A Cooperative Federated Learning Mechanism for Collision Avoidance using Cellular and 802.11p based Radios Opportunistically

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Abstract— **Reinforcement learning (RL) is a powerful learning framework which can be used in complex environments such as autonomous driving. Generally, in autonomous driving, vehicles run RL algorithm locally. However doing so will not give a desirable performance as each vehicle will only consider its own environment. So in autonomous driving it is very important that the vehicles make actions with the knowledge learned by other vehicles as well which can be received using V2X technology. However, relying on a single radio or V2X mode of communication is not desirable. In the absence of communication infrastructure on the road side, one can depend on technologies such as 4G/5G for V2N (Vehicle-to-Network) communication and Wi-Fi Direct for V2V (Vehicle-to-Vehicle) communication. Vehicles can depend on cellular technologies for indirect mode of communication (V2N), if direct V2V communication is not possible with other vehicles present in the close vicinity. To reap in the benefits of both Federated learning and V2X, we present a federated learning architecture with support from V2X, where all the participant agents make their actions with the knowledge received using V2X, even when they are acting in very different environments. Effectiveness of the proposed V2X federated learning system is demonstrated using collision avoidance application using Flow, Veins and SUMO. Simulation results suggest that it important to use a federated learning to significantly improve the reliability of of the collision avoidance application.**

I. INTRODUCTION

World death rate due to road accidents in 2016 was 18.2 per 100 K population. South-East Asia's and Africa's death rates are higher than the world death rate [1]. Hence, there is a need to develop a novel solution for collision avoidance. Nowadays, mobile devices and car infotainment system are equipped with increasingly advanced sensing, computing and storage capabilities. Coupled with advancements in Reinforcement Learning (RL), this opens up countless possibilities for meaningful applications, e.g., in medical purposes, robotics and autonomous driving. Reinforcement Learning (RL) is used in autonomous driving by vehicles to learn environment on their own. However, in general vehicles run reinforcement learning locally and take actions on the basis of knowledge learned by its own. This may lead to unstable system causing many accidents because of lack of knowledge of the environment. This problem can be solved using federated learning. The primary intended application of federated learning is to provide safety to road users. Federated learning is a machine learning technique that trains an algorithm on multiple decentralized edge devices or servers holding local data samples, without exchanging their data samples. Main advantage of federated learning is data privacy as well as improved stability of system. However, one problem remains of how knowledge learned by vehicles will be disseminated to other vehicles. To tackle this, we use Vehicle-to-Everything (V2X) communication technology. V2X [2] is the communication paradigm enabling Intelligent Transportation Systems (ITS). V2X includes V2V (Vehicle-to-Vehicle), V2I (Vehicle-to-Infrastructure), V2N (Vehicle-to-Network), and V2P (Vehicle-to-Pedestrian). V2V aims at providing peer-to-peer (P2P) and multi-hop based short range communication between vehicles' on-board units (OBUs). V2I aims at providing indirect communication between OBUs and road-side units (RSUs) i.e., between vehicles and road infrastructure like signs and traffic signals and CCTVs. V2N mainly aims at providing long range communication between vehicles and network infrastructure like cellular Base Stations (BSs), edge/cloud computing servers, and Wi-Fi Access Points (APs). V2X based ITS applications can be deployed on vehicles by equipping them with one of the radio access technologies (RAT) like Wi-Fi, IEEE 802.11p (DSRC), 4G LTE, 5G, or Cellular-V2X. Since, it is not practical to have the same RAT on all the vehicles plying on the roads, to maximize dissemination of ITS messages, these heterogeneous RATs can be exploited opportunistically, to achieve low latency as well as high coverage needed for ITS applications. .

The previous works considered only one of V2X modes of communications i.e., either V2V, V2N, or V2I for dissemination of knowledge learned. To the best of our knowledge, no work has ever considered both cellular and 802.11 based radios along with federated learning architecture. The main contributions of this paper are as follows:

1) We propose a V2X federated learning architecture by using 4G cellular and 802.11 based radios present in vehicles.
2) We propose a cooperative collision avoidance solution.
3) We evaluate the performance of the proposed collision avoidance solution by realizing the V2X federated learning architecture using 4G LTE and IEEE 802.11p (DSRC) radios on SUMO, Veins, and FLOW platforms.

