BFLEdge: Blockchain based federated edge learning scheme in V2X underlying 6G communications

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***Abstract*—Sixth generation (6G) vehicle-to-anything (V2X) networks support intelligent edge computing that leverages data sensing, computation, and offloading among vehicular nodes (VN) with ultra-low latency. Data is heterogeneous with high complex interactions among V2X users and pass via open channels that induce privacy and security concerns. Thus, federated learning (FL) protects user privacy and fine-tunes the learning models at resource-constrained edge nodes to address security and computational concerns at the edge. However, to ensure reliability and trust, we propose a blockchain (BC) and FL-based edge scheme, *BFLEdge*. It also improves the overall learning rate of the FL model. The proposed scheme consists of three phases, where the first phase uses local machine learning (LML) to model the VN data and store it into the local BC network. The LML block updates are verified in the second phase through a proposed distributed consensus mechanism. Lastly, through 6G communication services, the channel dynamics are modelled as a Markov chain process to reduce end-to-end delay of local BC propagation updates at the edge that improves the V2X system throughput. Simulation and analytical results are proposed based on channel loss, block mining rate, edge latency, and FL-learning rate. The obtained results indicate the viability of the proposed framework against conventional state-of-the-art approaches.**

***Index Terms*—Blockchain, Federated Learning, Edge, 6G, Vehicle-to-anything**

I. Introduction

In In modern vehicle-to-anything (V2X) ecosystems, the sixth-generation (6G) network has opened new horizons in communication, sensing, and computing capabilities. 6G-V2X offers services like further-enhanced mobile broadband (FeMBB) and extremely reliable low-latency communications (ERLLC), allowing uninterrupted service, even in high mobility and densely populated areas. Through terahertz (ThZ) connectivity, 6G opens up ubiquitous air-space-ground connectivity at over-the-air latency of 100 μ s and persistent 99.9999999 % connection availability. Through direct 6G links, vehicular nodes (VN) exchange massive heterogeneous data for supporting a plethora of applications of cooperative sensing, collaborative control, responsive network orchestration, and intelligent content offloading [1]. Artificial intelligence (AI)-empowered mobile edge computing (MEC) supports real-time dense model interactions processed near edge nodes, reducing training cost and end-user latency. Thus, with 6G, edge-intelligence (EI) has gained prominence, but due to edge nodes' computational bottlenecks, data training is a complex task.

Thus, EI requires effective model provisioning that allows small and local AI models to be deployed, which computes the predictions [11]. However, humongous sensor-driven data is generated at the edge, containing private sensor readings and VN user secure key information. It is estimated that $\approx$ 1 gigabyte (GB) data is produced by the sensor nodes of automated vehicles (AV) in V2X [1]. With the rise in AVs, more data is ingested in the network, and thus 6G-V2X requires effective EI provisioning to manage the offloading ratio, overheads, and reduce the overall power consumption. Also, the data is highly heterogeneous, and thus EI-models take longer to predict useful information out of the data and converge slower. Along with resource-provisioning, the data is shared over open channels and thus is subject to privacy and security linkage attack vectors. Collectively said, the issues of data privacy among EI nodes and resource provisioning to EI is a critical issue, with open challenges. A malicious adversary can gain control over EI nodes and thus gather sensitive information to manipulate sensor controls, resulting in sensor malfunctioning. In V2X, this might result in numerous accidents, sensor hijacks, and false information updates. Moreover, in the compromised V2X network, an adversary can

TABLE I: Comparative analysis of proposed scheme with existing state-of-the-art FL schemes in V2X.

