A Big Data Federated Learning-based Traffic Optimization Routing Scheme for Emergency Services Provision in Autonomous Vehicles Environment

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***Abstract*—Most of the future intelligent transportation services will rely on onboard sensing and communication protocols used in modern vehicles for providing uninterrupted services such as lane change, on demand audio-video entertainment, and emergency services to end users. Most of these services generate a huge amount of big data used for analytics to take intelligent decisions. However, keeping in view of the complex decision making and limited resources, the deployment and use of these services has various challenges and constraints including data safety, intelligent decision making, and route planning. Specifically, handling emergency situations for the end users traveling on road can be considered as an interesting problem which requires an efficient solution resilient to the aforementioned constraints and challenges. Motivated from the above, in this paper, we propose a prioritize route selection strategy using Federated learning (FL). The proposed scheme first envisions a futuristic road network scenario in which vehicles rely on an onboard intelligent route movement algorithm for reaching to its destination. By assigning higher priority to vehicles on emergency duties, the proposed scheme provides an uninterrupted route discovery by facilitating them to reach their destination on time. The proposed scheme has been validated using simulations on benchmark data sets traces using various performance evaluation metrics in comparison to the other existing state-of-the-art proposals. Results obtained prove the efficacy of the proposed solution on comparison with other existing schemes in literature.**

***Index Terms*—Intelligent Transportation System, Intelligent Sensing and Communication, Autonomous Vehicles, Federated Learning.**

I. Introduction

In future, the role of Intelligent Transportation System (ITS) based services will increase many folds especially with the advent of Autonomous Vehicles (AVs). It can play a crucial role in the development and deployment of AVs by providing efficient data communication, and safety features to support their safe and efficient operations. They can make better decisions and navigate more safely by using real-time information on traffic flow, road conditions, weather etc. It helps in improving the transportation system in terms of safety, efficiency and sustainability by leveraging advanced technologies [1]. ITS facilitates communication between AVs and the transportation infrastructure, allowing for an efficient and coordinated movement. They can take appropriate action and prevent crashes with the availability of advanced warnings. Their adoption gets accelerated with the support in development of its infrastructure support [2] [3].

A. Related work

Artificial Intelligence enables the safe and efficient operations of autonomous vehicles, allowing them to operate in complex and dynamic environments with minimal human intervention [4] [5]. It supports the development of mapping and localization technologies to enable precise and accurate vehicle positioning. Emergency situations in autonomous vehicles can benefit greatly from Federated Learning (FL) [6] [7]. FL approach is considered as one of the most promising technologies for implementing next generation ITS infrastructure. It allows multiple devices to train a model in collaboration without sharing raw data with each other or to a central server [8]. It offers a promising and effective approach for training the machine learning models in a privacy-preserving and collaborative manner, with potential applications in various industries, such as healthcare, finance, and telecommunications [9] [10] [11].

Artificial Intelligence based services are reliant on vehicle-to-everything (V2X) for satisfying their communication needs [12]. 6G networks provides exceptional solution for enabling AI based vehicular applications [13] [14]. These are more intelligent and autonomous with advanced AI and machine learning algorithms, and can optimize network performance and resource allocation. A 6G based V2X environment where vehicles are communicating within them selves, infrastructure and the cloud server can be used [15], [16], [17], [18], [19].

B. Motivation

Despite of research conducted for AVs for providing effective utilization of AVs on roads, there are a lot of challenges and constraints which needs to be tackled before a complete AV based ITS is implemented. Although movement of AVs on road increases safety but their localized decision making capabilities may not be able to provide an optimized path for the movement of emergency vehicles. A futuristic vehicle navigation control system to regulate the movement of AVs, using intelligent road infrastructure is the need of the hour. Motivated from this, a traffic routing scheme for provisioning emergency services needs to be designed that augments the localized decision making with an infrastructure based intelligent globalized decisions. The scheme should prioritize route to service vehicle to reach the emergency location without any interruption. Moreover, to secure the data shared among vehicles, a secure and lightweight computation model is required which can give an efficient solution with respect to the aforementioned constraints.

C. Contributions

Following are the major contributions of this article.