The rest of the paper is structured as follows: Section II presents related work. Section III presents the proposed V2X federated learning solution. Section IV describes simulation setup, performance results, and comparison with a baseline work. Finally, the conclusions are drawn in Section V.

TABLE I: Heterogeneous Communication Scenarios in the proposed V2X Federated Learning Architecture: V2V and V2N

Scenario No.	*Vehicle A*	*Vehicle B (Own vehicle)*	*Vehicle C*	*V2X Comm. flow from B $\Longrightarrow$ A*	*V2X Comm. flow from C $\Longrightarrow$ A*
1	Cellular	Cellular	Cellular	B $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ A	C $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ A
2	802.11	802.11	802.11	B $\rightarrow$ A	C $\rightarrow$ A
3	802.11	Both 802.11 and Cellular	Cellular	B $\rightarrow$ A	C $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ B $\rightarrow$ A
4	Both 802.11 and Cellular	Both 802.11 and Cellular	Both 802.11 and Cellular	B $\rightarrow$ A or B $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ A or B $\rightarrow$ C $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ A	C $\rightarrow$ A or C $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ A or C $\rightarrow$ B $\rightarrow$ BS $\rightarrow$ Relay Server $\rightarrow$ BS $\rightarrow$ A

II. Related Work

The authors in [3] present an online federated RL transfer process for real-time knowledge extraction where all the participant agents make corresponding actions with the knowledge learned by others, even when they are acting in very different environments. To validate the effectiveness of the proposed approach, they constructed a real-life collision avoidance system with Microsoft Airsim simulator and NVIDIA JetsonTX2 car agents, which cooperatively learn from scratch to avoid collisions in indoor environment with obstacle objects. The authors in [4] introduces the background and fundamentals of Federated Learning (FL). Then the paper highlights the aforementioned challenges of FL implementation and review existing solutions. Furthermore, they present the applications of FL for mobile edge network optimization. Finally, they discuss the important challenges and future research directions in FL.

One of the most important tasks for transfer reinforcement learning is to generalize the already-learned knowledge to new tasks [5], [6], [7]. [8] proposed a decentralized end-to-end sensor-level collision avoidance policy for multi-robot systems, with the pre-trained process conducted on stage mobile robot simulator. [9] studied the problem of reducing the computationally prohibitive process of anticipating interaction with neighboring agents in a decentralized multi-agent collision avoidance scenario. The pre-trained model of the RL model used is based on the trained data generated by the simulator.

The authors in [10] provides a comprehensive analysis of the usage of FL over ML in vehicular network applications to develop intelligent transportation systems. Based on the real image and lidar data collected from the vehicles, the paper illustrates the superior performance of FL over ML in terms of data transmission complexity for vehicular object detection application. In this overview paper [11], data-driven learning model-based cooperative localization and location data processing are considered, in line with the emerging machine learning and big data methods. Paper demonstrates various practical use cases that are summarized from a mixture of standard, newly published, and unpublished works, which cover a broad range of location services, including collaborative static localization/fingerprinting, indoor target tracking, outdoor navigation using low-sampling GPS, and spatio-temporal wireless traffic data modeling and prediction. Work in [12] proposes to integrate the Deep Reinforcement