Author	Year	Objective	Parameters 1	2	3	4	5	Pros	Cons
Xu *et al.* [2]	2018	A secured blockchain based V2X ecosystem with a success rate of 97.09% is achieved.	✗	✗	✓	✗	✗	Detailed analysis on privacy based security using blockchain is mentioned.	Not used FL.
Dai *et al.* [3]	2019	Proposed a blockchain based scheme which increases the utility of the model.	✗	✓	✓	✗	✓	Privacy and security is increased.	Exploitation of consortium blockchain.
Gao *et al.* [4]	2019	Proposed a model for optimal transmit power allocation.	✗	✗	✗	✓	✗	System overall throughput in V2X communication is alleviated.	.
Shayan *et al.* [5]	2020	Proposed a framework with a decentralized P2P system with blockchain ledger.	✓	✗	✓	✗	✗	Secure multiparty is distributed within P2P settings.	The proposed framework is vulnerable to attacks.
Pokhrel *et al.* [6]	2020	Proposed a framework for privacy preservation and efficient vehicular communications.	✓	✓	✓	✗	✗	Optimal block arrival rate and performance is obtained.	Low delay internet services are not used.
Lu *et al.* [7]	2020	A framework is proposed with Deep Reinforcement Learning for improvement in efficiency.	✓	✓	✓	✗	✗	Efficiency and accuracy is increased.	Comparitive analysis is not mentioned in detail.
Zhang *et al.* [8]	2021	Proposed a FL secured aggregated framework with blockchain technologies.	✓	✓	✓	✗	✗	Detailed analysis for edge computing is mentioned.	Comparative analysis is not mentioned in detail.
Peng *et al.* [9]	2021	More accurate and faster model is proposed.	✓	✓	✓	✗	✗	FL architecture is explained in detail.	High energy consumption and storage cost.
Mizmizi[10]	2021	A method based for hybrid mm Wave based on terminals in mobility	✗	✗	✓	✗	✗	Less sensitive to positioning error.	Privacy and security is not obtained.
Proposed	2021	A framework which provides privacy and security with amalgamation of FL and blockchain.	✓	✓	✓	✓	✓	Fulfills the gaps from the earlier papers which results into better privacy and security of the model.	-

Parameters- 1. Local Training, 2. Edge Model, 3. Trust, 4. 6G Service, 5. Data Offloading

change the results of EI model predictions. Thus, it can result in false updates among VN nodes related to route information, energy sources, infrastructure connections, and many more. Thus, there is a pressing need to address decentralised EI's security and privacy issues in V2X ecosystems.

The security and privacy issues can be easily solved by integration of FL in 6G-V2X ecosystems. Researchers globally have proposed stochastic models on delay estimation in V2X to predict optimal offloading scenarios, and have proposed optimization algorithms supported through blockchain (BC)-MEC-provisioned servers [12][13]. For example, Xiong *et al.* [14] has proposed a QFL based scheme that minimizes computational budget and offloads failure probabilities. Fast convergence is obtained, and heavy communication overhead is reduced during model training phase. Then, Pokhrel *et al.* [5] proposed a BC-based FL model for V2X, however, privacy leakage, and sophisticated mobility models are not discussed. Zhang *et al.* [8] has proposed a BC-leveraged secure FL aggregation protocol that improves consensus through long-short term memory (LSTM)-operated traffic prediction at cell sites. Table I shows the comparative analysis of various state-of-the-art FL-based schemes in V2X environment. However, with FL-leveraged 6G-V2X, it can support resource-constrained edge nodes through low-latency 6G-ERLLC connections. For the same, a federated Q-Learning (FQL) approach is suitable, that supports edge nodes through effective global aggregation and balanced resource offloading, that improves the quality-of-experience (QoE) of user. FQL allows optimal action state selection and provides quick convergence, through an intelligent selection of local Q-learning process. An optimization condition is presented that decouples LML updates, based on effective local action Q-states. The search space represents possible offloading scenarios, and action space presents the V2X traffic assignment.

