\|\bar{\mathbf{w}}^t - \mathbf{w}^*\|^2\right] - 2\mu\xi \cdot \mathbb{E}[F(\bar{\mathbf{w}}^t) - \\ &\quad F(\mathbf{w}^*)] + \mu^2\delta\end{aligned} \tag{20}$$

for some $\xi > 0$ (related to convexity) and δ bounded by model divergence across neighbors.

Using recursion, we get:

$$\mathbb{E}\left[F(\bar{\mathbf{w}}^t) - F(\mathbf{w}^*)\right] \le \frac{C}{t} \tag{21}$$

This implies that under diminishing step sizes or fixed small μ, the local models collectively converge to a neighborhood of $\mathbf{w}^*$.

B. Proof of Stability Score Boundedness

Given:

$$\mathcal{S}_i^t = \frac{\gamma_1}{1 + \mathrm{Var}(\mathbf{v}_i^{[t-k,t]})} + \gamma_2 \cdot \hat{q}_i^t \tag{22}$$

a) Claim: $\mathcal{S}_i^t$ is bounded within the interval $\left[\frac{\gamma_1}{1+\sigma_{\max}^2}, \gamma_1+\gamma_2\right]$.

b) Proof:

- Since $\mathrm{Var}(\cdot) \in [0, \sigma_{\max}^2]$, the first term satisfies:

$$\frac{\gamma_1}{1+\sigma_{\max}^2} \le \frac{\gamma_1}{1+\mathrm{Var}(\mathbf{v}_i)} \le \gamma_1 \tag{23}$$

- Since $\hat{q}_i^t \in [0,1]$, the second term is bounded by:

$$0 \le \gamma_2 \cdot \hat{q}_i^t \le \gamma_2 \tag{24}$$

Adding both gives:

$$\frac{\gamma_1}{1+\sigma_{\max}^2} \le \mathcal{S}_i^t \le \gamma_1 + \gamma_2 \tag{25}$$

C. Softmax Weight Normalization

Given:

$$\alpha_{vi}^t = \frac{\exp(\beta\eta_{vi}^t)}{\sum_{j\in\mathcal{N}_v^t} \exp(\beta\eta_{vj}^t)} \tag{26}$$

a) Claim: $\sum_{i\in\mathcal{N}_v^t} \alpha_{vi}^t = 1$ and $\alpha_{vi}^t \in (0,1)$.

b) Proof: The softmax function is a standard, normalized exponential function. Since all $\exp(\cdot) > 0$ for real inputs, all $\alpha_{vi}^t > 0$. By construction:

$$\sum_{i\in\mathcal{N}_v^t} \alpha_{vi}^t = \frac{\sum_i \exp(\beta\eta_{vi}^t)}{\sum_j \exp(\beta\eta_{vj}^t)} = 1 \tag{27}$$

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