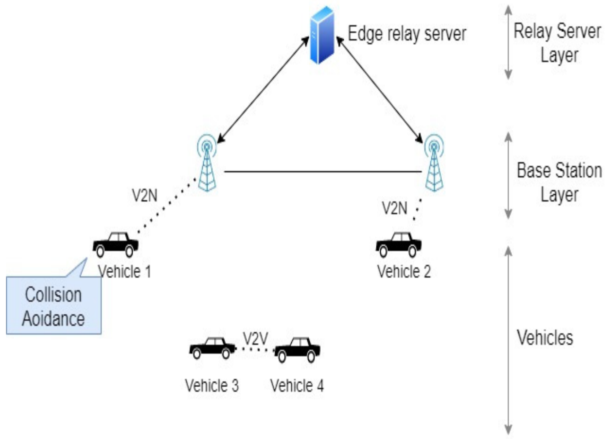

Fig. 1: Distributed V2X architecture for safe navigation

Learning techniques and Federated Learning framework with mobile edge systems, for optimizing mobile edge computing, caching and communication. And thus, they design the "In-Edge AI" framework in order to intelligently utilize the collaboration among devices and edge nodes to exchange the learning parameters for a better training and inference of the models, and thus to carry out dynamic system-level optimization and application-level enhancement while reducing the unnecessary system communication load.

Many ITS solutions using single radio for inter-vehicle communication have been proposed in the literature. In [13], 4G LTE is used for the communication between vehicles and pedestrians and V2V communication is still in its infancy, particularly when considering smartphones [14]. In [15], a system model for geographically separated edge clouds is developed by considering Chicago city and co-locating edge computing clusters with known Wi-Fi AP locations. The authors have proposed to deploy edge servers at base stations that allows vehicles to connect with a set of base stations alongside roads, so as to provide flexible vehicle-related services. Many studies talk about efficient offloading of the tasks to a nearby edge server in order to reduce the computational load on vehicles or benefit from collaborative communication and computation among vehicles [16].

III. Proposed Work

Fig. 1 shows the proposed V2X federated learning architecture for collision avoidance which consists of three layers:

vehicles, base stations, and an edge relay server. We can run RL in vehicles or at edge server. In this paper, we consider the first approach where the proposed collision avoidance application runs in each vehicle in a distributed fashion by opportunistically using 4G cellular and 802.11 based radios present in vehicles for realizing V2V and V2N modes of communication. In this architecture, various heterogeneous scenarios are possible for inter-vehicle communication as shown in Table I. In this table, $Vehicle\ A$ is assumed as the own vehicle of interest and $Vehicle\ B$ and $Vehicle\ C$ are its nearby vehicles which are in close vicinity of each other on the road. Fifth and sixth columns in the table show how $Vehicle\ A$ receives parameters learned by $Vehicle\ B$ and $Vehilce\ C$ using V2V or V2N modes of communication.

In $Scenario\ 1$, since all three vehicles are having on-board units (OBUs) fitted with cellular radios (4G or 5G), they make use of V2N mode of communication. The communication flow from $Vehicles\ B$ to $Vehicle\ A$ is as follows: $Vehicle\ B$ sends its awareness message (timestamp, reward, learning rate, discount factor, velocity, location, acceleration, etc.) to cellular base station (BS), then the BS forwards it to the edge server acting as the relay for exchange of awareness messages among the vehicles. Then the awareness message of $Vehicle\ B$ is pulled by $Vehicle\ A$ from the relay server via BS. $Vehicle\ C$'s awareness message reaches to $Vehicle\ A$ in the similar manner.

In the $Scenario\ 3$, $Vehicle\ A$ is 802.11 enabled, $Vehicle\ B$ is both cellular and 802.11p enabled, whereas $Vehicle\ C$ is cellular enabled. Here $Vehicle\ B$ talks directly with $Vehicle\ A$ over 802.11p in V2V mode. But, $Vehicle\ C$ cannot be able to communicate with $Vehicle\ A$, as both have different radios. If a vehicle with both cellular and 802.11 radios is in the vicinity of $Vehicle\ C$ and $Vehicle\ A$, such as $Vehicle\ B$ in this case, then communication flow from $Vehicles\ C$ to $Vehicle\ A$ is as follows: $Vehicle\ C$ sends its awareness message to BS which in turn forwards it to the edge relay server. $Vehicle\ B$ then pulls $Vehicle\ C$'s message from the relay server via BS and piggybacks it in its own awareness message sent over 802.11 link, so that it could be received by $Vehicle\ A$.

Further we explain basic reinforcement learning block diagram, collision avoidance application and finally federated averaging process.

