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IMPROVING THE QUALITY OF VANET COMMUNICATION USING FEDERATED PEER-TO-PEER LEARNING

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Abstract

Vehicular Ad hoc Networks (VANETs) are one of the most advanced transportation networks that have attracted much attention in recent years. The VANETs are characterized by a large number of traffic flows, which make them a good choice for a wide range of applications. However, due to the unique characteristics of the VANET, routing algorithms present a significant obstacle that must be surmounted. In order to improve the communication quality, the research uses federated learning. The research demonstrates the capacity of the model to learn from its previous errors while also delivering more accurate projections using the federated learning. The findings of the simulation demonstrate that the model with a prediction accuracy of 4 packets/s has the highest accuracy when compared to its contemporaries as well as other predicted models. The results show that the proposed method achieves higher rate of accuracy in transmitting the packets with reduced overhead than the other existing methods.

Keywords:

Communication Quality, VANET, Federated Learning, Overhead

1. INTRODUCTION

Vehicular Ad hoc Networks (VANETs) have gathered a lot of attention as a result of the possibilities they present for more advanced transportation networks [1]. By utilizing the VANET, which removes the necessity of relying on any established infrastructure, individual vehicles are afforded the opportunity to engage in safe and encrypted communication with one another. Professionals in the relevant sector have lauded it for the choices it gives users in terms of both protection and entertainment. It is still difficult to create a navigation system that is able to function in an environment that has a lot of motion going on in it.

Data may become out of current as a consequence of increased mobility and variable topologies, which raises concerns regarding disconnectedness and the dropping of packets across vehicle networks. In an effort to find a solution to these problems, a number of different transportation strategies have been put into place. Both of these forwarding methods rely on a network topology to determine routes.

The information that is included in routing modifications is what serves as the basis for topology-based forwarding. Both proactive and reactive routing are considered to be principal types of routing. Preemptive routing was developed first. Communication that is proactive has a low latency because it is based on having position information readily accessible in advance. Proactive routing methods incur a significant amount of additional work, also known as overhead, due to the frequent need to request for route updates. On the other hand, approaches call for a noticeably extended period of time due to the fact that the base station needs to determine the routes each time it sends out a communication [2].

Because of the one-of-a-kind characteristics of VANETs, routing algorithms present a significant obstacle that must be surmounted. This is the maximum number of packets that can be carried all the way from the input to the output of the device. Even relatively minor obstacles, such as traffic lights and bridges, have the potential to produce a network partition due to the large number of vehicles and the enormous nature with continuous density variations. This is because of the continuous density variations [3].

The task of routing provides a significant challenge. However, because of the design characteristics of routing systems, such as mobility restrictions and uninterrupted road mobility, VANETs are able to use these characteristics to their advantage. This is due to the fact that routing systems are designed. Algorithms centered on mobility that estimate the length and breadth of a route based on relative movement variables are one category among the presently available routing algorithms for VANETs [4].

Location routing protocols make use of coordinates to determine routes that bring the target vehicle closer to the user, whereas probabilistic routing protocols are used to anticipate incidents and ensure that VANET communication over the underlying infrastructure is dependable. Both of these types of routing protocols are used by probabilistic routing protocols. The proposed connectivity protocols are utilized to guarantee that VANET communication over the underlying infrastructure is carried out in a secure manner [5].

2. RELATED WORKS

GeOpps-N is introduced as a cutting-edge hybrid routing protocol that was developed specifically for implementation in Public Transportation Systems with the intention of making it easier for vehicles and process control centers to communicate with one another. A new location update for the bus is expected to be provided at least once every thirty seconds. Data has to be transmitted due to the relatively low population density of the network and the continuous congestion that it experiences. It has been discovered that topology-based routing approaches are superior to geographic-based routing or storm routing in terms of their suitability for use in low-quantity environments [6]. This finding was made possible by the fact that topology-based routing approaches take into account the network structure. Rather than attempting to identify the person responsible for the conception of an idea from within the group that conceived the idea, these methods look for the person who is the most qualified to convey an idea from the point where it was first conceived to the place where it will ultimately be implemented. When applied to networks that contain a large number of mobile devices [7], this strategy does not generate the optimal results that could be achieved.

