Robust Wireless Distributed Learning Empowered by Thz Communications Data for Internet of Unmanned Vehicles Agents: Efficient Cluster Driving Decision-Making

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***Abstract*—With the rapid development of the Internet of Unmanned Vehicles Agents (IUVA), efficient and secure communication has become a key requirement. However, unstable wireless channel conditions pose several challenges to existing Wireless Distributed Learning (WDL) in the IUVA environment. First, the parameter transmission of WDL in the IUVA will be interfered by dynamic changes in vehicle position, which will affect the training accuracy and the loss of the learning model. Second, increased communication overhead due to the large amount of data generated by vehicles sensors, and third is the complexity of making real-time driving decisions with diverse vehicle data. This paper presents an innovative WDL framework based on Terahertz (Thz) communication technology, addressing communication and data processing challenges in the IUVA environment. Our framework designs a Thz communication encoding method, treating each vehicle as a local model node participating in the WDL process. First, we established a IUVA cluster based on Thz communication, addressing the current issues of high latency and low efficiency in IUVA communications. Second, we designed a WDL framework where vehicles within the IUVA act as distributed learning participants, reducing communication overhead in IUVA wireless communication. Finally, our proposed wireless distributed driving decision-Making model leverages the physical parameters of participating vehicles to derive collective driving decisions for the IUVA cluster, enhancing the accuracy of IUVA driving decisions. Overall, the framework proposed in this paper provides a new approach for achieving efficient and secure IUVA communication and contributes significantly to intelligent unmanned decision-making in IUVA.**

***Index Terms*—Internet of Unmanned Vehicles Agents, Wireless Distributed Learning, Terahertz Communication, Intelligent Traffic Management System**

I. Introduction

A. Background

In the era of unmanned systems, the Internet of Unmanned Vehicles Agents (IUVA) is becoming central to autonomous transportation and intelligent traffic management systems. The interaction between vehicles, road infrastructure, and decision-making agents is crucial for improving road safety, optimizing traffic flow, and advancing smart cities. However, these systems depend heavily on secure and efficient communication technologies, particularly in environments that involve unmanned agents. Traditional wireless communication technologies, such as Wi-Fi, 5G, and Dedicated Short-Range Communications (DSRC), face significant challenges in Internet of Unmanned Vehicle Agents (IUVA) environments. These challenges include limited bandwidth, high latency, and network congestion, which become bottlenecks for real-time data transmission and decision-making in highly dynamic vehicular networks. Such limitations hinder the ability to support applications requiring large-scale data exchanges and frequent model updates, such as Wireless Federated Learning (WFL).

Terahertz (THz) communication, with its ultra-high bandwidth and low latency, offers a promising solution to these issues. Although its short propagation range limits its use to localized scenarios, it is particularly well-suited for high-speed, short-distance communication between vehicles operating in dynamic clusters. These characteristics make THz communication ideal for enabling efficient and timely synchronization of model updates in WFL, thereby ensuring real-time collaborative decision-making while maintaining data privacy.

The high-speed and low-latency characteristics of THz Communication align seamlessly with the requirements of WFL, where timely synchronization of model updates is critical.

Simultaneously, as a typical representative of distributed learning, WFL supports distributed learning across vehicles while preserving data privacy by ensuring raw data remains local. Only model updates are transmitted, reducing the risks of centralized storage and data breaches.

Integrating THz Communication with WFL introduces innovative opportunities to address the challenges of IUVA operations, particularly in real-time collaborative decision-making. Traditional wireless methods, which suffer from latency and bandwidth limitations, often fail to meet the stringent requirements of real-time distributed learning in IUVA. By leveraging THz communication's high data rate and low transmission delay, our framework enables vehicles to exchange model updates efficiently and collaboratively train driving decision

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models. This integration significantly reduces communication delays, enhances the learning process, and optimizes the system's ability to make accurate, real-time driving decisions in dynamic vehicular environments.

In our proposed framework, WFL ensures that raw sensor data remains strictly local to each vehicle, and only model updates are transmitted over the THz communication channel. This design leverages the ultra-high data rate and low latency of THz communication to facilitate efficient and timely model synchronization among vehicles while inherently protecting data privacy. By combining the advantages of WFL and THz communication, our framework ensures secure, decentralized collaborative learning while addressing the challenges of high-speed vehicular environments and dynamic network conditions.

The exploration of intelligent transportation systems has evolved significantly with the concurrent advancements in the IUVA [1], [2], [3], Terahertz (Thz) communication [4], [5], [6], [7], , [8], [9]and Wireless Federated Learning technologies [10], [11], [12], [13]. Originating from vehicle information systems in the 1990s, IUVA has transformed into a comprehensive network, integrating vehicles with road infrastructure, pedestrians, and internet services. This evolution has substantially propelled the development of intelligent traffic management [14], [15], [16], [17], [18], [19], [20] and advanced driver-assistance systems [21], [22], leading to marked improvements in road safety and traffic efficiency. The application of Wireless Federated Learning in IUVA can significantly enhance the efficiency and quality of data processing and decision-making. By processing data locally on vehicles, federated learning models can share knowledge without exposing user privacy. However, the high dynamism and heterogeneity of vehicular networks pose challenges to federated learning. For instance, the joining and departure of vehicles can cause uneven data distribution, affecting the accuracy of the model. Additionally, federated learning requires frequent exchange of model parameters between vehicles, imposing demands on the bandwidth and stability of wireless networks. Therefore, researching how to optimize federated learning algorithms to adapt to the characteristics of vehicular networks is key.

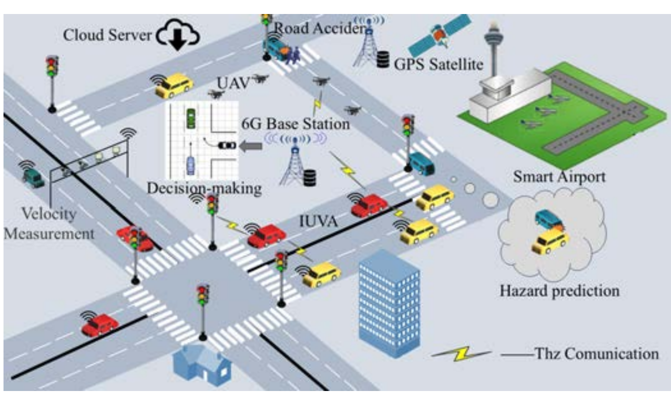


Fig. 1: Knowledge exchange by wireless transmission in IUVA.