- We propose a FL based secure communication model for data sharing among vehicles.
- An optimized route planning and congestion avoidance algorithm for smooth transition of AVs is proposed.
- The proposed scheme has been evaluated in simulated environment on OMNET++ with random waypoint model with 100 nodes using various performance evaluation metrics.

D. Organization

Rest of the paper organization is as follows. Section II describes the proposed scheme in details. Section III illustrates the simulation environment and result analysis. Finally, Section IV concludes the article.

II. The Proposed Scheme

The objective of the proposed scheme is to get immediate emergency service for a user in emergency on road. When a driver less vehicle detects an emergency to the user. Firstly, it parks itself on the closest Emergency Bay (EB). Then an automatically generated sensed signal or user initiated signal in the form of message request is sent from AV to cloud server as shown in Figure 1. According to the request message, the distance between EB and the nearby service delivery point (SDP) has been computed on cloud server based on its database and the SDP with shortest distance is selected. A priority signal by that selected SDP is sent to service vehicle (SV) to move towards the EB. The SV follows the shortest distance path to reach the location of emergency and serve the user in need. For instance, in case of a medical emergency, the person can be taken to hospital using shortest distance. SV needs to be made available with uninterrupted path so that the patient could get the medical help in minimum possible time. For the proposed scheme, the following assumptions have been made:

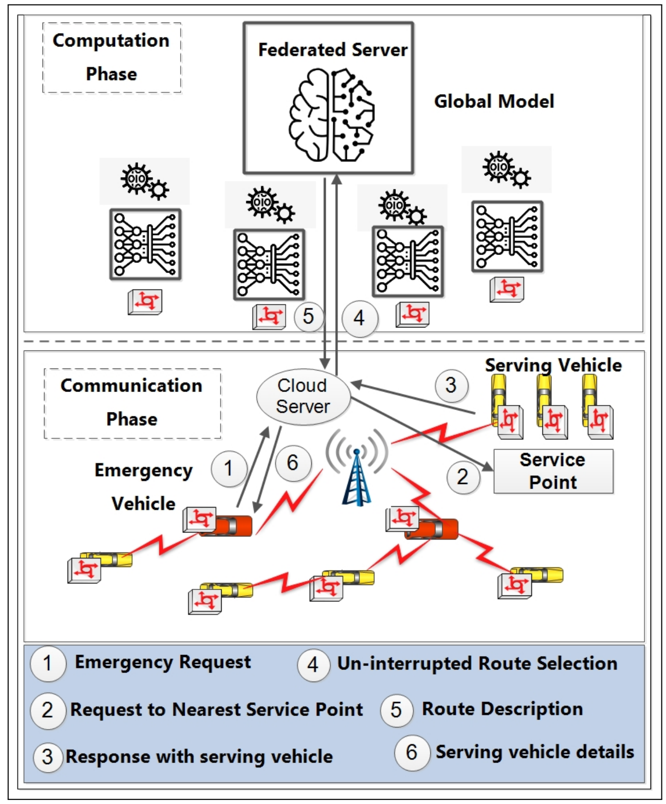

Fig. 1. Architecture layout for Proposed Route Selection Scheme

- All the vehicles are Autonomous Vehicles and moving with a regulated speed.
- Each vehicle is assigned with a priority level based on its type.
- Vehicles are equipped with high end computational capacity.
- There are no traffic light on the roads and route management for each vehicle is performed at vehicle itself.
- Each vehicle has an intelligent on board routing system that is used for vehicle movement.
- All vehicles are in secure environment.

The proposed two phase deep learning based framework for AVs uses V2X as the communication protocol for message transmission and FL to provide uninterrupted path consists of following: Communication phase and Computation phase which are described as below.

A. Communication Phase

In the proposed model, the communication phase describes that how vehicles can be connected to provide service to emergency vehicles. Here, we consider autonomous vehicles which are capable of communication, computation, and data storage in the vehicular network. During communication, these vehicles share data with other vehicles through V2X communication mode.

