Improving TCP Performance Over WiFi for Internet of Vehicles: A Federated Learning Approach

Shiva Raj Pokhrel, *Member, IEEE*, and Jinho Choi, *Senior Member, IEEE*

***Abstract*—We propose a novel communication efficient and privacy preserving federated learning framework for enhancing the performance of Internet of Vehicles (IoV), wherein on-vehicle learning models are trained by exchanging inputs, outputs and their learning parameters locally. Moreover, we use analytic modeling as a tool for reasoning and developing the required IoV scenario and stabilize their data flow dynamics by considering TCP CUBIC streams over WiFi networks to prove our idea.**

***Index Terms*—Autonomous vehicles, connected vehicles, federated learning, internet of vehicles, Q-learning, TCP, WiFi.**

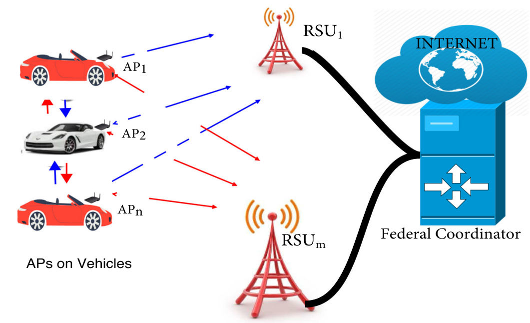

Fig. 1. An IoV network scenario where vehicles with WiFi Access Points (APs) are connected to a Federal Coordinator and Internet via Road Side Units (RSUs). Learning modules inside vehicles are trained locally and are also communicated using TCP CUBIC to others forming an ad-hoc network of neighbouring vehicles.

I. Introduction

Machine learning techniques in various fashions have already been applied to improve the performance of Internet of vehicles [1]–[6]: such as, computer vision for analyzing obstacles, machine learning for adapting their communication performance (e.g., speed variation due to bumpiness of the road). However, in the anticipated Internet of Vehicles (IoV) networking scenario, due to latency requirements, bandwidth, computing and privacy concerns it is often impractical to collect all the data to a centralized server [1], [5]. Due to the potential high number of IoVs and the need for them to quickly respond to real world applications, traditional cloud-based learning approaches are relatively sluggish and inadequate. To this end, we believe that federated learning can enhance the internet performance for the volume and variety of data transfer by accelerating the learning processes of the data transport protocols, such as TCP.

Understanding and improving the IoV performance using federated-learning has become more and more important in vehicular networks due to the anticipated growth of connected autonomous vehicles with diverse quality of service requirements. Most of the existing works [5]–[9] that explain and quantify the performance of federated learning over wireless focus on the distributed learning part and do not consider the impact due to the interaction with the packet transmission mechanism in the lower layers of wireless networks.

Furthermore, the existing models [5]–[9] only provide expressions for computing their performance when loss and delay are exogenous quantities. However, loss and round trip times ($rtts$) vary over time with packet sending rate and with the lower level transmission details of the wireless networks. Moreover, the impact of loss and *rtt* on the block rates varies with the operational details in different versions of TCPs and the number of vehciles sharing the bottlenecks. Therefore, the assumption of a given and constant value of loss and delay provides a good estimation only for wired networks, but it is unable to capture the impact of the erratic and fluctuating nature of the wireless networks (due to wireless channel errors, shared channel and access protocols).

A. Background

Our research problem is motivated with an anticipated outcome: *a systematic approach for IoVs' networking design that transforms our vehicles into mobile data centers, performs federated learning to enhance TCP performance and reacts timely to Internet for their needs*. Resulting benefits include a better provision of seamless messages transfer and low delay internet services on the move for the connected autonomous vehicles.

Thinking beyond 5G and witnessing the recent advances in distributed learning and communication, we envisage that autonomous vehicles will have on-vehicle learning capabilities, thereby promptly performing operations and taking actions locally [8], even when the network links and connections are lost for sometimes. It is worth noting that such disconnections are quite often in vehicular networks. Therefore, we propose a federated learning setting [9] as illustrated in Fig. 1 and exploit an alternative approach, where learning is performed locally based on the i) newfangled data, ii) updated environments and iii) the trained parameters and short messages are communicated via ad-hoc networking of on-Vehicle WiFi Access Points (oV-APs). Our proposed approach illustrated in Fig. 1 also prevents sending raw private data from vehicles to the centralized cloud server thus guaranteeing *privacy*.