The advent of Terahertz communication technology [23] has opened new possibilities for data transmission within IUVA. Occupying the spectrum between microwaves and infrared waves, Terahertz band possesses unique physical properties such as ultra-wide bandwidth and high frequency, supporting extremely high-speed data transfers. Despite its relatively short propagation range, the efficiency of Terahertz communication in short distances is particularly suited for rapid data exchange between vehicles, thus providing a technological basis for real-time traffic information sharing and high-speed data processing. However, Terahertz communication also faces several limitations. Its high path loss and short propagation range constrain its application to localized scenarios, such as communication within clusters of vehicles. Additionally, THz signals are highly susceptible to environmental factors like atmospheric absorption and physical obstructions, which can significantly degrade signal quality and reliability. These challenges necessitate careful base station deployment and advanced signal processing techniques to mitigate environmental impacts. Addressing these limitations is critical to ensuring stable and efficient communication in the highly dynamic environments of IUVA. To enhance the feasibility of THz communication deployment in real-world scenarios, several practical strategies can be implemented. Advanced beamforming techniques can focus signal strength and reduce path loss, while relay-assisted communication and multi-hop networking can extend the effective range of THz signals. Strategic placement of base stations and dynamic cluster management further mitigate the impact of environmental factors, ensuring reliable data transmission even in challenging vehicular environments. By addressing these challenges, our framework effectively combines the high-speed and low-latency benefits of THz communication with solutions that enhance its practical applicability in IUVA systems.

In IUVA applications, this means that large amounts of data from vehicle sensors, such as video monitoring, radar scanning, and environmental perception information, can be processed in real-time. This is vital for advanced driver-assistance systems (ADAS), autonomous driving, and fleet management. However, technical challenges of Terahertz Communication, such as its weak signal penetration capability and susceptibility to atmospheric absorption, necessitate careful planning of base station layouts and signal attenuation compensation strategies in urban and highway environments.

Simultaneously, the emergence of Wireless Federated Learning has introduced a new paradigm in data processing and intelligent decision-making in IUVA [24], [25], [26]. This distributed learning approach allows multiple nodes, like vehicles and traffic signals, to collaboratively train and update shared models while maintaining data privacy. This not only reduces reliance on central servers and lessens bandwidth demands for data transmission but also enhances the system's scalability and adaptability. And in the IUVA context, this implies that various vehicles can share traffic patterns, road conditions, and driving behavior models while safeguarding individual privacy. However, implementing effective federated learning requires addressing issues like uneven data distribution, unstable participation of nodes, and limitations in computational resources.Consequently, IUVA can more effectively process a large volume of dynamically changing data and achieve more precise intelligent decision-making.

Combining Terahertz Communication with Wireless Federated Learning provides a new perspective for data processing and decision-making in IUVA. Utilizing the high bandwidth and low latency characteristics of Terahertz Communication, a large volume of data generated by vehicles can be transmitted quickly, supporting the rapid model training and updating of Wireless Federated Learning. At the same time, the distributed nature of federated learning helps to alleviate the network load of Terahertz Communication. By processing data locally and learning on-site, it reduces the need for centralized data storage and processing. However, this integration also presents new challenges, such as how to coordinate resource allocation and scheduling between Terahertz Communication and federated learning, and how to ensure learning efficiency a nd model accuracy in dynamically changing network environments.

In summary, the real-time information exchange capabilities of IUVA, the high-speed data transmission properties of Terahertz communication, and the distributed intelligent processing ability of Wireless Federated Learning collectively provide a solid technological foundation for building a more efficient and safer intelligent transportation system. The integration of these technologies not only optimizes traffic management and network operational efficiency b ut a lso p lays a c rucial role in enhancing road safety and supporting the development of smart cities.

Implementing efficient Terahertz Communication and Wireless Federated Learning in the IUVA environment faces a series of challenges. First, the speed of vehicular networking communication is affected by various factors, such as signal interference, physical obstacles, vehicle density, mobility, and communication distance. Second, Thz communication is the foundation of intelligent and assisted driving, and the accuracy of driving decisions can be affected by Thz communication. Finally, in different scenarios of vehicle networks, such as urban road or highway scenarios, the stability of Vehicle-to-Vehicle communication will affect the performance of driving decisions.

This paper introduces a framework that integrates Terahertz Communication and Wireless Federated Learning (WFL) in the Internet of Unmanned Vehicle Agents (IUVA). By combining these two advanced technologies, the framework effectively addresses the unique challenges of IUVA systems, including high-bandwidth communication demands, real-time decision-making, and the need for privacy-preserving data exchanges. While traditional approaches tend to treat Terahertz Communication and Federated Learning independently, this work brings them together to enhance communication performance while enabling decentralized, privacy-conscious decision-making. The integration of Terahertz Communication helps to mitigate issues of latency and optimize data transmission, whereas Wireless Federated Learning facilitates distributed learning without the need for sharing raw data. This dual approach proves particularly advantageous in overcoming the challenges of intermittent connectivity and high latency that are common in dynamic vehicular environments. Through comprehensive theoretical analysis and extensive simulation studies, we demonstrate that this framework offers substantial improvements in the intelligence, efficiency, and security of IUVA systems when compared to existing solutions.

The key innovations of this paper lie in the integration of Terahertz (THz) communication and Wireless Federated Learning (WFL) to address the unique challenges of the Internet of Unmanned Vehicle Agents (IUVA). Unlike existing approaches, our framework leverages THz communication to establish efficient IUVA clusters, reducing latency and ensuring stable data transmission in high-mobility environments through an innovative encoding method. Additionally, the WFL framework enables vehicles to participate in distributed learning as local nodes, effectively reducing communication overhead while maintaining scalability and optimizing the processing of large volumes of sensor data. By introducing a wireless distributed driving decision-making model, we utilize collective learning from vehicle parameters to enhance the accuracy and safety of driving decisions. This comprehensive approach not only addresses real-time decision-making complexities but also ensures robust performance and reliability in dynamic IUVA environments.