The fuzzy systems contribute the coordination and analysis of competing measures. This will be accomplished through the use of fuzzy logic. The method that has been proposed takes into consideration a number of different aspects, including the position and orientation of the vehicle, the standard of the network, and the amount of bandwidth that is available in order to select the next-hop that will provide the best possible path for the transmission of data packets. This allows the method to select the next-hop that will provide the best possible path for the transmission of data packets. On the other hand, when implemented in a dynamic high-speed network, this approach generates performances that are satisfactory [8].

A hop-greedy routing (HGR) method was developed as part of their research. In addition, the nodes that comprise the backbone are responsible for maintaining a record of the locations of the sender and the addressee. This enables the payload to be redirected through a different conduit, which gives the option to do so. Numerical models have demonstrated that the proposed routing strategy can increase the percentage of packets that are successfully delivered and can reduce the end-to-end latency. However, the increases in productivity are not nearly as substantial as one might expect [9].

Wherever urban environments are concerned, the AODV protocol Intersection-based Geographical Routing Protocol (IGRP) for VANETs functions more effectively than the other options that are currently accessible. IGRP pays special attention to the networks that act as road intersections because a signal must travel through a number of different networks before it can reach an HTTP server. The Quality-of-Service (QoS) criteria for acceptable latency, network capacity, and confidence interval are all satisfied, and the decision is constructed in such a way that an internet connection is guaranteed with a high probability between the two endpoints. However, its effectiveness is only about average when applied to networks that contain a significant number of mobile devices [10].

An investigation was conducted into the method by which data is transmitted in metropolitan VANETs, and an algorithm known as parking-area-assisted spider-web routing (PASRP) was proposed as a possible solution. The PASRP produces a spread arrangement in the form of a spider web based on the parking lot by making use of remote sensing, GPS, and a digital map. By sending out two control packets known as a request-spider and a confirm-spider, the network is able to determine the path that will result in the least amount of delay between the transmitting device and the receiving device. Following that, the research sends the data that is the most important as it travels along the route using a multi-mode greedy approach that takes into consideration the concept of dynamic multi-priority. Calculating the packet delivery ratio and the throughput are the only two metrics that the technique in question is concerned with [11].

The Traffic-Aware Routing for urban VANETs by employing RSU-assisted Q-learning is used to transport packages to their intended locations, a routing strategy in QTAR is comprised of a large number of high-availability road segments, and these road segments are selected on the fly. Routing packets within a road segment with Q-greedy geographical forwarding and distributed R2R Q-learning to reduce transmission delay, and routing packets at every transitional link with distributed R2R Q-learning to reduce the impact of high-speed traffic flows on path vulnerability. Both of these strategies aim to reduce transmission delay. Both of these routing techniques have the goal of minimizing the amount of time spent in transmission delay. On the other hand, this approach places an unhealthy amount of importance on performance and latency [12].

3. SPARSIFICATION

The relationship between variables such as the size of the model, the number of training epochs, and the number of users determines how much it costs to communicate between nodes in FL. Many FL activities experience insufficient throughput. Our primary emphasis is on lowering the number of parameters that need to be passed between nodes in order to cut down on the cost of communication between them. This is one of the factors that determines how much it costs to communicate between nodes. In order to accomplish this, the research demonstrate that model sparsification offers a viable alternative for accomplishing the desired result by cutting down on the quantity of data that is utilized by the model.

The process of sparsifying a model involves making use of only a small portion of the available parameters and setting the values of the remaining parameters to zero. The k variables that need to be chosen in compliance with the sparse ratio r are those that have the greatest magnitude in the gradient. The r serves as a symbol for the proportion of variables that need to be simplified into sparse form, and it represents this proportion as a symbol. During the succeeding training iteration, which will center on the residual set known as W_r, the remaining $|W|$-k parameters are going to be scrutinized for accuracy.