B. TCP CUBIC Source Dynamics

Perhaps the most well-known and successful example of fast and long-distance data transport protocol that guarantees reliable delivery now (being adopted as a default protocol by both Linux and Windows systems)[1] is TCP CUBIC [10]. TCP CUBIC will be widely deployed very soon and therefore play a central role in future IoV communications. The working procedures of TCP CUBIC is as follows [10]. TCP flow records $W_{\max}$ to be the congestion window size in packets where

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The authors are with the School of Information Technology, Deakin University, Geelong, VIC 3220, Australia (e-mail: shiva.pokhrel@deakin.edu.au; jinho.choi@deakin.edu.au).

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[1] *'Updates on Windows TCP,' Microsoft, November 2017*

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the loss has occurred and decreases the congestion window multiplicatively by a factor of β (β is the backoff factor). This backoff of TCP after loss of packet(s) is followed by the regular recovery/retransmission of those packet(s). After recovery, CUBIC starts to increase the window from $W_{\max}/\beta$ by using a concave cubic function with its plateau at $W_{\max}$ (i.e. the concave growth continues only until the window hits $W_{\max}$). Mathematically, the window growth evolution of CUBIC over time is given by [10]

$$W(t) = S(t - T)^3 + W_{\max} \tag{1}$$

where S is the scaling parameter, $0 < S < 1$, t is the elapsed time from the window reduction, and T is the time period that $W(t)$ in Eqn. (1) takes to increase W to $W_{\max}$ computed as

$$T = \sqrt[3]{\frac{W_{\max}\beta}{S}}.$$

C. Ultra-Reliable Low Latency IoV Communication

In this paper, we focus on achieving ultra-high reliability and very low latency for our vehicular networking scenario [6] and settings (see Fig. 1), by using reliable TCP CUBIC connections. To achieve the proposed *Ultra-Reliable Low Latency Communication* (URLLC) the following two conditions should hold during packet transmission and processing in our network settings over all time:

$$\text{1) Aggregate latency} \leq (\text{Firm deadline} - \text{current time});$$

$$\text{2) } \Pr\{\text{Successful packet transmission}\} \geq 1 - \epsilon,\ \epsilon \ll 1.$$

Observe that Condition 1) demands virtually zero delay (from the applications' prospective) and 2) requires an extremely low packet transmission failure rate, ϵ, which is highly challenging to attain. In fact, the performance of TCP tends to be poor when used over lossy WiFi links and/or in mobile scenarios. The erratic nature of the WiFi channel can lead to severe back-to-back (or correlated) losses of packets and the mobility induces handovers on vehicles leading to the loss and/or increase in latency (due to retransmission/out or order arrival of the packets). To ensure ultra-high reliability, the lost packets must be detected and retransmitted by the sender which however result in long latency due to $rtts$. Moreover, the rate at which new packets are sent also decreases due to reordering of packets.

In the case of vertical handovers, the network address of vehicle changes which usually results in the termination of the TCP connection. Overall, the synchronised losses due to buffer overflows and mobility induced handovers, the correlated packet losses due to an erratic wireless channel and the fluctuations in *rtt*s have significant impact on the data transport and packet congestion mechanism. In such network settings (recall Fig. 1), our primary objective in this paper is to attain a perception of virtually zero end-to-end delay and highly successful packet transmission (a low packet loss probability) for TCP CUBIC connections over the IoV system.

To that end, we design a comprehensive framework for TCP CUBIC over WiFi-based network settings (recall Fig. 1), which captures the data flow (and congestion) dynamics of multiple competing oV-APs, as well as the Medium Access Control (MAC) layer dynamics (i.e., collisions, contention, handovers and re-transmissions) that arise from different delay/loss perceived by vehicles. Our framework provides accurate estimates of TCP-perceived packet loss probability and latency for vehicles when wireless channel suffer from different magnitudes losses and transmission delays. More importantly, with the developed insights from the framework, we design federated learning algorithms for oV-APs and the federal controller (coordinating group of APs) to achieve the required URLLC for autonomous vehicles. The developed algorithms monitor the loss and latency dynamically, and drive the system dynamics to the desired operating point (satisfying condition 1 and 2), which alleviate the adverse impacts of delay/loss differences, and serve only the maximum possible autonomous vehicles in the system.