The remainder of this article is organized as follows. In section II we will introduce recent related works about Thz communication, WFL and IUVA. Section III we will introduce the system model of our Thz communication empowered WFL driving decision making framework. Section IV shows the algorithm we designed to implement the Thz communication empowered WFL driving decision making framework. In Section V we designed experiments to simulate two real IUVA environments (urban environment and highway environment), compared the latency of different IUVA communication methods, and trained to obtain the loss of the driving decision model of every vehicle involved in the learning as well as the performance parameters of the global model. Finally, Section VI concludes this paper and points out future work.

II. RELATED WORK

With the development of the Sixth Generation (6G) wireless communication technology [27], [28]and the Internet of Vehicles (IUVA), Terahertz (Thz) communication and Wireless Federated Learning (WFL) have emerged as cutting-edge technologies to support high-speed data transmission and intelligent decision-making [29]. Despite significant progress in research in recent years, challenges remain in effectively integrating these technologies.

The [30] introduces the concept of leveraging the Thz frequency band to enhance federated learning communication in the 6G context. It delves into the propagation characteristics and link design of Thz communication, highlighting its potential to increase data transmission rates. However, it provides limited information on implementing efficient data transmission and intelligent decision-making in dynamic IUVA environments.

The [31] introduces a Federated Multi-Task Learning (FMTL) strategy to address the complexity of Thz channel estimation, showcasing the potential to improve communication efficiency while protecting privacy. By sharing model parameters instead of raw data, the study optimizes the data transmission process. Although this method makes progress in channel estimation and beam-split correction, it lacks a comprehensive exploration of how to effectively integrate WFL in complex IUVA networks to enhance the overall data processing and decision-making capabilities of the system.

In [32], researchers explore the performance of vertical networks deploying hybrid FSO/sub-Thz links in IUVA. The study provides a comprehensive analytical framework by considering soft and hard switching schemes to improve the last-mile access performance. Despite offering valuable insights into the physical layer and upper-layer performance assessment, discussions on how to effectively integrate federated learning in IUVA to optimize the intelligent decision process are still missing.

The [33] discusses how intelligent edge computing can reduce data transmission and response latency in IUVA, offering a new method for processing deep learning tasks. By processing data locally on vehicles, the study proposes a strategy to alleviate the network transmission burden and response time. However, while providing solutions to reduce data transmission, it does not detail how to combine Thz communication and WFL to further optimize data transmission efficiency and intelligent decision-making capability in the IUVA system.

In [34], a multi-UAV decision-making framework is introduced for mission planning, focusing on autonomous decision-making in the face of unexpected disruptions. The approach integrates real-time task scheduling and resource management to optimize mission completion, but it does not consider the challenges posed by the communication and data processing requirements in dynamic, large-scale UAV networks. In contrast, our research leverages robust wireless distributed learning and Terahertz (THz) communications to improve decision-making efficiency for unmanned vehicle agents, addressing these communication bottlenecks in real-time mission execution.

In [35], the authors propose a dynamic resource allocation strategy for AR services in the IoV, focusing on minimizing latency and enhancing energy efficiency. While this study highlights the importance of resource optimization for AR in IoV, it does not address the challenges of safe decision-making in real-time interactions, which is a key focus of our work.

In [36], a swarm intelligence model inspired by pigeon flock behavior is used for coordinating UAVs in complex environments. While the model enhances collaboration and communication among UAVs, it does not incorporate the resilience-oriented recovery strategies that are critical for maintaining operational continuity during unexpected disruptions.

These studies reveal the intricacies of THz communication and the potential of ML in enhancing system performance. However, they also point out the shortcomings like the need for more adaptable network topologies and efficient handover strategies, underlining the complexity of implementing THz communication in dynamic environments like IUVA. Incorporating these insights into your paper can provide a comprehensive understanding of the current state of research and identify areas where your work contributes new knowledge or solutions.

The motivation for this research stems from the limitations of traditional wireless communication technologies, such as Wi-Fi, 5G, and Dedicated Short-Range Communications (DSRC), in addressing the unique demands of Internet of Unmanned Vehicles Agents (IUVA) systems. These technologies struggle with limited bandwidth, high latency, and network congestion, particularly in highly dynamic and dense vehicular environments. Such constraints hinder their ability to support real-time data transmission and frequent model updates required for Wireless Federated Learning (WFL).

In contrast, Terahertz (THz) communication offers ultra-high bandwidth and low latency, making it a promising solution for the high-speed data exchanges needed in IUVA. THz communication enables rapid and efficient synchronization of model updates in WFL, ensuring timely decision-making while maintaining data privacy. Although its short propagation range limits its application to localized scenarios, this characteristic aligns well with IUVA systems, where vehicles often operate in clusters.

Moreover, THz communication's ability to handle the massive data throughput generated by vehicular sensors, such as video monitoring and environmental perception systems, makes it ideal for supporting the computational demands of WFL. By leveraging these advantages, THz communication can address the challenges of real-time collaborative decision-making and high mobility in IUVA systems, where traditional wireless methods fall short.

Despite its advantages, the deployment of THz communication in IUVA also faces challenges, including signal penetration issues, atmospheric absorption, and the need for strategic base station placement. Addressing these challenges is critical to ensuring reliable and efficient communication in real-world IUVA applications. Through this research, we aim to demonstrate how the integration of THz communication with WFL provides a robust framework for achieving intelligent, efficient, and secure vehicular networks.

Simultaneously, while Wireless Federated Learning offers a promising approach to enhance privacy and reduce central server dependency by processing data locally and sharing model updates, it introduces complexities in managing distributed learning across highly dynamic and heterogeneous vehicular networks. These include ensuring consistent model training and updates amidst the variable participation of network nodes and addressing the computational limitations of in-vehicle systems.