It is possible that certain parameters, which frequently contribute to large magnitudes in the gradient, can dominate the sparsification process, and other pertinent parameters may not be shared with the peers, despite the fact that the gradients of parameters in the most recent iteration are stored as residuals. This is because it is possible that certain parameters frequently contribute to large magnitudes in the gradient. This is due to the fact that it is feasible for particular characteristics to take control of the sparsification process.

When only a portion of the model is distributed to numerous clients, particularly in situations that do not involve IID, the local model performance on those clients is negatively affected. This is particularly the case when the IID situation is not present. In order to lessen the effect of the current gradient, our plan calls for an increase in sparsification, which would be accomplished by giving velocity to the residual. The training will consequently become more consistent as a consequence of this, which will ultimately result in enhanced performance. The momentum residual, which is denoted by R can be calculated with the help of the following algorithm:

$$R_{t,i} = \beta R_{t-1,i} + (1\text{-}\beta)\ \nabla F(W_{t,i}), \tag{1}$$

where $\beta \in [0, 1]$ controls the balance between the current residual set and the residual set from previous rounds. The problem in which only the model parameters with the largest magnitudes in the gradient are found as a result.

The component $\nabla F(W_{t,i})$ in the equation is a representation of an expected gradient of the local model. This gradient is determined based on client i at the moment t that it is calculated.

The majority of the input consists of the two hyperparameters, β and r, as well as the parameters of the local model that will be used in a fashion that is shared with the neighbors. Additionally, there are some other parameters. Both the initial number of the filter and the remainder have been adjusted so that they both read zero.

At the t^{th} communication round, both the gradient that is obtained from the present $W_{t,i}$ and the gradient that has been accumulated from previous iterations are considered in the process of determining the value of the residual $r_{t,i}$.

Both lines 4 and 5 illustrate how the sparse ratio r determines the number of common parameters k, and how the mask m_t, which is a binary tensor, is constructed by making use of the k largest values of the remainder $r_{t,i}$. Lines 4 and 5 also demonstrate how the sparse ratio r determines the number of common parameters k. The very last step in the procedure

$$w_{t,i} = m_t \circ W_{t,i} \tag{2}$$

where ◦ - Hadamard product.

In the algorithm, line 6 explains how to calculate the residual for the following round, which is indicated by $r_{t+1,i}$. This step is required before moving on to the next round. It is possible to achieve this result by subtracting the disguised gradient from the current residual, which is represented by the symbol $r_{t,i}$.

Algorithm 1: Sparsification Algorithm

Input: $W_{t,i}$, β, and r

Output: Sparse output: $w_{t,i}$

1: Initialize the mask: $m_0 = 0$

2: Initialize the residual: $m_0 = R_0 = 0$

3: Find the gradient $\nabla F(W_{t,i}) \leftarrow \nabla(W_{t,i})$

4: Estimate $R_{t,i} = \beta R_{t-1,i} + (1-\beta)\nabla F(W_{t,i})$

5: $k \leftarrow r * numel(R_{t,i})$

6: Generate the mask m_t in ascending order from $R_{t,i}$

7: $R_{t+1,i} = R_{t,i} - m_t \circ \nabla F(W_{t,i})$

8: $w_{t,i} = m_t \circ W_{t,i}$

4. FEDERATED LEARNING

According to the FL learning paradigm, a large number of participants exercise together; however, they do not centralize their data nor do they share it with one another.

Let function L, which stands for global loss function is acquired by the weighted combination of K local losses, $\{L_k\}K_k$=1, which is computed from information X_k that is kept in private hands and is never shared among the parties involved in the transaction. Specifically, this information is never shared among the parties involved in the transaction. The formula for this function is:

$$\min_{\phi} L(X;\phi) \text{ with } L(X;\phi) = \sum_{k=1}^{K} w_k L_k(X_k;\phi) \tag{3}$$

Each of the weight coefficients are denoted by $w_k > 0$, and the minimum value of this function is X.

Individuals acquire and perfect a global consensus model by conducting a few iterations of optimization on their own, after which they communicate updates either directly or through a parameter server. This process results in the model being more accurate and complete. The model ends up being more accurate as a consequence of going through this procedure. The more repetitions of local training that are carried out, the less confidence one has in the procedure ability to reduce the equation that was discussed earlier.

