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A Blockchain-Enabled Framework For Traffic Rerouting And Task Offloading On The Internet Of Vehicles (Iov) Using Federated Learning

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Abstract:
The Internet of Vehicles (IoV) has great potentials in traffic regulation and vehicle synchronization. However, there are challenges of traffic congestion, data confidentiality and optimal allocation of computational resources. Traffic congestion is an important issue with an impact on travel time, fuel consumption and emissions. In the edge-cloud ecosystem, task delegation needs effective methodologies for improving latency, resource efficiency and computational burden. The proposed framework is Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading of Consumer IoV in Edge-Cloud Environment. This framework solves these issues by integration of federated learning and blockchain technologies. Federated learning allows vehicles to jointly train a global model while not sharing their local data, which preserves data privacy and saves bandwidth. Blockchain ensures the security and integrity of model changes and builds up confidence among the stakeholders. Task offloading techniques can improve the utilization of edge and cloud resources, reduce latency and save energy consumption. The methodology is validated against a large dataset and shows significant improvements in traffic forecasting accuracy, security and overall system effectiveness. This shows that the comprehensive solution is effective to solve the problems related to Consumer Internet of Vehicles (CIoV) .

Keywords: Blockchain Network, Task Offloading, IoV, Traffic Rerouting, Federated Learning.

I. INTRODUCTION

The Internet of Vehicles (IoV) is a result of the fast development of Internet of Things (IoT) and vehicular networks. IoV stands for an interconnected environment where cars can communicate among themselves and with the infrastructure around them, improving safety, traffic control and the driving experience in general. This ecosystem can revolutionize urban mobility by allowing complex data-driven decision making, real-time communication, and traffic coordination [1], [2]. With the expansion of IoV, it faces challenges such as traffic congestion, data privacy issues, and the requirement of efficient allocation of computational resources in the edge-cloud settings.
Traffic congestion is a major challenge in urban areas, which has a negative impact on fuel consumption, travel time and environmental sustainability. The increasing number of connected cars in IoV networks offers new opportunities for rerouting and dynamic traffic management. However, these tactics require efficient data processing and the ability to make decisions in real time to be successful [3], [4].

Therefore, efficient task offloading techniques are critical to cope with the computational load, minimize latency and improve utilization of resources in edge cloud systems [5]. Furthermore, the integration of IoV raises privacy and security concerns as a lot of sensitive data is generated and exchanged between the infrastructure and automobiles.
These problems cannot be solved by traditional centralized data management techniques and increase the risk of delay and data breaches [6, 7]. Federated learning [8] is a promising solution. It is a decentralized

machine learning method, which allows cars to cooperate and build global models without sending raw data, thus preserving privacy and reducing bandwidth.

The decentralized ledger of blockchain technology also improves data immutability and integrity, thus increasing the confidence of the participants and enhancing the security of model updates in federated learning [9], [10]. This paper proposes a comprehensive solution to the IoV problems by combining efficient job offloading techniques with blockchain and federated learning technologies. This paper proposes a novel approach for Internet of Vehicles in edge-cloud scenarios: Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading. This proposed system is aimed at optimizing computing resources, enhancing data privacy and security and improving traffic management [11].

This work contributes to the literature by proposing a holistic strategy that integrates blockchain technology, federated learning, and efficient job offloading to address the complex challenges of IoV.

II. RELATED WORKS

The Internet of Vehicles (IoV) is a novel communication paradigm based on the latest communication technology, which aims to change the way that cars interact with their environment and with each other to improve safety and traffic management. The IoV has potential benefits, but also significant challenges that need to be addressed to enable its full potential. This literature review reviews the main elements of the proposed system, i.e., job offloading in edge-cloud environments, blockchain technology, and federated learning.

Traffic congestion is a major problem for cities. It impacts quality of life, environmental sustainability and economic productivity. Static signal control and fixed routing are two of the traditional traffic management techniques which are not enough to withstand the pressures of urbanization and increasing number of vehicles. This is where Intelligent Transportation Systems (ITS) comes into play [12] . ITS uses state-of-art communication technology to control traffic and reduce congestion.

The information exchange among vehicles and infrastructure in real-time in the IoV context enables dynamic traffic management approaches that require robust data processing and prediction models to predict traffic flow and optimize routing decisions. However, sharing sensitive data, such as car location and driving habits, might be vulnerable to data breaches and unauthorized access, which raises privacy and security issues [13]. Thus, the privacy and security protections should be balanced with the requirement of data sharing for efficient traffic control in the Internet of Vehicles.