Once the LML updates are generated through FQL, they are stored as interplanetary file systems (IPFS) transactions to ensure trust and privacy among multiple nodes. The locally trained gradients are aggregated, and then the main global server computes the globalized gradient. The globalized gradient is used to train the global model. The result of the global trained model is stored in BC, as it reduces the chances of data corruption and minimizes data invasions. The updated model then communicates to edge nodes that communicate with VN through 6G-directed short-range communication (DSRC) links. Thus, the proposed scheme, *BFLEdge*, integrates FL and BC to address the key issues of data offloading, such as privacy, and security. It also improves the precision and accuracy of the main model through FQL. The LML updates are locally converged faster, and communication updates are handled in near real-time through 6G-LLC.

A. Contributions

- We propose a BC-based LML edge learning model to optimize the hidden layers and aggregates VN data from edge nodes to lower computations and facilitate lower delay in mined transactions to be appended as local on-chain units.
- The local on-chain data is verified through a resource-constrained consensus mechanism *Proof-of-Local Learning (PoLL)* that improves the computations at global chain units and increases the learning accuracy of LML at successive iterations.
- Through *PoLL*, the global on-chain blocks are modelled as markovian inputs to the 6G communication queue, which reduces the end-to-end delay of edge computation at near-responsive edge updates to facilitate trading and exchange services to V2X nodes.

B. Article Structure

The paper is organized into five sections. Section II discusses the proposed *BFLEdge* scheme. Section III shows the performance evaluation of *BFLEdge*. Finally, Section IV concludes the paper.

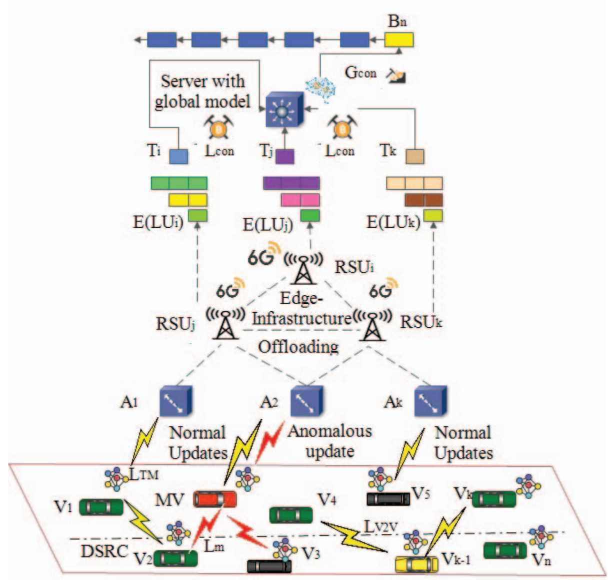


Fig. 1: *BFLEdge*: The proposed scheme

II. *BFLEdge*: The Proposed Scheme

In this section, we present the schematics of the proposed scheme, *BFLEdge*, that presents the integration of FL and BC to manage trusted resource offloading through 6G-V2V link estimates. Fig. 1 presents the details of the proposed scheme. We consider a set of n vehicular nodes, represented as $V = \{V_1, V_2, \dots, V_n\}$, that exchange data over the 6G-V2V link. Any V_n has it own associated local data D_n, and a mapping $M : V \rightarrow D$ exists to show the association. The federated model contains a set of k local aggregators, represented as $\{A_1, A_2, \dots, A_k\}$, that collects data $\forall V_n$. The collected data is passed to road side units (RSUs). RSUs mainly form the edge infrastructure backbone, and in the scheme, we consider m RSU units, shown as $\{RSU_1, RSU_2, \dots, RSU_m\}$. The edge backbone is supported via 6G-V2V. Once data is collected, the RSUs, communicate the data to local units, denoted as LU. The data is encrypted through public encryption algorithms, and the result is denoted as $\{E(LU_1), E(LU_2), \dots, E(LU_k)\}$. The encrypted results are timestamped as $\{T_1, T_2, \dots, T_k\}$, and are presented to local miners, denoted as L_{con}. From L_{con}, the data is verified and transaction updates are added to BC. To support the resource orchestration, a computational offloading mechanism is presented that employs federated Q-learning (FQL), and finally the global data is verified as G_{con}, and subsequently, a new block proposal B_n is added to the chain. We next present the scheme modelling in detail.