Overall, the main contributions in this paper are two-fold:

1) *We propose a mathematical framework that can accurately capture the loss and latency of IoV connections over WIFi in the presence of wireless channel impairment.*

   Our framework explains the observed unfairness due to different loss and delay perceived by the vehicles. The accuracy of our framework is demonstrated by *ns-3* simulations.
2) With relevant insights provided by our framework, *we design federated learning mechanism that not only appropriately manages the oV-APs locally, but also accomplishes the global monitoring and coordination by federal controller and ameliorates observed unfairness (if any).*

Our proposed algorithm at oV-APs guarantees ubiquitous connection among the vehicles and presents a local mechanism to satisfy the reliability and latency requirements of autonomous vehicles. We validate both the algorithms for the IoV scenario in Fig. 1 with extensive simulations and derive convergence conditions for the system dynamics with our algorithms.

At a higher conceptual level, we provide a technical feasibility analysis of federated learning with oV-APs for an IoV system. A key finding for stability of overall IoV system dynamics is that the TCP protocol parameters need to be jointly designed with the federated learning parameters.

II. Modeling IoV Data Transport

We perform a simple mathematical analysis to compute the latency and loss perceived by vehicles in our network system by accounting multiple TCP CUBIC connections. The Markovian approach that is successful for non-saturated WiFi analysis would be intractable here, for the realistically sized IoV network with multiple vehicles, because of the prohibitively large dimensionality from the differences in loss and delay perceived by vehicles (recall IoV dynamics with highly time varying network settings and unpredictable channel conditions). Rather we adopt an approximate pragmatic approach which remarkbly reduces the analysing complexity of TCP controlled transmissions over WiFi-based IoV system.

Our idea is based on the following equilibrium principle which holds true due to rate balance nature of TCP. The rate balance nature of TCP states that, every TCP CUBIC connection maintains the following rate equilibrium principle: '*the average rate of data in packets/sec transmitted from the ov-AP is (cumulatively) proportional to the total rate of acknowledgements (acks) in packets/sec arriving at that vehicle from all other associated vehicles and devices*'.

For tractability, we divide the analysis of different aspects of the network and their dynamics into smaller components to derive their mathematical expressions. The different components of our overall analysis operates independently and the derivation of closed-form expressions for each component assumes that the variables used as inputs from the other components has already been computed and known. All of the developed expressions are finally knitted together using fixed-point approach. Below, we show the derivations of expressions for the components.

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A. TCP CUBIC Traffic

Most IoV applications demands small data transfers ($\ll 64$ KB), the performance of such transfers using short-lived TCP connection is quite challenging to estimate. Moreover, short-lived TCP CUBIC flows are dominated by their slow-start (SS) phase, wherein, for each *ack* received on connection i, TCP congestion window (W_i) is increased as $W_i \leftarrow W_i + 1$. In particular, the congestion window $W_i(t)$ of the connection approximately doubles (increases exponentially) every *rtt*, $rtt_i(t)$, in which no loss is detected:

$$W_i(t) = 2^{\frac{t}{rtt_i(t)}}. \tag{2}$$

The SS phase ends at time $T_s = rtt_i(t)\log_2(\mathrm{SST})$, when $W_i(t)$ arrives at the SS threshold (SST) and the congestion avoidance (CA) phase starts, while any loss during SS phase leads to timeout with probability $p_{\mathrm{to}}(t) \approx \min\{1, 3W_i(t)\}$. Therefore, the short-term average sending rate for small flows can be estimated as

$$\lambda_i(t) = \int_0^{T_s} 2^{\frac{t}{rtt_i(t)}}(1 - p_{\mathrm{to}}(t))/rtt_i(t)\mathrm{d}t. \tag{3}$$

B. Traffic Fraction at Each oV-AP

Assuming $\lambda^i_{\mathrm{ap}}(t)$ as the packet sending rate at time t from the oV-AP of a tagged vehicle to another vehicle/RSU i, then, in a short interval, the likelihood that the packet at the head of the oV-AP belongs to vehicle/RSU i, denoted by $h_i(t)$, can be estimated as [11]

$$h_i(t) = \lambda^i_{\mathrm{ap}}(t) \Big/ \sum_j \lambda^j_{\mathrm{ap}}(t). \tag{4}$$

C. WiFi MAC Analysis

Next, we derive expressions for the modules to quantify aggregate latency and losses at MAC level.