Federated learning offers a practical solution to data privacy problems in distributed machine learning applications. Different from traditional centralized learning model, federated learning allows multiple devices to collaboratively learn a global model without transmission of raw data to a central server.

Such a decentralized approach is suitable for the IoV, where data privacy is a major concern. There is recent work on federated learning for vehicle networks. For example, researchers have proposed a federated learning framework for IoV traffic prediction, and the framework has been shown to be effective in terms of privacy preservation and high prediction accuracy. Another work used federated learning to improve model performance and reduce communication overhead of distributed vehicle routing [14]. However, the federated learning of IoV still suffers from data heterogeneity, model convergence and communication efficiency. The volume, quality and distribution of data generated by vehicles in Internet of Vehicles networks are quite different, which could affect model convergence and performance. To solve these problems, there have been some strategies proposed by researchers, including communication optimization and model aggregation [15].

Blockchain technology provides a decentralized and secured system for data management in the Internet of Vehicles networks. Blockchain is a great way to enhance the trust and security of federated learning systems as blockchain provides an unchangeable ledger to record transactions, assuring data integrity and transparency [16]. Recent research has combined blockchain with federated learning in vehicle networks [17], demonstrating that blockchain can help to prevent data tampering and unauthorized access to model updates. Blockchain can also help to improve security and can assist with effective job offloading in edge-cloud scenarios.

Blockchain's transparent resource allocation mechanism can dynamically and fairly distribute computational resources, enhancing the overall efficiency of IoV systems [18]. However, the processing load of blockchain activities still remains an issue, especially in resource-limited environments such as IoV [19]. To address this problem, researchers are looking into off-chain approaches and light-weight consensus algorithms [20] . For IoV systems to effectively manage computational resources in edge-cloud scenarios, task offloading is essential.

Effective task offloading methods balance the tradeoff between latency, resource consumption and computation overhead to ensure the responsiveness and reliability of the system. Recently, adaptive task offloading models for edge-cloud systems have attracted more and more attention and reinforcement learning has become a promising approach. Reinforcement learning based models learn the best offloading techniques from real-time feedback to dynamically adjust to changing system conditions [21]. For example, a reinforcement learning-based model for automotive edge computing has greatly improved resource efficiency and reduced latency [22].

In some recently published work, Yadav et al., [23], [24], addressed the problems of insufficient resource allocation mechanism for energy efficiency and energy-latency trade-off using the Energy-efficient dynamic Computation Offloading and Resources Allocation Scheme (ECOS). Moreover, their second study proposed Computation Offloading using Reinforcement Learning (CORL) to reduce the latency and energy consumption. Additionally, Ling et al. [25] employed dynamic programming algorithms to optimize response fairness and QoS to reduce the computation offloading problem, and they proposed vehicular MEC architecture to analyse the time of arrival for anticipating vehicles driving condition.