Consequently, there is a critical need for a comprehensive framework that not only addresses the technical intricacies of Thz communication within the IUVA context but also harnesses the power of WFL to facilitate secure, efficient, and intelligent data processing and decision-making. Such a framework must effectively integrate these technologies to overcome the limitations of existing systems, offering scalable solutions that enhance IUVA's capability to support advanced applications like autonomous driving, real-time traffic management, and enhanced vehicular safety.

This paper proposes a novel framework and approach for the application of Terahertz Communication and Wireless Federated Learning in IUVA. It aims to fill the gaps identified in the literature by providing a detailed exploration of how these technologies can be synergistically integrated to address the efficiency, privacy, and intelligent decision-making challenges in IUVA. Through this research, we seek to contribute to the advancement of IUVA technologies, making a significant step towards realizing the full potential of intelligent transportation systems in the 6G era.

In the next section, we present our design of Thz communication empowered wireless federated learning driving decision-making model for IUVA and our design goal.

III. SYSTEM MODEL AND DESIGN GOAL

In order to reduce the impact of wireless channel stability on IUVA communication as well as to improve the efficiency of IUVA decision-making. We designed a wireless federated learning framework with a small range of IUVA clusters as participants and Thz communication as the means of wireless communication for IUVA, which enables efficient and stable vehicle-to-vehicle networking communication between each vehicle participating in wireless federated learning and the cloud server under different scenarios, and allows faster decision-making to the IUVA clusters. Next, we describe in detail the wireless federated learning framework for IUVA driven by Thz communication that we designed.

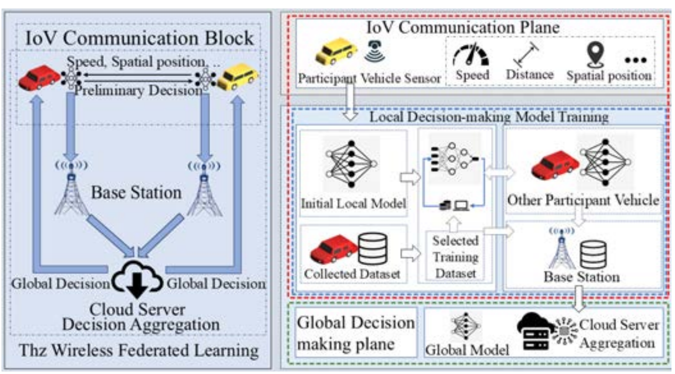


Fig. 2: Thz communication empowered IUVA WFL driving decision-making model.

Our proposed terahertz communication-driven wireless federated learning framework for IUVA is shown in Fig. 2 and consists of three parts.

A. Internet of Vehicles Communication

We consider two scenarios, a high-speed scenario and an urban scenario, where the high-speed scenario represents vehicles moving at high speeds and inter-vehicle occlusion has less impact on inter-vehicle communication, while the urban scenario represents vehicles moving at slow speeds and inter-vehicle occlusion often has more impact on inter-vehicle communication.

B. THz Channel Model

Due to THz signals' nature of extremely high frequency, transmitting them significantly suffers from two serious environmental impairments, i.e., severe attenuation and molecular absorption. For a THz channel with frequency f, its channel response for transmitting a signal over distance d, denoted by complex vector $\mathbf{h} \in \mathbb{C}^N$, can be modeled as [30]

$$h = G\left[1 + \sum_{l=1}^{L} \Lambda_l(f)\right] a_l(f,d) a_t(\theta_t) \tag{1}$$

It is worth noting that THz communication is subject to thermal noise and molecular absorption loss, which can degrade signal quality, especially in long-range transmissions. However, in our proposed framework, communication occurs over short distances within localized IUVA clusters, which significantly mitigates these effects and ensures stable, low-latency data transmission.

The term G refers to the combined antenna gain, which accounts for both the transmitting and receiving gains from the antenna array. The variable L signifies the number of non-line-of-sight (NLoS) paths, while $\Lambda_l(f)$ is a frequency-dependent parameter that encompasses factors such as reflection coefficients and surface roughness, which are influenced by material properties and reflective surfaces. Furthermore, the term $a_L(f,d)$ can be described as:

$$a_L(f,d) = \frac{c}{4\pi f d} e^{-\frac{1}{2}\rho(f)d} \tag{2}$$

In this case, c refers to the speed at which light travels, while $\rho(f)$ is the absorption coefficient associated with frequency f. Moreover, when utilizing a uniform linear array at each base station, the term $a_t(\theta_t)$ is expressed as:

$$a_t(\theta_t) = \frac{1}{\sqrt{N}}\left[1, e^{j\frac{2\pi}{\lambda}d_a \sin(\theta_t)}, \ldots, e^{j\frac{2\pi}{\lambda}d_a (N-1)\sin(\theta_t)}\right]^T \tag{3}$$

Here, θ_t represents the departure angle, constrained within the range $\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$, and d_a is the spacing between adjacent antennas. The symbol T indicates the transposition of the vector. It is important to note that the channel h, as given in equation (1), includes both direct line-of-sight (LoS) and indirect non-line-of-sight (NLoS) paths. The term $Ga_L(f,d)a_t(\theta_t)$ describes the LoS component, while the remaining part captures the NLoS paths.

Consider $\mathbf{w}_k \in \mathbb{C}^N$ as the beamforming vector for base station (BS) k, and $x_k \in \mathbb{C}$ as the unit-powered signal that BS k sends to user equipment (UE) k. In a scenario with K BSs within the network, we assume the worst case where all BSs create mutual interference as they communicate with their respective UEs. The signal received by UE k can thus be expressed as:

$$y_k = \sqrt{P} h_{k,k}^H \mathbf{w}_k x_k + \sum_{\substack{j=1 \\ j \neq i}}^{K} \sqrt{P} h_{j,k}^H \mathbf{w}_j x_j + n_k, \tag{4}$$