Estimating Latency: MAC backoff mechanism follows a so-called time-slotted pattern (say, $b_x :=$ average backoff in slots at the $\mathrm{x^{th}}$ attempt for a packet), as a result, the aggregate latency perceived by vehicle i, denoted by D_i, can be computed by using a renewal reward theory,

$$D_i = \frac{\text{Observation Time}}{\text{Aggregate Successful Packets}} \approx \frac{\mathbb{E}[T]}{\tau_i(1-\pi_i)}, \tag{5}$$

where τ_i and π_i denote the expected attempt and failure probabilities of all recipient vehicles/RSUs respectively (experiencing wireless channel and handover losses, say channel losses with probability p_w and handover losses with probability p_h). Here, $\mathbb{E}[T]$ is the mean time between two successive services of packets from the oV-AP (see [12] for details).

With TCP traffic, oV-APs are saturated and always contending for the WiFi channel [12], therefore, the aggregrate throughput perceived by vehicle/RSU i, $\theta_i = 1/D_i$. As a result, the attempt probability for transmission of a packet from each oV-AP, τ_{ap}, can be interpreted in terms of transmission loss probability as (quite similar to [13] but enhanced with handovers and channel impairments), $\tau_{\mathrm{ap}} = G(\pi_{\mathrm{ap}}) = (1 + \pi_{\mathrm{ap}} + \cdots + \pi^k_{\mathrm{ap}})/(b_0 + b_1\pi_{\mathrm{ap}} + \cdots + b_x\pi^x_{\mathrm{ap}} + .. + b_k\pi^k_{\mathrm{ap}})$ where π_{ap} is the (conditional) loss probability from the oV-AP (either due to collisions, handovers or impairments).

Rate Equilibrium for Unsaturated Analysis: As discussed earlier, with rate equilibrium principle, the packet attempt probability from one oV-AP belonging to vehicle/RSU i in a network can be approximated by their h_i. In particular, the probability of a packet transmission attempt (to vehicle/RSU i) from the oV-AP is, $\tau_{\mathrm{ap,i}} = h_i\tau_{\mathrm{ap}}$. On the reverse feedback path, the acks from vehicles/RSUs responding the sequence of successfully received data packets from the oV-AP, provide the attempt probability of acks from the vehicles/RSUs,

$$\begin{aligned}\tau_i &= \frac{\mathbb{E}[\text{Data packets attempts to } i]\tau_{\mathrm{ap,i}}}{\mathbb{E}[\text{Ack packets attempts from } i]}\\ &= \tau_{\mathrm{ap},i}\frac{(1-\pi_{\mathrm{ap}})\left(1-(\pi_i)^{k+1}\right)}{(1-\pi_i)\left(1-(\pi_{\mathrm{ap}})^{k+1}\right)}.\end{aligned} \tag{6}$$

Given n active oV-APs and m RSUs, the combined (aggregate) MAC layer loss probabilities due to collisions, handovers and channel errors, π_{ap} and π_i are computed as [14]

$$\pi_{\mathrm{ap}} = 1 - \prod_i (1-\tau_i)^{(n+m)}(1-p_w)(1-p_h)(1-\tau_{\mathrm{ap}})^{(n-1)}$$

$$\pi_i = 1 - (1-\tau_{\mathrm{ap}})^n(1-p_w)(1-p_h)(1-\tau_i)^{(n+m-1)}$$

Estimating Aggregate TCP-level loss: The MAC-level probability of data from the oV-AP can be estimated by using a fixed point function, $G^{-1}(.)$, based on saturation contention analysis, $\pi_{\mathrm{ap,i}} = G^{-1}(\tau_{\mathrm{ap,i}})$. Recall that $\tau_{\mathrm{ap,i}}$ is the average probability of (re)transmission attempt for a packet from the oV-AP to vehicle/RSU i. Therefore, the TCP-level packet loss probability perceived by the source at the vehicle and coordinator is given by

$$P^{\mathrm{tcp}}_i = (\pi_{\mathrm{ap,i}})^{k+1}, \tag{7}$$

where k is the maximum number of (re)transmission allowed before drop (such drops need to be recovered by the TCP-level retransmission of packets, which is not desirable in our IoV system).