A. Reinforcement learning

Fig. 4 shows basic RL block diagram. In our work environment is complete simulation setup, agents are vehicles and actions are path on which vehicle moves by deciding whether to accelerate or decelerate. Vehicles take action on environment and reward is returned according to state of environment.

B. Collision Avoidance

Algorithm 1 is the collision avoidance algorithm running in $0-th$ vehicle. Every autonomous vehicle runs reinforcement learning locally. To avoid collisions we should maximize the minimum distance between vehicles.

Algorithm 1 **Collision avoidance algorithm running in 0-th vehicle**

```
input : Current Vehicle V = {vel, loc, acc, t_headway, timestamp, vehicleid}
output: FM_i
while not terminated do
    Get current time t_1
    if t_1 - t_0 > t_u then
        t_0 = t_1
        reward_0, learning_rate_0, discount_factor_0 = getTrainedModel(0)

        s ← getCurrentState()
        if t_headways ≤ 2 then
            reward_0 = 0
        else
            reward_0 = max((t_headway - t_min)/t_min, 1)
        end if
        if type= 1 then
            BroadcastMessage (vel_0,loc_0,acc_0,
            t_headways,timestamp_0,vehicleid_0,reward_0,
            learning_rate_0,discount_factor_0)

            reward_{1,2,3....,N_1}, learning_rate_{1,2,3....,N_1},
            discount_factor_{1,2,3....,N_1} =
            GetWifiVehicle()
        end
        if type= 2 then
            PushMessageToCloud(vel_0,loc_0,acc_0,
            t_headways,timestamp_0,vehicleid_0,reward_0,
            learning_rate_0,discount_factor_0)

            reward_{1,2,3....,N_2}, learning_rate_{1,2,3....,N_2},
            discount_factor_{1,2,3....,N_2} =
            PullCellularVehicle()
        end
        if type= 3 then
            BroadcastMessage (vel_0,loc_0,acc_0,
            t_headways,timestamp_0,vehicleid_0,reward_0,
            learning_rate_0,discount_factor_0)

            PushMessageToCloud(vel_0,loc_0,acc_0,
            t_headways,timestamp_0,vehicleid_0,reward_0,
            learning_rate_0,discount_factor_0)

            reward_{1,2,3....,N_3}, learning_rate_{1,2,3....,N_3},
            discount_factor_{1,2,3....,N_3} =
            PullCellularVehicle() ∪
            GetWifiVehicle()
        end
        updateModel()
    end

    Function updateModel:
        get federated model(FM) from Algorithm 2
        LM_0 = FM
    End Function
end
```

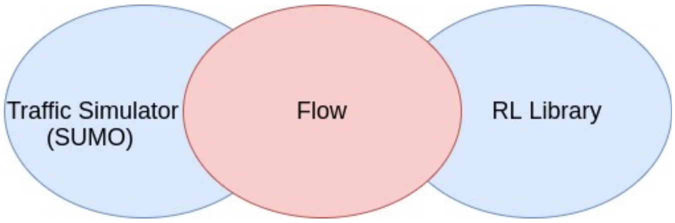

Fig. 2: Flow architecture.

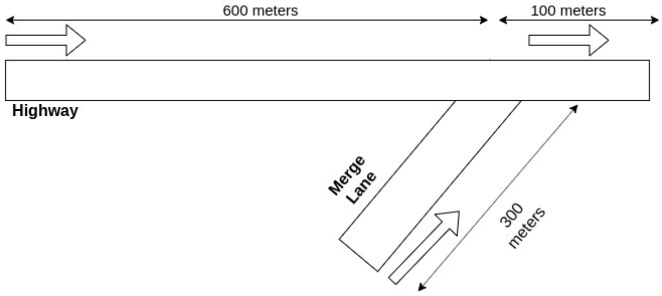

Fig. 3: Simulation map.