In the need of any emergency service, vehicle sends a request to the cloud server which is further processed using locations of nearby SDPs through the cloud server as shown in Figure 1. The selected SDP is signalled to perform various functions to give the appropriate service to the emergency vehicle with the information contained at the nearest serving station. The whole communication infrastructure is supported through a 6G based cellular network which speeds up the data flow between the network entities. Once a request is initiated by the cloud to the selected SDP, it communicates with its SV to provide appropriate service. Therefore, the major function of the communication layer is to provide the best resource to provide service to the emergency vehicle situated anywhere in the urban areas through inter-communication between autonomous vehicles. SDP_k is finalized by cloud server based on the optimum path from various SDPs to EB.

Let SDP are the SDPs in the vicinity of EB as given below:

$$SDP = \{SDP_1,\ SDP_2,\ ...,\ SDP_i,\ ...,\ SDP_n\} \tag{1}$$

The cloud server has processed the location of each SDP from SDP_1 to SDP_n. The shortest path from all SDP to EB is calculated as explained in Algorithm 1. The SDP_k with smallest distance has been selected as follow:

$$D_v = D_u + W_{(u,v)} \tag{2}$$

where
$D_v \rightarrow$ Distance between starting node and node v.
$D_u \rightarrow$ Distance between starting node and node u (the current node).
$W_{(u,v)} \rightarrow$ Weight of the edge between node u and node v.

The one with smallest SD among these distances has been selected as optimum route and named as R.

$$R = \min_{d} D(d) \tag{3}$$

The route R is communicated to SV to be followed to reach the EB.

B. Computation Phase

Once the SDP_k and Optimum route R is finalized by the communication phase, a SV is signalled to start following the optimum route to make it reach at required location as quickly as possible. Next, FL has been used to provide uninterrupted path to the SV so that the user can get the emergency service in minimum possible time. It checks for the collision probability (Col_Prob) between SV and each V_i. If it is more than a threshold (T_h) then will regulate the speed of V_i as explained in algorithm 2. The AVs present on the route of SV acted as local models of FL as shown in Figure 2, which are being trained with the local information of vehicles. These updates after training are aggregated to global Model mounted on cloud server. This centralized global model is then communicated to local devices for better training of local models which helps in setting their speed, so that emergency vehicle can reach the destination without any halt.

Let there be N number of intersection points from source to destination where FL has been executed. The number of vehicles present on each intersection are:

$$V = \{V_1, V_2, ..., V_v\} \tag{4}$$

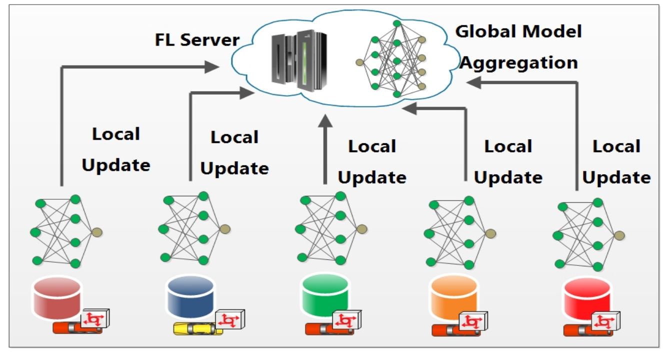

Fig. 2. Federated Learning based Computation Model for Emergency Service Providers

Each of these vehicles acts as local server which stores the local data of the vehicle. These vehicles information update about the current location of SV and they adjust their speed communicated by FL model so that the SV should get uninterrupted path. The model is trained locally using local vehicular data, and intermediate updates are sent to a global server in the cloud. With each update, the global model grows better. The Shared Global model of distributed local vehicles is trained using the FL technique. Local servers download the shared model from the cloud server. The training model updates with multiple iterations, are shared with the global server and required speed of vehicles is communicated to them. Location, speed, and route, among other local variables, are taken into account for speed finalization. The aim in federated process is to lower the local objective function:

$$\min_{w} F_n(w), where F_n(w) := \sum_{i=1}^{P} p_i F_i(w) \tag{5}$$

Here, P $\rightarrow$ Total vehicles at each intersection point on the route. $p_i \rightarrow$ The effect of i^{th} vehicle, $p_i \geq 0$ and $\sum ip_i = 1$. $F_{n_i} \rightarrow$ Local objective function for the i^{th} vehicle as computed below:

$$F_{n_i}(w) = 1/s_i \sum_{j_i=1}^{n_i} f_{j_i}(w; x_{j_i}, y_{j_i}) \tag{6}$$

where $s_i \rightarrow$ samples used in one segment.
s is the total number of samples used.
$p_i \rightarrow$ The effect of each vehicle with $p_i = (1/s)$ or $p_i = (s_i/s)$.
The federated learning based algorithm, FedAvg is used for computation of the average of all the model updates given by global model in every round. Vehicle data made available locally is used by the local models. Local training takes place with all the P vehicles with local data. The updates with respect to the weight are passed on to global server. The training at global and local models is done to make the F_{n_i} function minimize and developing the final global model G_i as shown below:

$$G_i = \frac{\sum_{j=1}^{P} Pk_j w_j}{J} \tag{7}$$

Weighted sum of all the local model updates, divided by total number of segments (J) gives the G_i. Stochastic Gradient Decent (SGD) is taken as the optimizer for FL in process of local model training and is formulated as:

$$g_p = \nabla f_p(w) \tag{8}$$

After application of SGD, the modified weight is calculated and passed to global server as follows.

$$w^{t+1} \leftarrow w^t - \Lambda \sum_{j=1}^{P} \frac{k_j}{J} g_p \tag{9}$$

where Λ shows the learning rate of local server. The basic idea is that the global model gets updated by aggregating the local model updates received from each vehicle, weighted by their respective loss functions. This approach allows the global model to be updated based on a larger and more diverse set of data sources, while preserving the privacy and security of the local vehicles' data.

Algorithm 1 Optimum Route Selection ORS

Inputs:
1. Location of Emergency Bay EB.
2. Service Delivery Points SDP in the vicinity of EB.
Outputs:
Selected Service Delivery Point SDP_k for which distance to EB is minimum.

Begin
T_X (EB, Req_{type});
if (T_X received) **then**
  flag = validate(Req_{type});
end if
if (flag) **then**
  SD_i = INT-MAX;
  for each SDP_i, i=1 to n **do**
    SD_i = compute $SD_i(EB, SDP_i)$;
    if ($SD_j > SD_i$) **then**
      SD = SD_i;
      SDP_j = SDP_i;
    end if
  end for
end if
store (SD, SDP_k);
End

Based on the local vehicular information provided at local servers and after going through the federated learning, the vehicles in the vicinity are provided with a speed to be adjusted to give a clear path to service vehicle as discussed in algorithm 2. As per algorithm, information about each vehicle on the route till N intersection points is passed to Global Server. At each local server, the weight w_0 is first initializes to 0. Local model at each vehicle is trained with information of normal vehicle and priority vehicle. The global server is aggregated with the training updates received as weighted sum, using that Global server model also gets aggregated. Depending on the aggregated values at Global server, local servers/vehicles are provided with speed value.

Algorithm 2 Uninterrupted Path Algorithm

Inputs:
1. $N \rightarrow$ Number of intersection points on SD.
2. $V \rightarrow$ Number of vehicles on each intersection point.
3. $SV \rightarrow$ Service vehicle of selected service delivery point, i is the number of steps.
Outputs:
1. Global Model G_i.
2. Speed of each vehicle on SD.

Begin
$SV \leftarrow SDP_k \leftarrow call\ ORS()$;
$SD \leftarrow call\ ORS()$;
$State(SV) \leftarrow ON$;
$w \leftarrow 0$;
for each N_i **do**
  for each V_i **do**
    $\underline{SP} = speed(SV)$;
    $\widetilde{SP}$ = $speed(V_i)$;
    $CP \leftarrow Col\_Prob((SP, \widetilde{SP})$;
    if ($CP > T_h$) **then**
      $w^{t+1} \leftarrow w^t - \Lambda \triangle F(w^t), \leftarrow Train(V_a, V_b)$; // using Eqs (7), (8)
      $G_i \leftarrow Update(w^{t+1})$; //using Eqs. (9, 10)
      Insert(V_i, G_i);
    end if
  end for
end for
End

III. Performance evaluation

The performance of proposed scheme has been analyzed using NS3 simulator by considering various locations of hospitals in Chandigarh city along with the availability of ambulances/service vehicles at these hospitals.