The specific method for aggregating parameters is one that must take into account the structure of the network. This is due to the fact that nodes may be divided into sub-networks on account of geographical or legal restrictions. Either in a centralized fashion or in a decentralized fashion, aggregation can be carried out. When using a centralized FL aggregation technique like the one used in Algorithm 1, only websites that are directly connected to one another have the ability to trade model updates.

In the process of learning from one peers, it is possible to establish connections with all of the participants or with only a subset of them. Clients have the option of choosing to only share a subset of the parameters of the model in order to cut down on the amount of communication overhead, improve the level of privacy protection, generate multi-task learning algorithms with only a subset of their parameters learned in a federated manner, all of which may be used by aggregation strategies, or for any of the other reasons that have been listed above.

Algorithm 2: Federated Algorithm

Input: num_rounds T

1: **procedure** Aggregate

2: Initialise the FL: $W^{(0)}$

3: **for** $t \leftarrow 1$ to T **do**

4: **for** packet $k \leftarrow 1 \cdots K$ **do**

5: Send $w_{t,i}$ to k

6: Enable training with iterations $(\Delta w_{t,i}, N_k)$ with $L_k(X_k;w_{t,i})$

7: **end for**

8: $w_{t,i}(t) \leftarrow w_{t-1,i} + (\sum_k N_k \sum_k N_k \cdot w_{t,i}(k))^{-1}$

9: **end for**

10: **return** $w_{t,i}$

11: **end procedure**

4.1 FL ASSESSMENT

In this section, the proposed method is tested in terms of communication efficiency and peer-to-peer learning ability.

4.1.1 Communication Efficiency:

Instructional material is still dispersed across a large number of clients in a federated learning environment, the vast majority of which have Internet connections that are either slow or inconsistent. In the context of federated learning, the following equations provide the total number of bits necessary for uplink (client-server) and downlink (server-client) communication by each of the K clients while they are being trained, assuming that a naive synchronous algorithm is being used:

$$B^{up/down} \in O(U \times |w| \times (H(\triangle w^{up/down}) + \beta)) \tag{4}$$

where

U - total updates by a client,

$|w|$ - model size and

$H(\triangle w^{up/down})$ - weight entropy updates.

β - difference between the true and minimal update size.

There are three possible courses of action that can be taken in order to bring down the expense of communication, and they are as follows: It would be beneficial to cut down on (a) the number of users K, (b) the quantity of updates, and (c) the number of times updates are carried out U.

4.1.2 Peer-to-Peer Learning:

When it comes to federated learning, having a centralized server is an essential requirement in order to be able to manage the education for the worldwide model. However, if there are a considerable number of clients actively participating in the activity, the cost of communication to the central server may become excessive.

Many peer-to-peer networks that exist in the real world are changeable, which means that it is not always possible to access a single server that is always online. This is one of the reasons why accessing a single server that is always online is not always possible. The training process for all clients would be halted if the central server were to become unavailable because all clients are dependent on a single, dependable central entity. This is because the training process is dependent on the availability of the central server.

The immediate effect of this was that researchers started looking into various alternatives to the conventional centralized solution. Due to the fact that the data is only disseminated on a local level, clients can only communicate with their immediate neighbors in the graph or network. Each person starts by gathering information from their immediate neighborhood, which they then use to update their own local opinion based on the data they have collected based on the information they have gathered.

When training the centralized model, the goal is to minimize loss in comparison to the standard distribution, which is defined as:

$$D = \sum_{k=1}^{K} n_{k,n} D_k \ , \tag{5}$$

where D pertains to the distribution of interest for the training collection. The problem is that making use of this particular regular distribution as an option is virtually never one that is prudent.

5. PERFORMANCE ANALYSIS

GrooveNet v2.0.1 was the tool that was used for the simulation; it is a hybrid simulator that incorporates mobility and network modeling, and it is both open source and free to use. The parameters of simulation is given in Table.1.