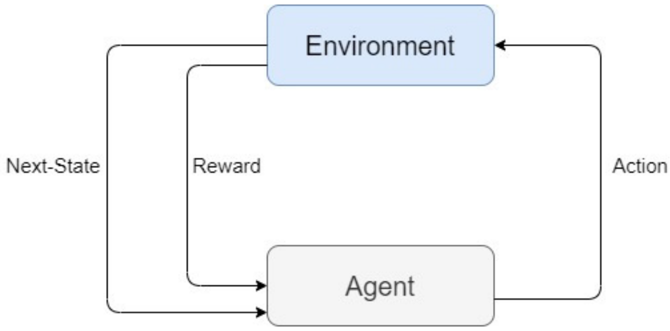

Fig. 4: RL block diagram

Algorithm 2 **Federated averaging in the 0-th vehicle**

input : $\text{reward}_{1,2,3...,T}, learning\_rate_{1,2,3....,T}, discount\_factor_{1,2,3....,T}$
output: Federated Model FM
$\text{reward}_{temp} = 0$
$\text{learning\_rate}_{temp} = 0$
$\text{discount\_factor}_{temp} = 0$
for $i \leftarrow 0$ **to** T **do**
  $\text{reward}_{temp} = reward_i + reward_{temp}$
  $\text{learning\_rate}_{temp} = learning\_rate_i + learning\_rate_{temp}$
  $\text{discount\_factor}_{temp} = discount\_factor_i + discount\_factor_{temp}$
end
$\text{reward}_{Fed} = reward_{temp}/T$
$\text{learning\_rate}_{Fed} = learning\_rate_{temp}/T$
$\text{discount\_factor}_{Fed} = discount\_factor_{temp}/T$

Create a federated model FM using $\text{reward}_{Fed}, learning\_rate_{Fed} and discount\_factor_{Fed}$

return FM

This can be achieved by setting reward function as follow:

$$reward = max((t\_headway - t\_min)/t\_min, 1) \quad (1)$$

Where, t_{min} is minimum time headway system should achieve. Time headway is the distance between vehicles in a transit system measured in time. We set t_{min} to 2. Reward will be positive if t_{headway} will be greater than 2. Reward, learning rate and discount factor in collision avoidance application is sent instead of complete model, using Cellular and 802.11p based Radios Opportunistically as shown in above scenarios. As we are not sending complete model, due to this overload in the network will be less and latency of communication will reduce. Further, distributed architecture helps to communicate between vehicles which are in close vicinity only through edge relay server. This will distribute the communication overload between edge relay servers. As we are considering heterogeneous scenario, we have to consider three types of vehicles. These types are based on the radios available in the vehicle. Vehicle of type 1 is having only 802.11 based radios. Vehicle of type 2 is having only 4G cellular based radios. Vehicle of type 3 is having both 802.11 and 4G cellular based radios.

When vehicle is of type 1, it will broadcast its velocity, location, acceleration, time headways, timestamp, reward, learning rate and discount factor. GetWiFiVehicle will collect the rewards, learning rate and discount factor of all other N_1 vehicles which has 802.11 radio.

When vehicle is of type 2, it will push its velocity, location, acceleration, time headways, timestamp, reward, learning rate and discount factor to the edge relay server using PushMessageToCloud function. PullCellularVehicle will collect the rewards, learning rate and discount factor of all other N_2 vehicles from edge relay server.

When vehicle is of type 3, it will take help of both the radios as shown in Algorithm 1.

C. Federated Averaging

Vehicles are acting in various environments so there is a need of model aggregation before each RL agent takes an action. Aggregation of all the parameters received is done at vehicle. This aggregation procedure is called as federated averaging (FedAvg) procedure. Algorithm 2 is the FedAvg procedure running in $0 - th$ vehicle. Reward, learning rate and discount factor are the parameters which are aggregated and final federated model FM is used for performing future actions such as acceleration or deceleration of vehicles.

To summarize, vehicle will be running two procedures:

1) **Collision avoidance:** Vehicle runs RL locally for collision avoidance and send the parameters learned over V2V and V2N opportunistically.