A. Channel Model

We assume the 6G-V2V link has a channel capacity C, and the link intelligently forms estimates based on associated traffic predictors from V_n. We assume ω to be the maximum rate at which V_n transmits link-layer frames to C. Any i^{th} vehicle V_i generates frames $\{f_1, f_2, \dots, f_q\}$, based on Poisson distribution, which is transmitted over C. The associated transmission delay is measured as follows.

$$t_d = \frac{f_q}{\omega} \tag{1}$$

Assuming that the speed of V_i vehicle to be s_i, and f_c as the operating frequency of the 6G-V2V link, the doppler frequency is measured as follows.

$$f_{df} = \frac{f_c.s_i}{c} \tag{2}$$

where c denotes the speed of optical light pulse. The channel is considered to have a fading margin F due to variation in modulation and line-coding scheme. The signal-to-noise interference ratio (SINR) is measured as

$$SINR_{C,\tau} = \frac{P_{\delta,\eta} G_{T_A}}{N_0 c_f + \sum_{B'\tau} G_{T_A,B',\tau}} \tag{3}$$

where $P_{\delta,\eta}$ denotes the transmitting power of RSU_k in its cell range δ, and G_{T_A} denotes the antenna gain. N_0 represents the spectral density, c_f denotes the sub-carrier spacing. Based on the computation of $SINR_{C,\tau}$, the channel capacity C is modelled as follows.

$$C = c_f.log(1 + \alpha.SINR_{C,\tau}) \tag{4}$$

where α denotes the channel exponent. The average probability that a particular frame f_q of V_i fails during transmission is modelled as

$$p_q = 1 - e^{-1/F} \tag{5}$$

where F is the number of failed transmissions on the common channel. Based on channel parameters, the frames are generated continuously and local data is captured, which is analyzed via FL model.

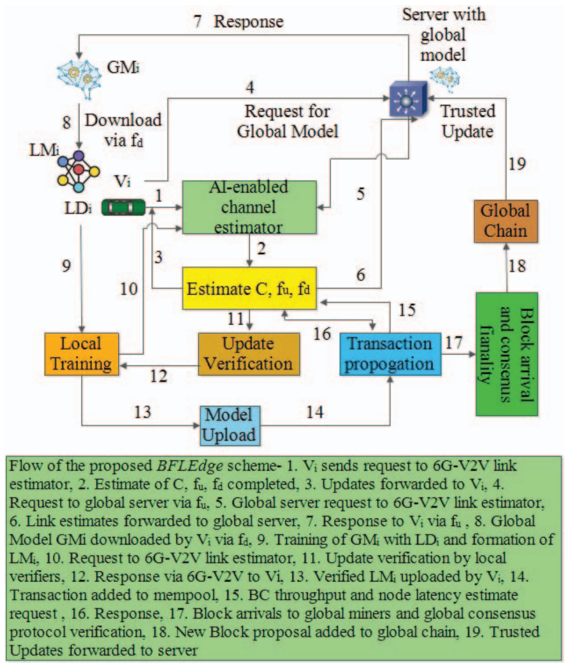


Fig. 2: The scheme flow diagram.

B. Federated Edge Learning Model

In FL edge model, we consider that a global server G_s communicate the global model GM to all the local V_n nodes for training. Every V_n node downloads GM, and train the model through local data D_n. The local training models for all n vehicles is represented as $\{L_{TM_1}, L_{TM_2}, \ldots, L_{TM_n}$. The local model updates are communicated to verifier nodes $V_p(V_1, V_2, \ldots, V_p\}$. Fig. 2 shows the basic flow model of the proposed *BFLEdge* scheme.The FL problem is formulated basically as a regression problem that consumes the entire model space as follows.

$$M(V) = \bigcup_{i=1}^{n} L_{m_i} \tag{6}$$

For any global vector G_v, the objective is to minimize $M(V)$, with the following constraints.