Table.1. Simulation Parameters

Parameter	Value
Area	0.5 Km^2
Maximum trip distance	1 km
Rate of Transmission	3 Mbps
Range of Transmission	300 m
SNR	20dB
Nodes mobility model	Car-following model
Group leader mobility	Uniform speed
Simulation Time	15 min
Number of Nodes	20, 50, 100
Iterated simulation	30 times/scenario
Message lifetime	1 min

Table.2. Performance of Routing metrics

Node	Delay	Packet Drop	Packet Delivery Ratio
20	97.99	1.67	20.20
40	37.38	10.09	33.34
60	50.51	14.83	48.49
80	95.96	51.06	59.60
100	68.69	57.73	64.65

Table.3. Performance of Network metrics

Node	Network Lifetime	Fairness Index (FI)	Energy Consumption (J)	Throughput (KB/sec)
20	342.97	4.29	0.25	1290.98
40	671.07	2.44	0.32	1939.50
60	529.32	1.81	0.35	1727.37
80	374.58	1.59	0.43	1358.66
100	310.84	1.41	0.52	1221.28

The quantity of energy that is consumed by each node is carefully monitored and recorded. The consumption of half of the total quantity of energy occurs at node 100. The greater the number of servers that are a part of the network, the greater the quantity of electricity that is required to maintain the network functionality.

Table.4. Energy Consumption (mJ) of higher nodes

Node	Date Rate					
	4	6	8	10	12	14
20	1353	905	682	505	396	392
40	2273	1591	1243	973	657	606
60	1873	1259	926	677	556	505
80	1384	942	625	506	404	399
100	1111	767	536	443	321	303

The amount of time that each node in the network was active for was recorded. This location contains information regarding the lifespan of network node 100. The increased number of nodes in the network led to an increase in the network stability over time.

The compilation of data includes a table that presents a breakdown of the throughput generated by the proposed method on a node-by-node basis. The results show that the proposed method achieves higher rate of accuracy in transmitting the packets with reduced overhead than the other existing methods as in Table.2-Table.5.

Table.5. Performance Assessment

Metris	**Techniques**	**Nodes**			
		20	**40**	**60**	**80**
Delay (s)	GeOpps	0.3021	10.1552	15.7753	15.8021
	IGRP	10.3310	29.9402	46.7015	46.5044
	FL	7.0127	17.3419	20.3831	19.7677
Energy consumption (mJ)	GeOpps	7.0711	3.0305	2.0203	2.0203
	IGRP	8.0813	5.0508	4.0406	3.0305
	FL	8.0813	4.0406	3.0305	2.0203
Packet Drop	GeOpps	0.6735	0.1805	0.1592	0.1566
	IGRP	1.0092	0.6204	0.4501	0.3938
	FL	1.0030	0.5269	0.3442	0.3120
Throughput (Bps)	GeOpps	42084	28279	30870	40502
	IGRP	13720	18976	204357	22525
	FL	25276	22267	26826	32261
Fairness Index (FI)	GeOpps	66.6703	17.1727	15.1523	15.1523
	IGRP	100.0055	61.6195	44.4469	38.3859
	FL	100.0055	52.5281	34.3453	30.3047

The output is significantly higher than that of the methods that have been used in the past. The technique that has been proposed deviates significantly from the methods that are being used at the moment in a number of essential respects, the most notable of which is the incorporation of a fairness score.

6. CONCLUSION

The goal is to improve the communication quality on the VANET, and the method that the research uses federated learning. The research demonstrates the model capacity to learn from its previous errors while also delivering more accurate projections for the future. Moreover, this enables us to make better use of the model. In contrast to other more traditional types of time series prediction models, this learning framework is able to improve its predictive accuracy with each training session that it undergoes. In addition, the evaluation of the traffic number that is produced by the model will be more accurate the more data that is input into it. The real-time traffic prediction can produce more accurate results, making it an important component of the process. The findings of the simulation demonstrate that the model with a prediction accuracy of 4 packets/s has the highest accuracy when compared to its contemporaries as well as other predicted models. This model also had the highest accuracy when it was compared to other predicted models.

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