where $k \in \{1, \ldots, K\}$, P denotes the transmit power per BS, and H represents the Hermitian operation on a complex vector. Here, $n_k \in \mathbb{C}$ symbolizes Gaussian noise, while $h_{k,k} \in \mathbb{C}^N$ and $h_{j,k} \in \mathbb{C}^N$ are the channel vectors connecting BS k to UE k, and interfering BS j to UE k, respectively. Both $h_{k,k}$ and $h_{j,k}$ follow the channel model outlined earlier. The signal-to-noise-plus-interference ratio (SINR) at UE k can be calculated as follows:

$$\Gamma_k = \frac{P|\mathbf{h}_{k,k}^H \mathbf{w}_k|^2}{\sum_{\substack{j=1 \\ j\neq i}}^{K} P|\mathbf{h}_{j,k}^H \mathbf{w}_j|^2 + \sigma_n^2}, \quad (5)$$

where $|\cdot|$ represents the absolute value, and σ_n^2 is the power of the Gaussian noise n_k. Given equation (4), the achievable downlink rate (or spectral efficiency) for BS k can be written as:

$$C_k = \log_2(1 + \Gamma_k), \quad \text{(bits/sec/Hz)}. \quad (6)$$

This applies for all $k \in \{1, \ldots, K\}$. In subsequent analysis, we will utilize C_k to formulate an optimization problem aimed at maximizing the overall sum rate across all BSs, especially under conditions where each BS only has access to limited channel state information (CSI).

The Free Space Path Loss (FSPL) formula, measured in decibels (dB), expresses how much signal power is lost as it travels through free space over a certain distance. The signal loss increases with both the distance d and the signal frequency f. This loss can be calculated using the following formula:

$$FSPL(\text{dB}) = 20\log_{10}(d) + 20\log_{10}(f) + 20\log_{10}\left(\frac{4\pi}{c}\right) \quad (7)$$

In this equation, c represents the speed of light, which is approximately 3×10^8 meters per second. As either the distance or the frequency increases, the signal experiences greater attenuation.

In addition to path loss, high-frequency signals like THz waves also experience attenuation due to atmospheric conditions. The Atmospheric Absorption Loss accounts for this environmental factor and is represented as follows:

$$L_{\text{atm}}(\text{dB}) = K(f, T, RH) \times d \quad (8)$$

Here, the loss is influenced by distance d, signal frequency f, and environmental conditions such as temperature T and relative humidity RH. The function $K(f, T, RH)$ captures the relationship between the atmospheric factors and the signal attenuation.

The Link Budget formula sums all relevant gains and losses in a communication system to estimate the received signal strength. It is calculated as:

$$\begin{aligned} L_{\text{total}}(\text{dB}) = & P_{\text{tx}}(\text{dBm}) + G_{\text{tx}}(\text{dBi}) \\ & + G_{\text{rx}}(\text{dBi}) - L_{\text{FSPL}}(\text{dB}) \\ & - L_{\text{atm}}(\text{dB}) - M \end{aligned} \quad (9)$$

In this formula, P_{tx} is the transmitted power, G_{tx} and G_{rx} are the gains of the transmitting and receiving antennas, and M accounts for margin losses, such as hardware inefficiencies. By combining both free space path loss L_{FSPL} and atmospheric absorption loss L_{atm}, this equation provides a comprehensive view of signal transmission performance.

In wireless federated learning, the Cross-Entropy Loss function is used to measure how well the model's predicted output aligns with the true labels. It is expressed as:

$$L_{\text{cross-entropy}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right] \quad (10)$$

In this equation, N is the number of data points (e.g., vehicles), y_i is the true label for data point i, and $\hat{y}_i$ is the predicted probability. The function computes the difference between the true labels and predicted probabilities, guiding model training.

The Accuracy function evaluates the proportion of correct predictions by comparing the predicted values $\hat{y}_i$ with the true values y_i:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{1}(\hat{y}_i = y_i) \quad (11)$$

Here, the indicator function $\mathbf{11}(\cdot)$ returns 1 if the predicted value matches the true value, and 0 otherwise. This function gives a clear metric for the overall performance of the model.

In this section, we first summarize the system model applied in the Thz Communication Empowered Robust WFL framework, followed by the detailed algorithm description. The system model consists of a network of IUVA (Internet of Unmanned Vehicle Agents) vehicles, base stations, and cloud servers, where vehicles are organized into small, dynamic clusters. Each vehicle is equipped with sensors that gather data, which is processed locally using federated learning techniques. The communication between vehicles and base stations leverages Terahertz (Thz) communication, enabling ultra-fast data transmission with low latency. The base stations act as intermediaries, forwarding model updates from vehicles to a central cloud server for aggregation, while also facilitating communication within the clusters. This model ensures that driving decisions are made in real-time, balancing high data throughput with the need for secure and efficient communication.

IV. Algorithm Approach

The following algorithm describes the application of THz communication in a wireless federated learning setting, where data from multiple vehicles are transmitted to a base station and then to a cloud server for aggregation:

A. *Input and Output*

Input:

- Sensor data D_i: Data collected from various sensors installed on each vehicle, capturing critical driving parameters such as speed, position, and environmental conditions.
- Initial local model M_i: The starting point for the local model parameters that each vehicle will use to begin training. The model is specifically designed to assist in driving decisions.

- Base station B: A communication relay point for transmitting local model parameters to the cloud server.
- Cloud server C: The central server responsible for aggregating local models from all vehicles to form a comprehensive global model.

Output:

- Global model G: The aggregated model parameters that reflect the collective learning from all participating vehicles after convergence. This global model is used to inform driving decisions.

Algorithm 1 Thz Communication Empowered Robust WFL Algorithm

Input: Sensor data D_i, Initial local model M_i, Base station B, Cloud server C.
Output: Global model G.

for $convergence$ == 0 **do**
  D_i = collect_data(i); `// Collect data from vehicle sensors.`
  M_i = local_training(M_i, D_i));
  `// Perform local model training using collected data.`
  send_to_base_station(M_i, B);
  `// Perform wireless transmission to base station via THz communication.`
  send_to_cloud(M_i, C);
  `// Base station forwards local model parameters to cloud server.`
  G = aggregate(C);
  `// Cloud server aggregates local model parameters`
  if $convergence$ == 1 **then**
    output(G); `// Output global model parameters`
    Break; `// Convergence`
  else
    $M_i = G$; `// Next round`
End

B. Initialization

The algorithm begins with the initialization phase, where network parameters and communication protocols are set up to support Thz communication. Thz communication is chosen for its high data rate and low latency, which are essential for the real-time requirements of IUVA applications.