III. Federated Learning Design

We apply the insights from our fraction (Eqn.(3)), latency (Eqn.(4)) and TCP-level loss (Eqn.(6)) analysis, to formulate the federated learning problem and attain the URLLC requirements (recall two conditions discussed in Section I). In particular, the desired level of reliability and latency can only be implemented by learning from private datasets (reflect newfangled environment timely) locally at the oV-APs while monitoring (and mandating) the global system capacity and its stability continually from the federal coordinator.

a. Local Policy: Local policy at each oV-AP has two phases. See Algorithm 1 for details. PHASE-I: Monitor and control latency D_i (by continuously observing the deviation of queue occupancy $Q(t)$ from the desired Q^*) and admitting traffic belonging to each vehicle into the oV-AP buffer only when ($Q(t) < Q^*$), and forward current magnitude of latency and blocking probability to the federal coordinator. Specifically, we aim to min $(Q(t) - \alpha(t)Q^*)^2$, where $\alpha(t)$ is supplied by the federal coordinator. PHASE-II: Continuously track the packet arrival rates $\lambda_i(t)$ (by observing the deviation of $h_i(t)$ from the required h^*_i) and admitting traffic belonging to each vehicle into the oV-AP buffer only with desired probability $1 - P^{\mathrm{tcp}}_i(h^*_i)$. The difference in the values of P^{tcp}_i among vehicles can maintain different priority access mechanism in the network (a higher value of $P^{\mathrm{tcp}}_i(h^*_i)$ mandates a lower access priority and vice-versa).

b. Global Policy: Global policy at the federal controller aims at maintaining low standing queues at all oV-APs $Q(t) := \alpha(t)Q^*$; where $\alpha(t)$ is a global parameter to control the aggregate loss/latency requirements, $0.5 < \alpha(t) < 1$. See Algorithm 2 for details. It computes short-term aggregate of the loss and latency information provided by the oV-APs and compute $\alpha(t+1)$ based on desired application constraints. In addition, federal coordinator tracks active vehicles using the system and permits new vehicles to enter into the system by guaranteeing that the system capacity strictly satisfies loss and latency requirements.

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Algorithm 1: for Vehicles.

procedure START
Target fraction (h_i^*), Queue Target (Q^*), $\alpha(t)$
end procedure
procedure ACCESS SYSTEM
Compute $h_i(t)$ and $Q(t)$
  while ($Q(t) \leq \alpha(t)Q^*$) **do**
    if ($h_i(t) > h_i^*$) **then** $P_i^{\mathrm{tcp}}(t) = 1.0$
    end if
    procedure UPDATE LOSS/LATENCY
      while ($(Q(t) - \alpha(t)Q^*)^2 > tol$) **do**
        if ($h_i(t) > h_i^*$) **then** $P_i^{\mathrm{tcp}}(t) = 1.0$
        else $P_i^{\mathrm{tcp}}(t) = 0.0$; Update $D_i(n)$
        end if
      end while Send $h_i(t),\ P_i^{\mathrm{tcp}}(t),\ D_i(t),\ Q(t)$
    end procedure
  end while
end procedure

Algorithm 2: for Federal Coordinator.

procedure START
Global fraction (h_g^*), Global Queue (Q_g^*)
end procedure

if ($P_i^{\mathrm{tcp}}(t) < P^\star$ & $D_i(t) < D^\star$) **then**
  procedure AGGREGATE LEARNING
    while ($(Q(t)^* - \alpha(t)Q_g^*)^2 > tol$) **do**
      if ($h_i(t) > h_g^*$) **then** $Q_g^* = \frac{\sum Q_t^*}{N}; h_g^* = \frac{\sum h_i^*}{N}$
      else $Q_g^* = Q_t^*;\ \ h_g^* = h_i^*$
      end if
    end while
  end procedure
else Deny Access
end if
procedure DISTRIBUTE
Send h_g^*, $\alpha(t)$ and Q_g^*
end procedure