A. Simulation environment

We have considered seven hospitals as shown in Table I as service points that provide services to emergency vehicles at any location in the city. The emergency vehicles can be located at any point and send a request for service to the nearest hospital. The requested hospital provides an autonomous service vehicle towards the route of the emergency vehicle with uninterrupted path.

This vehicular mobility pattern has been evaluated using SUMO by taking the road network scenario from *OpenStreetMap* in that area. This mobility pattern has been considered "Ns2MobilityHelper.h" package for importing mobility pattern generated by SUMO in NS3. Table II describes the considered inputs for the simulation performance implemented

TABLE I
SIMULATION ENVIRONMENT PARAMETERS

Hospital Name	**Locality**	**Number of Service Vehicles**
Govt.Medical college & Hospital	Sector 32	20
Mukat Hospital	Sector 34A	10
Fortis Hospital	Airport Area	15
Government Multi Specialty Hospital	Sector 16A	30
Gmc Hospital	Sector 44	10
Max Super Specialty Hospital	Phase 6	25
PGIMER	Sector 12	50

with $DSRC$ for vehicle to vehicle communication and $6G$ for cellular communication by importing $ns3/yanswifihelper.h$, $ns3/wifi80211phelper.h$ and $ns3/thzchannel.h$ packages respectively. We also considered that about 10 - 50 service vehicles are there for serving emergency requests generated after 5 minutes within 30 minutes on the route from $Sector7$ to $PGIMER$ for time period 11.00 am to 11.30 am. The framework has been implemented using FL APIs($tff.learning$) on federated TensorFlow for providing uninterrupted route. We have evaluated the scheme on Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to measure the accuracy of the proposed scheme and shown in Table III.

TABLE II
PARAMETERS FOR EVALUATION ON NS3

Parameters for Simulation	
Variable Description	**Values**
Average Number of vehicles	[100,150]
Average Number of service vehicles	[10,50]
DSRC Data Rate	27Mbps
6G	1Tbps
number of emergency vehicles	[1,7]/5min
Simulation Time	300 seconds
Number of Hospitals	7

TABLE III
UNINTERRUPTED PATH EVALUATION

Vehicle Density Range per KM	**MAE**	**MSE**	**RMSE**	**MAPE**
71 - 80	6.95	97.87	9.59	14.79%
81 - 90	7.27	99.26	9.96	16.32%
91 - 100	7.52	99.98	10.11	16.95%
101 - 110	7.89	100.98	10.92	17.26%
111 - 120	7.96	101.59	11.14	17.92%

B. Results analysis and discussions

We have evaluated the results based on different communication parameters such as throughput, average execution time, communication overhead, computation time, service delay and success rate for the proposed model. The variation of these parameters has been evaluated with respect to number of requests coming after every T minutes, where T is taken as 5 minutes. Also, the extensive simulation is done with a test bed on vehicle density on the route and average number of emergency vehicles. The variation of the graph depends upon the increasing number of emergency requests towards the number of vehicles on the route.

Figure 3 illustrates the impact of throughput when the density of vehicles is increased on route. The value of throughput will be increased when network traffic increases. The graph is showing constant flow, which increases slightly due to less probability to have serving vehicles with the hospitals, which retain constant value when reaching a threshold value. Figure 4 depicts that as the number of emergency vehicles are increasing in the network, the variation in the graph is getting constant with increase in requests.

Figure 5 depicts the communication overhead which is increasing with respect to average number of emergency vehicles according to the packet size. It is higher when packet size has been increased because more packet load causes more overhead in the network. Also, the value of overhead is increasing as the number of emergency vehicles are sending requests for services. Figure 6 shows that the computation time is decreasing with respect to increasing average number of emergency vehicles in the network. It is higher when speed of serving vehicle i.e ambulance is lower because high speed vehicle will be connected and approach early as compared to slow speed vehicle.

Figures 7 and 8 depict the impact on the success rate for letting the service to the emergency vehicle on time with respect to the average number of serving vehicles and emergency requests. The success rate is almost constant with a minor decrease when more requests come and less number of serving vehicles are there. Also, the service delay is decreasing when more service nodes are provided for less number of requests. Therefore, our scheme is performing efficiently when there are a sufficient number of serving vehicles for the corresponding number of requests.