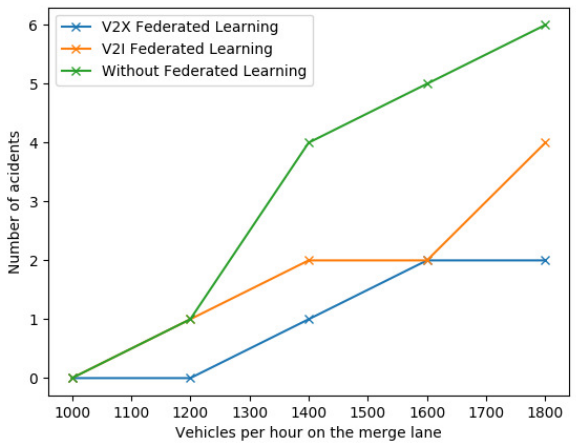

Fig. 5: Number of accidents vs flow rate on the merge lane.

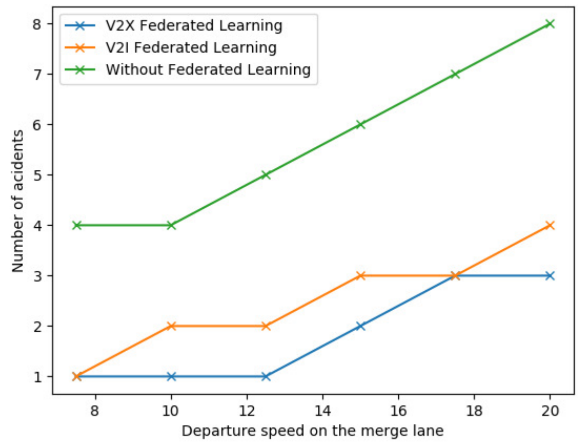

Fig. 6: Number of accidents vs departure speed on the merge lane.

2) **FedAvg Processing**: Aggregation of all the parameters received from nearby vehicles is done at the vehicle.

IV. Simulation Setup and Performance Results

A. Simulation Setup

We simulated the proposed architecture using SUMO [17], Veins [2], and Flow [18]. SUMO is an open-source traffic simulation software designed to handle large road traffic. Flow is a computational framework for RL and control experiments for traffic micro simulation. Flow acts as a bridge between SUMO and RL library as shown in Fig. 2. Veins is used for realizing V2V and V2N modes of communication and it is interfaced with SUMO. Simulation states are changed using Traci. The vehicles are randomly added in the map. They may not have the same departure time. Fig. 3 shows map used for simulation. There are two highway roads and merge lane intersecting at a point. Length of highway considered for simulation is 700 m where as for merge lane it is 300 m. Table II shows the simulation parameters that are considered in simulation. We studied scenario one and six presented in Table I for conducting the simulation experiments.

The first metric we considered is cumulative reward, which is collected for three cases: without federated learning, V2I federated learning (scenario one in Table I) and V2X federated learning (scenario six in Table I). Cumulative reward is the sum of the rewards of all cars present in the simulation. For this metric, we set vehicle per hour on merge lane, departure speed on the merge lane and simulation time as 1400, 7.5, and 5 $minutes$, respectively. On an average 292 vehicles are present in the simulation for collecting this metric.

The second metric we measure is the number of accidents, which is also collected for three cases: without federated learning, V2I federated learning (scenario one in Table I) and V2X federated learning (scenario six in Table I). First, it is measured against flow rate on the merge lane ($\mathrm{f_m}$). $\mathrm{f_m}$ is varied as 1000, 1200, 1400, 1600, and 1800 vehicles per hour. For this metric, we set departure speed on merge lane and simulation time as 7.5 and 5 $minutes$, respectively.

The number of accidents is also measured against departure speed of the vehicle on the merge lane ($\mathrm{s_m}$). $\mathrm{s_m}$ is varied as 7.5, 10, 12.5, 15, 17.5, and 20 m/s. For collecting this, we set $\mathrm{f_m}$ and simulation time as 1400 vehicles per hour and 5 $minutes$, respectively. The number of accidents is also measured against simulation time. Simulation time is varied as 5, 10, 15, 20, 25, and 30 minutes. For collecting this, we set $\mathrm{f_m}$ and $\mathrm{s_m}$ as 1400 vehicles per hour and 7.5 m/s, respectively.