c. Learning idea: Consider a set of N vehicles in our IoV system and let each oV-AP collects a set of data samples and computes their local learning update. The local learning update of the n^{th} oV-AP is then sent to the federal coordinator. Our federated training is a regression problem that focuses on solving the problem in parallel for a global vector v (say). Our objective is to [8], [9], [15]

$$Minimize\ \mathcal{F}(v),\ \text{where} \tag{8}$$

$$\mathcal{F}(v) = \frac{\sum^N \sum_{d_i \in s_n} (h_i^\intercal v - Q_i)^2/2}{|S|} \tag{9}$$

for convenience, $d_i = \{h_i, Q_i\} \in S$ denote the i^{th} data sample. With federated learning [8], [9], it is well-known that the default idea to solve Equation (8) is to perform local training at each oV-AP by using the stochastic gradient algorithm, followed by a global training for aggregating local updates via distributed Newton's method. In each stage, the oV-AP local model is recomputed with the number of iterations. Given the step-size $\delta > 0$, the local vector denoted by v_n is updated after every iteration. Every oV-AP in this learning sends $(v_n, \nabla\mathcal{F}_j(v))$, the local update, to the centralized global server, which then computes the global update, i.e. $(v, \nabla\mathcal{F}(v))$. We have developed two algorithms, Algorithm 1 and 2, based on the aforementioned policies and learning idea.

A. Convergence Conditions

When many TCP connections share a small oV-AP buffer, their window evolution satisfies

$$\frac{dW(t)}{dt} = \frac{W(t-rtt)}{rtt}\left(I(W(t))(1-p(t-rtt)) - D(W(t))p(t-rtt)\right), \tag{10}$$

where increments, $I(W(t))$, and decrements, $D(W(t))$, determine the SS and CA phase of the TCP. A lineralization of Eqn. (10) around equilibrium W^*, $W(t) = y(t) + W^*$, is

$$\frac{dy(t)}{dt} = -Ay(t) - By(t-rtt) \tag{11}$$

where, $A = (1-p(W^*))\frac{I(W^*)}{rtt}$ and $B = \frac{W^* p'(W^*)}{p(W^*)}\frac{I(W^*)}{rtt}$.

It has been established that the convergence of the *fixed-point* of Eqn. (10) is determined by that of the *fixed-point* ($y = 0$) of Eqn. (11). In particular, the stability condition of Eqn. (11) is based on the roots of the associated characteristic equations and is determined by analysing their exponential solutions. To this end, we adopt the equations arising from the first order delay equations by utilizing the following result.

Lemma III.A [16]: A differential equation $dy(t)/dt = -Ay(t) - By(t-rtt)$, where $A \geq 0$, $B > 0$, $B > A$, and $rtt > 0$ is stable iff (if and only if) $rttB < \pi/2$. Therefore, the convergence condition of Eqn. (10) is

$$I(W^*)W^*p'(W^*)/p(W^*) < \pi/2. \tag{12}$$

Indeed, Eqn. (12) provides insights into the convergence of our IoV system dynamics with federated learning algorithms. It depends on $p'(W^*)$ (the rate of change of loss), which in turn depends on the queuing dynamics at the oV-AP. Our proposed federated algorithms for IoV management therefore need to be carefully designed (and implemented) only by observing the stability measures, as it jointly depends upon Q^*, TCP parameters and the number of oV-APs, which needs further investigations.

B. Performance Evaluation

In our network settings with $Q^* = 100$ packets and 8% tol, simulation and analytic results are obtained for two group of vehicles competing with each other. Fig. 2 depicts the results from our analysis compared with *ns-3* simulations. Our analytic results accurately predict the *ns-3* outcomes. We can observe in Fig. 2(a), with high packet rates λ_i, the P_i^{tcp} aggregate loss probability of aggressive connections (due to handovers, collisions and channel impairments), is comparatively lower than that for vehicles with low λ_j from the same oV-AP. The corresponding throughputs experienced by both group of vehicles are shown in Fig. 2(b). In fact, with low λ_i the TCP retransmissions following high loss rates are time consuming and not enough to mask the packet failures due to higher loss, and throughputs are very low (see Fig. 2(b)). Fig. 2(b) shows that the difference in loss probability P_i^{tcp} and latencies D_i (shown in Fig. 2(a) and Fig. 2(c)) lead to a substantial difference in the QoS.

