Dynamic Vehicle Selection and Adaptive Aggregation for Asynchronous Federated Learning enabled VANET

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***Abstract*—The rapid advancement of vehicular networks has paved the way for intelligent transportation systems, offering enhanced traffic management and autonomous driving capabilities. Federated learning (FL) is emerging as a critical framework that enables the utilization of onboard information and computational resources while protecting data privacy. However, the high mobility of vehicles and the complex nature of wireless channels pose significant challenges for integrating FL into vehicular networks. This work proposes a Dynamic Vehicle Selection and Adaptive Aggregation Asynchronous based Asynchronous Federated Learning (DVSAA-AFL) scheme designed to optimize FL performance in vehicular networks. DVSAA-AFL introduces a novel approach to achieve dynamic vehicle selection corresponding to different conditions and an adaptive aggregation method that adjusts the weights of local models based on various factors. A preliminary study shows the proposed scheme outperforms the baseline FL framework by a large margin.**

***Index Terms*—vehicle selection, weighted aggregation, mobility, federated learning, vehicular ad-hoc network**

I. Introduction

Recently, intelligent transportation system (ITS) have become a vital solution for enhancing traffic efficiency, improving transportation safety, and assisting autonomous driving [1]. A crucial technological component of ITS is the vehicular ad-hoc network (VANET), which facilitates wireless communication between vehicles and roadside units (RSUs) [2]. Additionally, modern vehicles, equipped with various sensors and powerful computational units, can gather massive amounts of data while achieving fast processing. By taking advantage of the VANET, this processed data can be shared with other entities within the network, which significantly advances the effectiveness and potential applications of the VANET.

To better harness the vast amount of onboard vehicle data and its computing resources, various machine learning (ML) techniques are being incorporated into ITS [3]. However, due to data privacy concerns, it can be challenging to deploy ML algorithms within existing VANET. Federated learning (FL) has therefore emerged as a promising decentralized alternative [3]. Specifically, FL conducts iterative global aggregations at the RSU. During each round, vehicles first download the current global model from the RSU and then use their local data to train their individual models. These locally trained models are subsequently uploaded back to the RSU. Once the RSU receives all the updated local models from the vehicles, it performs a global aggregation to update the global model and broadcasts it to all vehicles. This approach ensures that vehicle data remain local, thereby addressing the privacy issue.

However, traditional FL requires the RSU to perform the global model aggregation only when all the local models have been uploaded, which can suffer from the straggler effect. Due to the dynamic characteristics of the VANET, it is very likely that the aggregation process will slow down significantly. For example, a vehicle might experience transmission delays due to an unstable network connection or computation delays because of sudden interruptions from higher priority computational tasks. Moreover, a vehicle might drive out of the RSU's coverage area, thus cannot participate in the aggregation process. Therefore, the high mobility of the vehicles and the volatile nature of the wireless communication in the VANET could seriously hinder FL convergence and lower the accuracy of global aggregation.

In this work, we aim to resolve these issues by proposing a dynamic vehicle selection and adaptive model aggregation-based asynchronous federated learning (DVSAA-AFL) scheme. This scheme leverages Asynchronous Federated Learning (AFL), which does not require updates from all local models to initiate the global model aggregation process. Moreover, we design a dynamic vehicle selection strategy to mitigate the straggler effect and improve the accuracy of the global model by increasing the proportion of the vehicle participating in the AFL process. Additionally, we propose an adaptive weighting-based aggregation to alleviate the staleness problem by assigning different weights to local model updates based on various factors.

II. Proposed Scheme

System Model. We consider a VANET consisting of U RSUs and V vehicles. We assume that the coverage of different RSUs overlap and that the number of vehicles passing the RSUs in a given interval of time follows a Poisson process.

Each vehicle i ($1 \leq i \leq V$) carries a varying amount of data D_i and has different computing capabilities. Here, we do not assume D is independent and identically distributed (IID) data. Meanwhile, each vehicle incurs time-varying channel condition, computational load, and driving condition.