IV. CONCLUSION

An effective traffic routing model based on AVs to reliant on an intelligent route selection algorithm supported by high speed communication infrastructure is proposed. The scheme has been implemented through a federated learning based traffic routing model that provides an efficient traffic services for emergency vehicles in an urban scenario. The scheme provides a clear path with lesser number of obstacles to service vehicle by synchronizing the movement of all the vehicles in its path. Thereby creating a traffic system that provides on time service for travelling users. In future, the scheme will be extended to a more holistic scheme for different types of vehicles.

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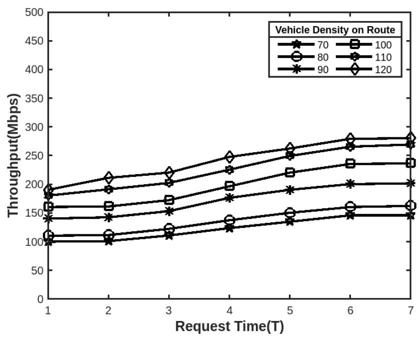

Fig. 3. Throughput(Mbps) w.r.t Request Time.

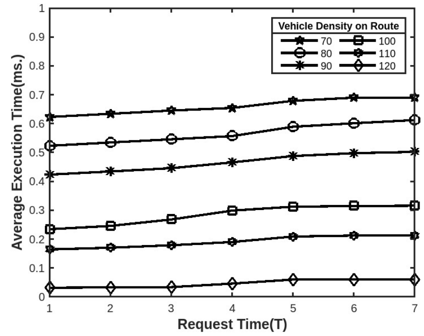

Fig. 4. Avg Execution time(ms.) w.r.t Request Time.

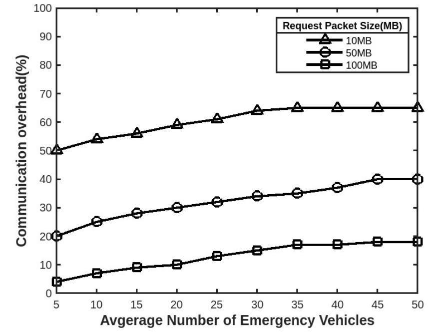

Fig. 5. Communication Overhead w.r.t number of emergency vehicles

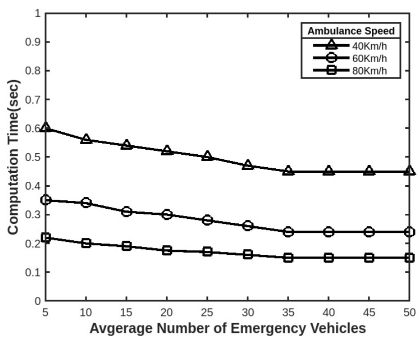

Fig. 6. Computation Time(sec.) w.r.t Avg number of emergency vehicles.

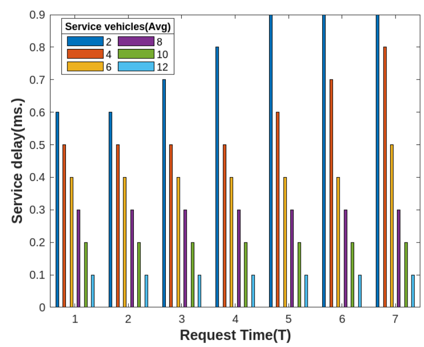

Fig. 7. Service Delay(ms.) w.r.t Request Time.

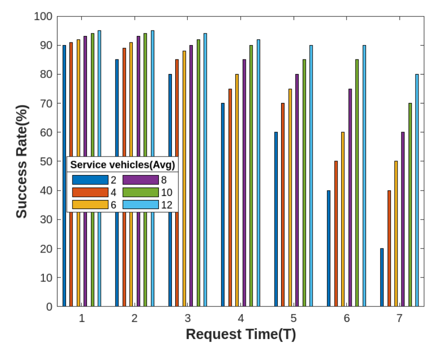

Fig. 8. Success Rate(%) w.r.t Request Time.

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