Fig. 3 shows results using Algorithm 1 at the oV-APs ($\alpha(t) = 0.7$). By setting h_i^* equal for all vehicles in the Algorithm, we can see in Fig. 3 that our Algorithm 1 solves the problem observed in Fig. 2.

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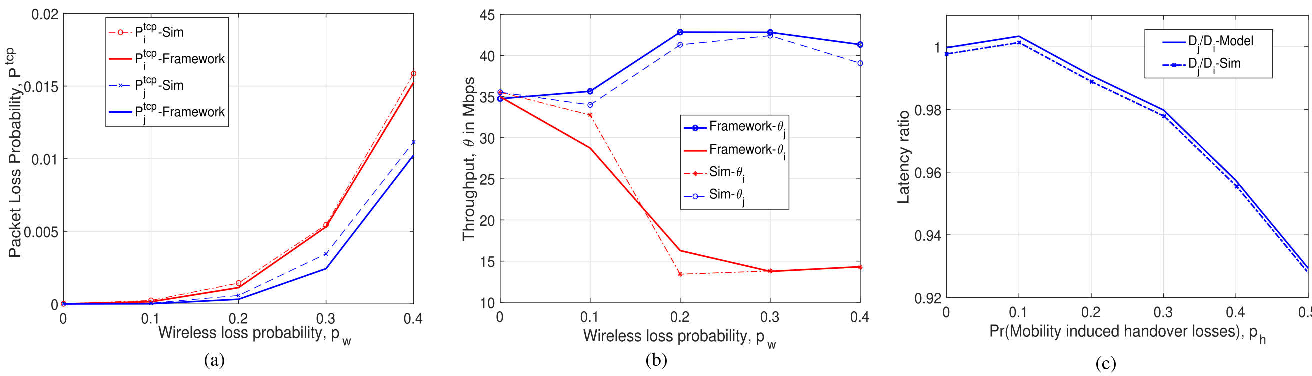

Fig. 2. (a) Loss comparisons. (b) Throughputs in packets per seconds obtained by two vehicles. (c) Their Latency ratio.

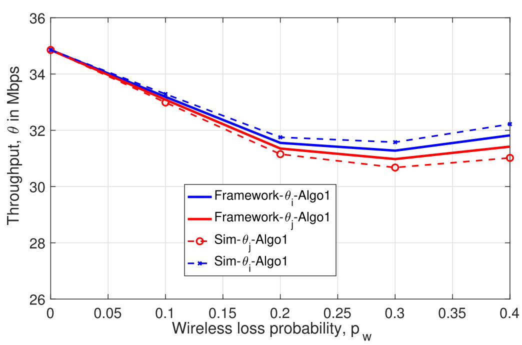

Fig. 3. Throughput obtained by vehicles after using Algorithm 1 (same settings of Fig. 2).

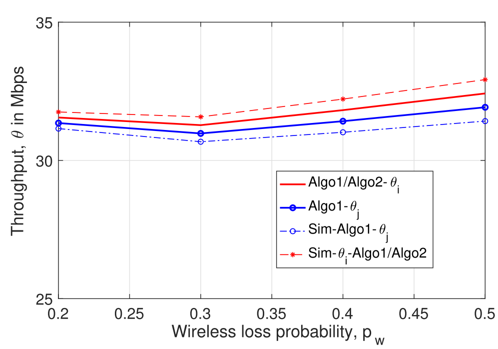

Fig. 4. Throughputs obtained by vehicles with both Algorithm 2 and Algorithm 1 in a dual oV-APs (settings of Fig. 3).

Under the same network settings of Fig. 3, but with dual oV-APs, we conduct an experiment to evaluate our federated learning approach using both Algorithm 2 and Algorithm 1. Fig. 4 illustrates that with the federated learning our IoV system achieves privacy without any loss in performance (outperforms local learning cf. Fig. 3). The small difference in throughputs between local and federated learning requires further investigations.

IV. Conclusion

We developed a concept of WiFi AP mounted vehicles and investigated their feasibility with federated learning approach. Our mathematical analysis provided important insights into developing the implementable network control federated learning algorithm, which is compatible with the existing WiFi standards and TCP protocol. Detailed analysis of the convergence conditions for our IoV system dynamics with proposed algorithm requires further investigations and is ongoing.

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