$$C1 : min(M(V)) = \frac{\sum_{i=1}^{n} \sum_{d_j \in L_{TM_n}} (a_j^T v - b_j)^2/2}{|S|} \tag{7}$$

where $d_j = \{a_j, b_j\} \in M$, and they denote the n-dimensional vector space. The local training is carried out via a stochastic gradient problem over Δ iterations, with a defined step-size of $I > 0$. The updated local vector after any w^{th} iteration is shown as follows.

$$V_n^{w+1} = V_n^w - \frac{I}{\Delta}((\nabla F_j(V_n^w - \nabla F_j(V) + \nabla F(v)) \tag{8}$$

where,

$$F_j(v) = (a_j^T v - b_j)^2/2 \tag{9}$$

The update $(V_n, \nabla F_j(v))$ is the local model which is sent to G_s, on which GM is updated. However, as the data is sent through distributed V_n nodes, the update transactions are recorded through a BC-based model.

C. PoLL: The Blockchain consensus model

In the BC-model, we present a trusted framework for sharing the LML updates, through a proposed consensus scheme, termed as *PoLL*. In *PoLL*, we assume that transaction set T include local updates, which is validated via m miner nodes. Every miner node $\{N_1, N_2, \ldots, N_m\}$ maintains a local ledger L_{con} with local LMLs. We consider LML updates are added to this ledger until it is occupied (in other words, $D(LML) > S(L_{con})$, where $S(L_{con})$ denotes the size of L_{con}. In such conditions, any N_m follows the standard proof-of-work (PoW) scheme to generate a hash smaller than target, and propose B_n. The newly generated block is added to the chain. However, to increase the block generation rate, the target value at local site is kept small. To support the local miners, the mining task can be offloaded to nearby edge nodes (RSUs), or local units, that solves the target problem. Algorithm 1 depicts the working of the proposed *PoLL* consensus mechanism.

Algorithm 1 *PoLL*: The proposed algorithm for LML updates

Input: Set of Vehicular nodes $\{V_1, V_2, \ldots, V_n\}$, associated data $\{D_1, D_2, \ldots, D_n\}$, GM, locally trained data $\{L_{TM_1}, L_{TM_2}, \ldots, L_{TM_n}$.
Output: A boolean value $B = \{0, 1\}$ to signify successful block proposal.

procedure LOCAL_UPDATE($L_{TM_1}, L_{TM_2}, \ldots, L_{TM_n}$)
  for $i \leftarrow 1$ to n **do**
    for $j \leftarrow 1$ to k **do**
      $V_p \leftarrow L_{TM_n}$
      for $l \leftarrow 1$ to w **do**
        Compute V_n^{w+1} as presented in Equation (8)
      end for
      Map L_{TM_n} to k LUs
      $N_m \leftarrow$ *Upload* $(\nabla F_j(v), Vn)$
      $t_m \leftarrow S(F_j(v))/C$
      Communicate (N_m, t_m) to GM
    end for
    $V_n \leftarrow$ Download GM post verification by N_m
    for $l \leftarrow 1$ to w **do**
      while $((V(w+1) - V(t)^2) > t_{max})$ **do**
        Compute $V(w+1) \leftarrow V(w) + \sum_n -\frac{I}{\Delta}(V(w) - V(t))$
      end while
    end for
  end for
end procedure
procedure VALIDATE($LU_1.LU_2, \ldots, LU_k$)
  $n_m \leftarrow$ *Broadcast* $T(LU_k)$
  while $(S(B_n) < B_{max}||(T_{curr} < T_{out})$ **do**
    if $(T(LU_k) == V(N_m))$ **then**
      $C_q \leftarrow T(LU_k)$
      $S(B_m) \leftarrow S(B_m) + S(T(LU_k))$
      $C_L \leftarrow C_L + 1$
      $B = 1$ and output **Block proposal success**
    else
      LU_k added to *WAITING* node
      $B = 0$ and output **Block proposal failed**
    end if
  end while
end procedure