C. Local Data Collection from Vehicle Sensors

For each vehicle participating in the IUVA network, the algorithm collects sensor data D_i from the vehicle's sensors. This data collection captures real-time driving conditions and vehicle performance metrics, providing the necessary input for training the local models. Using the collected data, each vehicle performs local training on its initial local model M_i. This process involves updating the model parameters to improve its predictive accuracy and decision-making capabilities based on the new data.

D. Transmission of Local Model Parameters via Thz Communication

After local training, the updated local model parameters M_i are transmitted to the base station B via Thz communication. The high-speed nature of Thz communication ensures that the data is relayed quickly and efficiently. The base station then forwards the local model parameters to the cloud server C. This step centralizes the data from multiple vehicles, setting the stage for model aggregation.

E. Aggregation of Local Models at the Cloud Server

At the cloud server, the received local model parameters from all participating vehicles are aggregated to form the global model G. The aggregation process combines the insights from individual vehicles, leveraging the diverse driving data to enhance the overall model. This global model encapsulates the collective knowledge and experiences from all vehicles, providing a robust foundation for making driving decisions.

F. Convergence Check and Model Update

Following the aggregation, the algorithm checks whether the global model G has reached convergence. Convergence indicates that the model parameters have stabilized, and further iterations are unlikely to yield significant improvements. If convergence is achieved, the global model parameters G are outputted, marking the end of the training process. This final global model is then ready to be deployed across the IUVA network to assist vehicles in making informed driving decisions. If convergence is not achieved, the local models M_i are updated with the global model G, and the algorithm proceeds to the next round of training. This iterative process continues until convergence is reached, ensuring continuous enhancement of the model's performance.

G. Summary

In this section, we present the detailed algorithm for the Thz Communication Empowered Robust WFL model used in the IUVA to make efficient driving decisions within small clusters of vehicles. This work is distinguished by its innovative use of Thz communication technology and the involvement of IUVA vehicles as active participants in a federated learning framework. The driving decision model aims to enhance vehicular safety and efficiency through collaborative learning.

To provide a detailed analysis of the computational complexity of our proposed algorithm, we focus on three key components: local training, model aggregation, and convergence checks. First, the complexity of local training depends on the dataset size for each vehicle and the chosen machine learning model, with the computational cost scaling linearly with the data size. Second, the model aggregation step, performed at the cloud server, involves a straightforward weighted summation of model updates from participating vehicles, which introduces minimal computational overhead. Lastly, convergence checks require evaluating the stability of the global model, a computationally lightweight process that adds negligible overhead to the overall system. These considerations demonstrate that the proposed algorithm achieves an optimal balance between computational efficiency and model performance. This makes it highly practical and scalable for real-time vehicular applications in dynamic IUVA environments.

V. Experiment

In this study, we embarked on a simulation experiment to meticulously compare the performance of Terahertz communication with Wi-Fi, 5G, and Dedicated Short-Range Communications (DSRC) within the context of a dynamic vehicular network. The primary aim was to evaluate the effectiveness of the proposed THz-empowered wireless federated learning framework, focusing on its ability to enhance model convergence, reduce training latency, and improve decision-making accuracy under real-world vehicular scenarios.

Fig. 3: IUVA Platform

To ensure a comprehensive evaluation, a diverse array of environmental and hardware parameters was carefully selected, encompassing variables such as the fluctuating number of vehicles, varying communication distances tailored to the specificities of each technology, and the sizes of the data packets exchanged during the learning iterations.

A. WFL driving decision making performance experiment

Following the foundational experiment, we proceeded to design a performance evaluation experiment focusing on wireless federated learning (FL) for driving decision models, employing various communication technologies including terahertz communication, Wi-Fi, 5G, and DSRC. This experiment aimed to elucidate the performance disparities across these communication mediums within a federated learning context, specifically in the realm of vehicular networks.

The experiment was conducted within a simulated small-scale vehicular cluster engaging in federated learning for driving decisions. Performance metrics centered on model loss and accuracy to gauge the effectiveness of the model under different communication technologies. It was assumed that all communication technologies operated under identical conditions, ensuring a fair comparison across the board. This included uniform vehicle numbers, data distribution, and computational resources, with the model's training iterations fixed to maintain comparability.

Through simulated experimentation, we graphically represented the variance in model accuracy and loss for the wireless federated learning driving decision model, facilitated by terahertz communication and contrasted with Wi-Fi, 5G, and DSRC. This simulation illuminated several key findings:

Model Accuracy: A consistent enhancement in model accuracy was observed across all communication technologies as the number of iterations increased. This progression signifies the gradual optimization of performance in the wireless federated learning driving decision model with deeper learning.

The superior data transmission capabilities provided by terahertz communication, coupled with its minimal latency, significantly contribute to enhancing the real-time efficacy of model training. Furthermore, the expansive bandwidth offered by the terahertz spectrum enables the transmission of voluminous data, supporting quicker iteration cycles, thereby accelerating the learning pace and facilitating faster convergence of model accuracy.

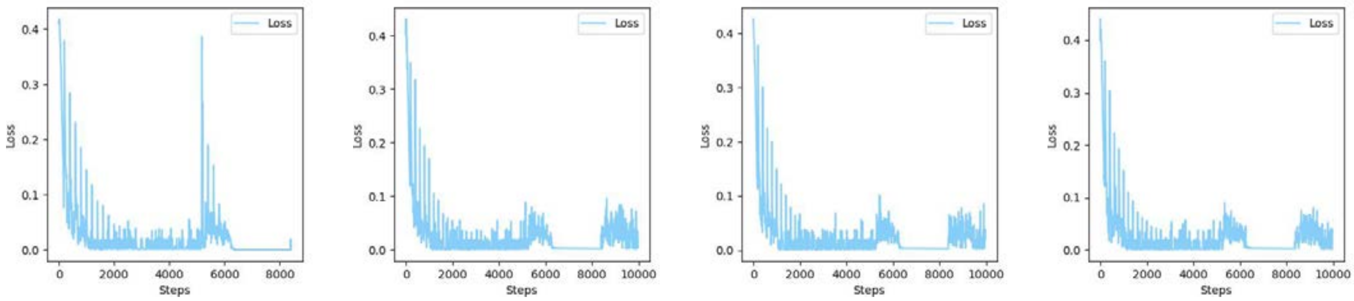
Model Loss: Analogously, a decline in model loss was noted with the advancement of iterations, indicating continuous improvements in the model throughout the learning process. The driving decision model under terahertz communication within the wireless federated learning framework demonstrated a more rapid convergence in model loss.