TABLE II: Simulation parameters

Parameter Name	Value
Flow rate of the vehicles on Highway (vehicles per hour)	2250
Departure speed of the vehicles on Highway	15 m/s
Max acceleration	1.5 $\mathrm{m/s^2}$
Max deceleration	1.5 $\mathrm{m/s^2}$
Target velocity	20 m/s
Length of left part of highway	600 m
Length of right part of highway	200 m
Length of merge lane	300 m
Number of seeds	10

B. Performance Results

1) Cumulative reward: Higher the reward better the performance of the system is. When we do not use FL, we get a cumulative reward of 1360. When we use V2I based FL, we get a cumulative reward of 2142. When we use V2X based FL, we get cumulative reward of 2518. This means that the performance of the FL is more stable in case of V2X based FL compared to V2I based FL and when we do not use FL.

2) Number of accidents: Following are the results for number of accidents by varying different parameters:

1. Number of accidents vs Flow rate on the merge lane: Number of accidents is zero when $\mathrm{f_m}$ is 1000 vehicles per hour for all three cases. Number of accidents when $\mathrm{f_m}$ is 1200

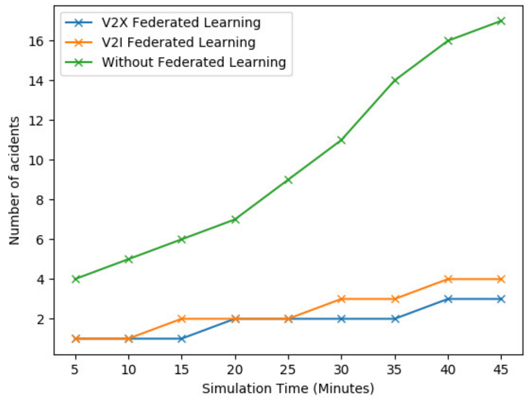

Fig. 7: Number of accidents vs simulation time.

vehicles per hour, is zero for V2X based FL, one for V2I based FL and one when FL is not used as shown in Fig. 5. Number of accidents when f_m is 1800 vehicles per hour, is two for V2X based FL, four for V2I based FL and six when FL is not used. So, we are able to reduce 4 accidents at f_m is 1800 when we use V2X based FL compared to when we do not use FL.

2. Number of accidents vs departure speed on the merge lane: Number of accidents when departure speed is 7.5 m/s, is one for V2X based FL, one for V2I based FL, and four when FL is not used as shown in Fig. 6. Number of accidents when departure speed is 20 m/s, is three for V2X based FL, four for V2I based FL, and eight when FL is not used.

3. Number of accidents vs simulation time: Number of accidents when we run simulation for five minutes, is one for V2X based FL, one for V2I based FL and four when FL is not used as shown in Fig. 7. Number of accidents when we run simulation for 45 $minutes$, is three for V2X based FL, four for V2I based FL, and 17 when FL is not used.

Above results show that when we do not use FL, the number of accidents increases exponentially. Number of accidents are nearly same for V2X based and V2I based FL. But V2X based FL is better compared to V2I based FL.

3) Comparison with a baseline work: In the baseline paper [3], the authors proposed a V2I based FL, whereas our approach uses V2X based FL which uses both IEEE 802.11p and LTE radios opportunistically. The latency of communication reduces as we use V2V mode of communication which indirectly reduces number of accidents. The comparison can be observed from the Figs. 5, 6, 7.

V. Conclusion and Future Work

In this paper, we presented a Cooperative V2X based FL system using LTE and 802.11p radios for collision avoidance. The proposed V2X based FL system makes good use of the radios present in vehicles, thereby performs better than the system which only used 4G LTE radio for V2X communication. In future, we will focus on extending the proposed architecture with V2X mode of communication with RSUs fitted with C-V2X/802.11p radios.

Acknowledgment

This work was supported by the project M2Smart: Smart Cities for Emerging Countries based on Sensing, Network and Big Data Analysis of Multimodal Regional Transport System, JST/JICA SATREPS, Japan

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