Algorithm 2 *FQL*: The Federated Q-Learning algorithm for task offloading

Input: Transition probability of offloading task to k^{th} edge node.
Output: Updated reward R_{up} and Q-table design for next round $Q(t+1)$

```
Determine η and ρ
for (t ← 1 to r) do
    Set Q_r ← Q(r − 1) + R(r − 1) + S(r − 1)
end for
for (i ← 1 to k do
    Initialize capacity C of 6G-V2V link
    while Offloading(T))¡ C do
        max(A) ← T_v
        T_v ← Initialize S
        Compute updates on T_v
    end while
    if Q − Table is not updated then
        R ← E_N
        Notify local nodes
        R_up ← R_p( Σ_{m=1}^{k} c_m(p) + A_m(p)
        Q_p ← E[Σ_{m=r−1} αmR_up|A_t = a* — C_t = ρ
        Update Q(t + 1) for all k and n nodes
    end if
end for
```

D. Task Offloading: Federated Q-Learning

As indicated, to guarantee a delay bound on BC-delay, we present the resource offloading to N_m via 6G-edge V2V. We consider that resources can be modelled via traffic $X(T)$ as a stochastic model, which is sum of incoming traffic in (η, ρ), where η denotes the resource-bound and ρ denotes the input arrival. The 6G-V2V transmits frames with Pareto-optimal tail exponent, with exponent value $-b$, such that $\eta^{-b} \approx x^{-a}$, where $-a$ is previous traffic window exponent [15]. Thus, the back-off increases with more V_n operating on link. Algorithm 2 explains the working of the proposed FDL scheme for task Offloading. Any task T is reserved a bandwidth B_k^T, with the local offloading condition defined as follows.

$$\phi_k^V(\eta - \rho) = [\theta_V + p_k V \rho_k - \frac{1}{N}\sum_{i=1}^{K}(1 - \rho_n + (N-1)\eta_n(\eta - \rho)] \tag{10}$$

The offloading is modelled as FQL that is modelled as $\{S, A, P, R\}$, where S denotes state, A denotes the actions, P denotes the task handover probability, and R denotes the reward state. The details are presented as follows.

1) *State S*- State $s = (p(t), A_\eta)$ is based on probability $p(t)$ of assigned task as follows.

$$p(t) = C^D - \sum_{i=1}^{K}(p^t + p^V)V_k(t) \tag{11}$$

2) *Actions A*- We consider the edge node that has maximum resource set R_{max}. However, assignment of traffic is based on offloading volume δ.
3) *Transition Probability* P- The probability p of offloading task T and q^{th} edge node.
4) *Reward* R- The node with maximum probability P_{max}, is bound for high rewards.

Based on the same, a Q-table is constructed and rewards are effectively selected.

III. Performance Evaluation of *BFLEdge*

This section examines the performance evaluation of the proposed architecture based on evaluation metrics such as scalability, latency and FL offloading concerning blockchain technology and 6G networks.

A. Data Description

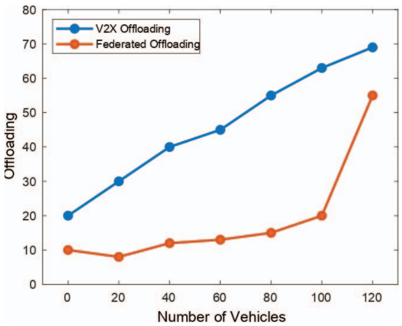
We have considered the In-vehicle Network Intrusion Detection dataset from information security R & D data challenge 2019 for the blockchain-based proposed system [15]. The dataset consists of five features: a timestamp (logging time), controller area network (CAN) id, data length code, payload, and class label. The dataset carries information about the CAN message exchange between two vehicles to increase road safety, traffic efficiency, and reliable road management. The output attribute comprises normal ('R') or malicious ('T') message exchange between vehicles. Various attacks are analyzed in the malicious message exchange, such as flooding, malfunction, and replay attacks, to analyze the proposed system. Next, we have pre-processed the dataset by verifying missing values, class imbalance issues, and normalization. The processed dataset is then forwarded to the federated training model to improve resource offloading.