Model Computational Complexity: In addition to accuracy and loss, the computational complexity of the proposed WFL model was analyzed to provide a more comprehensive understanding of its performance. The computational complexity can be broken down as follows:

- **Local Training:** The complexity is determined by the size of the local dataset and the architecture of the machine learning model. In our experiments, the local training process required manageable computational resources and converged efficiently, demonstrating its feasibility for real-time vehicular applications.
- **Model Aggregation:** The aggregation process performed at the cloud server involves a simple weighted summation of model updates from participating vehicles. This operation incurs minimal computational overhead and ensures scalability for larger networks.
- **Communication Overheads:** Leveraging Terahertz communication significantly reduces latency during the exchange of model updates, thereby optimizing the overall computational and communication efficiency of the framework.

These components collectively ensure that the proposed WFL model maintains a balance between computational efficiency and performance, making it suitable for deployment in dynamic and resource-constrained vehicular networks. This analysis further underscores the practical advantages of our framework in addressing real-time decision-making challenges.

Model Efficiency: From Fig. 4, it can be observed that the driving decision model for each vehicle converges efficiently



(a) Loss of Vehicle 1 (b) Loss of Vehicle 2 (c) Loss of Vehicle 3 (d) Loss of Vehicle 4

Fig. 4: Main figure with subfigures

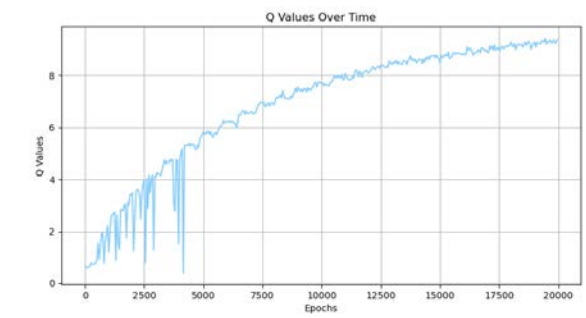


Fig. 5: Model Q Values

Fig. 6: Model Total Reward

within approximately 1000 iterations. The total training time for the wireless federated learning process is approximately 1 to 2 minutes, which ensures rapid convergence while maintaining model accuracy and stability.

This experiment underscores the potential advantages of terahertz communication in supporting the efficacious implementation of wireless federated learning for driving decisions, particularly highlighting its capacity to expedite the learning process and enhance model performance through its high-speed data transmission, low latency, and broad bandwidth capabilities.

The observed rapid convergence of the driving decision model highlights THz communication's suitability for dynamic IUVA scenarios. By minimizing communication delays and accelerating model synchronization, THz-based federated learning enables vehicles to make timely and accurate driving decisions, which is critical for ensuring safety and efficiency in real-world vehicular networks.

B. Communication stability experiment

Building upon the foundational experiments conducted to assess performance metrics, we delved into an additional dimension of communication technologies by examining their stability within a wireless federated learning (FL) framework, specifically for driving decision models. This segment of the study focused on comparing the stability of terahertz communication against that of Wi-Fi, 5G, and DSRC under identical experimental conditions previously established.

Stability Assessment Experiment Stability Indicator: The crux of this experiment revolved around a "Stability Indicator," a synthesized metric encapsulating the variations in packet loss rate, latency jitter, throughput stability, and connection dropout frequency. This indicator, expressed through the changing standard deviation of these parameters, aimed to provide a nuanced understanding of stability, with a lower standard deviation indicative of superior stability. Such a holistic approach to measuring stability is essential for ensuring the reliability and efficacy of communication technologies in supporting federated learning tasks within vehicular networks.

The experiment yielded insightful findings, highlighting the variance in stability across the communication technologies under scrutiny. Terahertz communication distinguished itself with the most commendable stability, evidenced by the minimal standard deviation in the stability indicator. This outcome suggests that terahertz communication's adeptness at ensuring consistent data transmission quality, coupled with its resilience against packet loss, minimal latency fluctuations, and steadfast throughput, renders it highly suitable for federated learning applications that demand robust and reliable communication channels.

In contrast, DSRC was found to exhibit the least stability, as denoted by the highest standard deviation in the stability indicator. This was largely attributable to its propensity for higher packet loss, significant latency variations, inconsistent throughput, and a heightened rate of connection disruptions. The stability performance of Wi-Fi and 5G was intermediate, with 5G showing a comparative edge closer to that of terahertz communication in terms of stability.

The introduction of the stability indicator as an aggregate measure derived from key performance metrics like packet loss rate, latency jitter, throughput stability, and connection dropout frequency, furnished profound insights into the stability characteristics of the evaluated communication technologies within a federated learning context. Terahertz communication emerged as the technology with superior stability, underscoring its potential to significantly bolster the reliability and efficiency of wireless federated learning, particularly for applications requiring high levels of data fidelity and consistency in vehicular networks. This analysis reinforces the critical importance of selecting a communication technology that not only meets the performance requirements but also aligns with the stability prerequisites of federated learning implementations.