AFL Model. We assume an AFL system with N devices and L corresponding labels participating in training a shared global model. The objective of the system is to find the optimal parameter vector θ that minimizes an empirical loss function. For one round of the iteration process, the RSUs will first establish communication and gather information from the vehicle (e.g., data size, speed, computation capability, channel state) as they enter the coverage. Then, the RSUs will broadcast the global model to all vehicles within their coverage. Next, each vehicle will conduct local training using the downloaded global model and its own data. After that, each vehicle will upload its trained local model to the RSU within its range. Lastly, the RSUs will perform aggregation and update the global model. Here, we adopt the AFL framework with periodic aggregation. This approach can address the straggler issue by allowing the RSUs to perform aggregation periodically without being constantly interrupted by incoming local model updates.

Dynamic Vehicle Selection. Due to the mobility of vehicles and the complex nature of wireless communication, vehicles could drop out of the AFL process at any of the stages discussed earlier. To minimize the impact of such uncertainty, we propose a dynamic vehicle selection strategy to choose the vehicles with higher probabilities of completing one round of global iteration. To achieve this, for each vehicle, we first calculate the combined time required to finish the tasks of global model download, local model training and local model upload for each vehicle entering the RSUs coverage area. Then, we estimate the time duration until that vehicle leaves the RSUs'coverage based on its current speed. This information, combined with other factors including the number of RSUs the vehicle will pass through, the remaining time to finish the current iteration, the specific stage within the current iteration, and the connection/computation status, will processed through a Bayesian Network to generate a probability value. Finally, the probabilities of all the vehicles will be ranked, and only the top K vehicles will be selected to participate in the AFL process. It is worth noting that the ranking will be periodically updated based on the most up-to-date information from the vehicle.

Adaptive Model Aggregation. Traditional FL aggregation methods, such as Federated Averaging [4], treat all local models equally regardless of the quality of the data [3]. However, in the VANET-based FL, data imbalance and the staleness problem can lead to suboptimal global model updates. Therefore, DVSAA-AFL incorporates an adaptive model aggregation component to mitigate these harmful impacts. This is achieved by adaptively adjusting the aggregation weights of local model updates based on various factors. These factors include the size of data used in local model training, the similarity between the local and global gradients, the freshness and the label variance of the local model update. Currently, we utilize a fuzzy logic approach to assign the weights to different factors, but these rules can be changed depending on the applications of the framework or the characteristics of the data.

III. Preliminary Study

We conducted a preliminary study using the MNIST dataset [5]. We used a multilayer perceptron (MLP) as the implementation model. For the simulation, we consider 100 vehicles and 3 RSUs. The number of vehicles in the coverage area follows a Poisson Distribution, the data and computing resources allocation obeys a truncated Gaussian distribution, and the channels are modeled as Rayleigh fading channels.

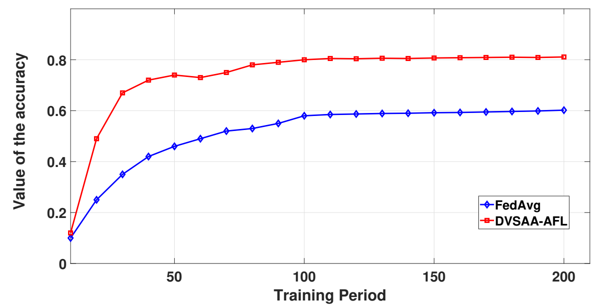

Fig. 1. The framework performance comparison with baseline scheme.

We compare the performance of the proposed framework and FedAvg [4]. The results are shown in Figure 1. We can observe that both framework become convergent as the training round increases. However, DVSAA-AFL outperforms FedAvg from the very beginning. These results demonstrate the effectiveness of the proposed work.

IV. Conclusion

In this work, we propose a VANET-based AFL scheme that utilizes dynamic vehicle selection strategy and adaptive weighting-based aggregation to address the issues caused by the existing FL framework and the dynamic nature of the VANET. The preliminary study shows that the proposed scheme can achieve better accuracy compared to the baseline. We plan to include more simulations under various scenarios and employ more sophisticated deep learning algorithms in weight assignment and vehicle selection to further improve the performance.

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