B. Scalability

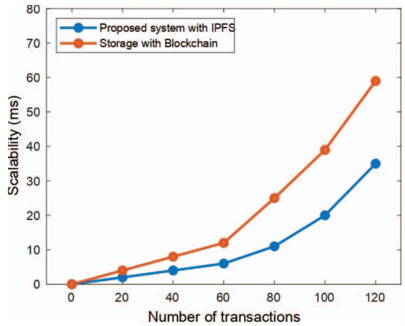
Fig. 3b shows the scalability comparison of the proposed system with the conventional techniques. It is apparent from the graph that, as the number of data transactions increases between V2X, the proposed system scalability gets improved compared to the conventional systems. This outperformance is due to the significant characteristics of blockchain, such as the inclusion of smart contracts that abolish the third-party system to ensure trust between blockchain entities and IPFS a replacement of ethereum due to its low cost.

C. Latency

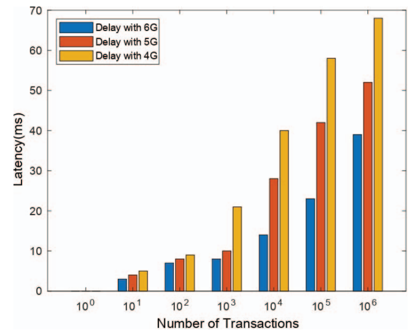
Fig. 3c depicts the comparison of latency with the number of data transactions under the influence of next-generation networks such as 4G, 5G and a 6G network. It shows that the latency is not affected by small data transactions. However, as the data transactions increased, the latency crumbled for the 4G and 5G systems. It is evident that the 6G systems have better properties compared to a 4G or 5G system, such as ultra-high reliability, ultra-low latency, and ubiquitous high data rate. Therefore, in the graph, a 6G enabled proposed system outperformed a 4G or 5G system in terms of latency.



(a) Comparison between V2X offloading and federated offloading



(b) Scalability comparison.



(c) Latency comparison.

Fig. 3: Performance comparison of the proposed system with different performance metric

D. Federated Offloading

The aforementioned dataset is suitable for machine learning models; however, it is trivial for FL. The reason behind this, the dataset is aggregated to a central location to which machine learning can train their models. Unfortunately, this conventional dataset cannot be used by FL as it requires federated data, which is independent and identically distributed (i.i.d). Therefore, we have first converted this conventional dataset to a federated dataset by incorporating a new column *client_id* in the dataset from the TensorFlow federated framework. As a result, the transformed dataset appears as a python dictionary, where the keys are features names and values are tensors. The dataset is already pre-processed; therefore, we can directly incorporate federated learning to improve the loss and accuracy parameters. Fig.3a shows the comparison between resource offloading and the number of vehicles. The proposed system outperforms when compared with the conventional machine learning approach. As the number of vehicles increases, the V2X offloading increases linearly. However, in federated learning, each *client_id* independently trains, resulting in reduced offloading to a threshold, and then it matches the result of the conventional machine learning model.

IV. Conclusion

The paper proposes a BC and FL-based scheme, *BFLEdge* to improve the learning rate of FL model. We have used the communication network as 6G, which improves the system latency and reliability. The proposed *BFLEdge* scheme also improves the overall system trust and security by maintaining data at the local BC network. In nutshell, *BFLEdge* addresses the key issue of data offloading, while processing the information, which in turn improves the accuracy of the main model. In order to mitigate the trust issues, we designed a consensus protocol, i.e., *PoLL* for sharing LML updates with the main model. The performance of *BFLEdge* scheme is evaluated by considering data offloading, scalability, and communication latency over the traditional non-blockchain and 5G-based systems.

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