C. Transmission rates and latency experiment

To simulate the complexities of real-world vehicular environments, the experiment was designed to reflect urban and highway conditions with vehicle speeds ranging from 30 to 120 km/h. Moreover, the selection of data packet sizes was influenced by the practical dimensions of the model parameters, setting a standard size of 1MB for each iteration. Transmission rates were assigned based on the technological capabilities, positioning terahertz communication as potentially the most superior due to its theoretical capacity to achieve transmission rates from several tens of Gbps to over a hundred Gbps. Ensuring fairness and consistency across the experiment, all vehicles were assumed to have comparable processing capabilities. The core of the experimental procedure involved the use of a wireless federated learning model specifically developed for driving decision-making tasks. Over the course of 100 iterations, the experiment dynamically adjusted the number of participating vehicles to mimic the natural ebb and flow of vehicular networks. This approach not only provided insights into the iterative learning process but also reflected the practical challenges of real-world deployment. Each iteration was meticulously measured for latency and transmission rate, capturing the essence of communication performance across the different technologies.

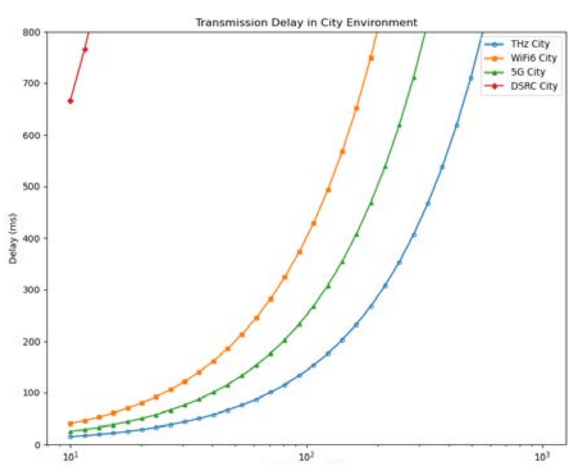


Fig. 7: Communication Delay Comparison in City Environment

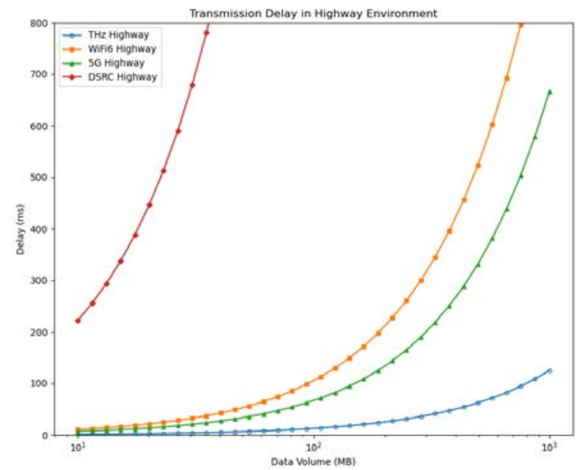


Fig. 8: Communication Delay Comparison in Highway Environment

Latency Comparison: The graphical analysis revealed terahertz communication to exhibit the lowest latency, positioning it as the most advantageous for scenarios demanding rapid responses.

Transmission Rate Comparison: Furthermore, terahertz communication significantly surpassed the other technologies in transmission rate, underscoring its exceptional capability to support high-speed data transmission in vehicular networks.

Through this experiment, we uncovered valuable insights into the capabilities of terahertz communication, affirming its prospective role in enhancing the efficiency and responsiveness of wireless federated learning models in dynamic vehicular settings.

VI. CONCLUSION

In this article, we proposed a Thz communication empowered WFL driving decision-making framework for the IUVA, which integrates FL and Thz communication to enhance the performance of data transmission rates and driving decision-making, while guaranteeing information privacy between the vehicles participating in the FL process. Our proposed framework addresses several challenges in IUVA environments, particularly the dynamic nature of wireless communication between vehicles and the complexity of real-time decision-making. First, we established a Thz communication-based IUVA cluster, effectively reducing latency and improving the efficiency of wireless communication in the IUVA network. By implementing an innovative encoding method for Thz communication, the system mitigates the challenges caused by the high-speed mobility of vehicles, ensuring stable and efficient communication. Additionally, we designed a WFL framework where vehicles act as local learning nodes, participating in a distributed learning process without sharing raw data, thereby reducing communication overhead while maintaining data privacy. This framework not only improves the scalability of the learning process but also optimizes the system's ability to handle large amounts of sensor data generated by vehicles. Finally, we proposed a wireless distributed driving decision-making model that utilizes the collective learning of vehicles to generate accurate and safe driving decisions for the entire IUVA cluster. The use of physical parameters from participating vehicles, combined with the power of federated learning, enhances both the accuracy of driving decisions and the safety of the overall IUVA network.

The results of our study demonstrate the effectiveness of combining WFL with Thz communication in solving critical communication and data processing challenges in the IUVA environment. This work leverages the strengths of wireless federated learning and advanced Thz communication technology to create a robust and efficient driving decision model for IUVA networks. By enabling vehicles to collaborate in the learning process, the WFL model improves decision-making accuracy and responsiveness, ultimately enhancing the safety and efficiency of vehicular networks. The use of Thz communication ensures rapid data transmission and model updates, which are critical for the dynamic and real-time nature of driving environments. Overall, our framework provides a novel approach to achieving efficient and secure IUVA communication and contributes significantly to intelligent unmanned decision-making within IUVA systems.

Moreover, the modularity and adaptability of the proposed framework allow it to be applied to a variety of dynamic and distributed environments beyond the IUVA context. For example, the framework could be adapted to unmanned aerial vehicle (UAV) swarms, where similar requirements for high-speed communication, decentralized learning, and real-time decision-making exist. Additionally, with minor modifications, it could be extended to intelligent factory automation or logistics networks, showcasing its potential for broader applicability. This generalizability highlights the versatility of the framework and its ability to address challenges in a range of high-mobility, data-intensive systems.

Looking ahead, there are several exciting avenues for future research. The deployment of the proposed framework in real-world vehicular networks presents a significant challenge due to the dynamic and unpredictable nature of the environment. We could focus on developing adaptive communication and learning models that can respond to the diverse and rapidly changing conditions in real-world IUVA networks. Another important research area involves the scalability of the system to handle larger fleets of vehicles while maintaining performance and ensuring low-latency communication. Finally, extending the framework to handle multimodal data, such as visual or LiDAR sensor data, could improve the robustness of the decision-making process and provide even more accurate and reliable driving decisions.

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