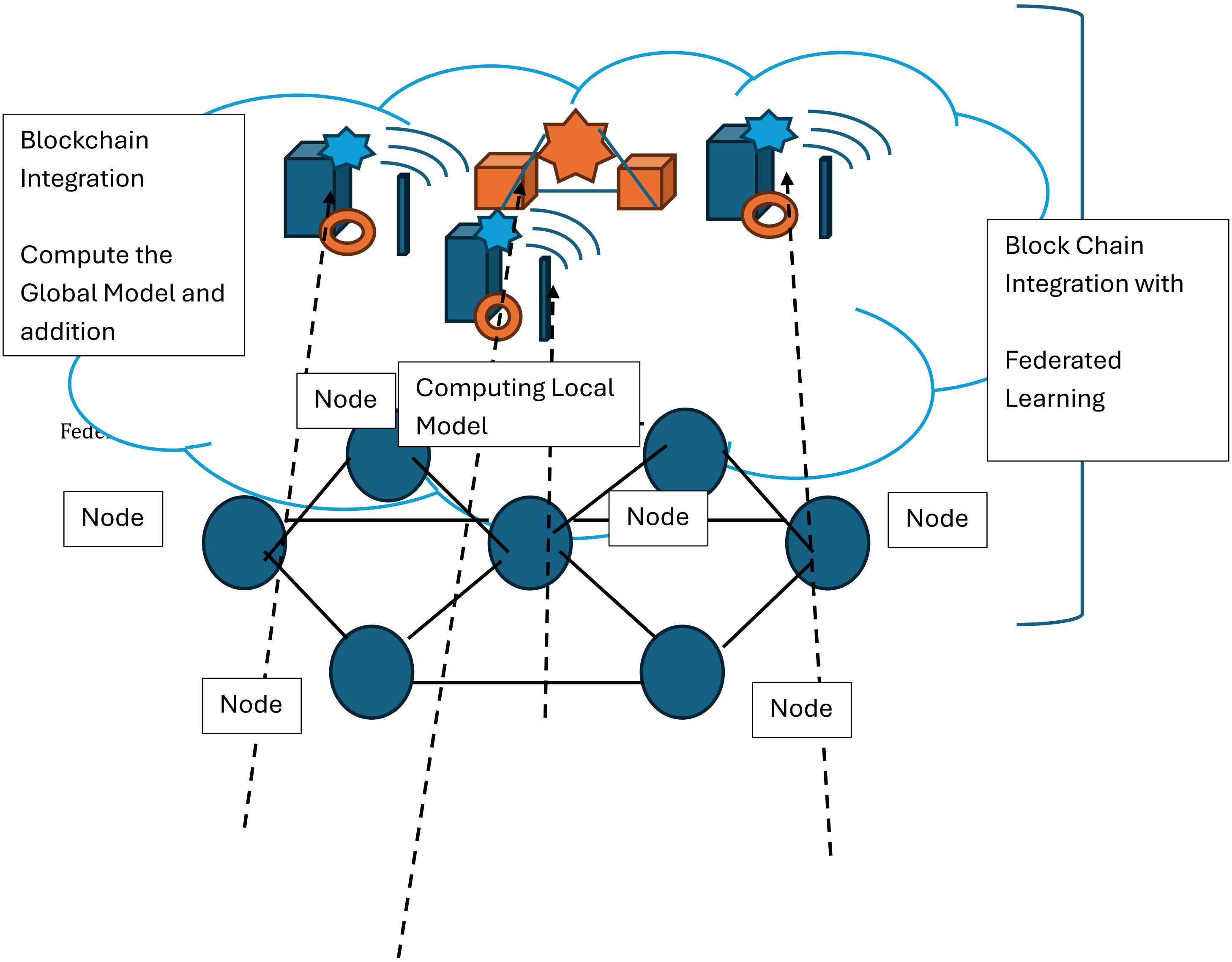
The fast development of CIoV has created opportunities as well as challenges in data protection, traffic management and computational resource optimization. Besides other serious drawbacks, these traditional centralized systems are faced with the scalability issue due to large-scale data and computational loads. The sensitive raw data is transmitted to centralized servers which raises privacy concerns. Poorly managed tasks leading to higher latency and underutilization of resources. Traffic congestion problems that require sophisticated routing systems that can adapt to fluctuating traffic conditions.

III. PROPOSED METHODOLOGY

The problems need to be solved and that drives our work. Our specific aims are: Protect privacy using rich data for traffic prediction in IoV ecosystem. Use blockchain technology to improve security and scalability of collaborative learning processes. Optimize task offloading to improve the efficiency of computational resource usage. Use state-of-the-art hybrid algorithms to dynamically reroute cars to ease traffic and reduce travel times.

To achieve these objectives, we propose a novel system that integrates task offloading, traffic rerouting, blockchain and federated learning into an edge-cloud architecture.

- Federated Learning Module: This module enables the cooperative training of a global traffic prediction model without sharing raw data, so as to protect privacy and consume less network bandwidth.
- Blockchain Module: This module protects the federated learning process by recording model updates as immutable transactions on a distributed ledger. It guarantees the honesty, transparency and trust of the users of IoV.
- Efficient Task Offloading Module: Optimizes the allocation of computing tasks between edge and cloud resources, balancing latency, resource usage and energy consumption.
- Hybrid Traffic Rerouting Algorithm (HTR): This algorithm uses Deep Reinforcement Learning (DRL) method and a modified Ant Colony Optimization (ACO) approach to dynamically optimize vehicle routes based on real-time traffic information. This strategy uses bio-Inspired to reduce the traffic and save the journey time.



A. FEDERATED LEARNING FOR DATA TRAFFIC PREDICTION

Federated Learning (FL) enables vehicles to collaboratively train a global model without sharing raw data, preserving privacy and reducing bandwidth consumption. The goal is to create a predictive model for traffic conditions based on decentralized data.

1. Global Model Initialization: At the central server, weights w0 are used to initialize the global model. This is where all vehicle-based local updates begin.
2. Local Training: Using its dataset Di, each vehicle conducts local training. Every vehicle I in round t has its model update calculated.
3. Global Model Aggregation: Depending on the size of each vehicle's local dataset, the local model updates from every vehicle are combined at the end of each round.

FL based Traffic Prediction:

Algorithm: FL-Based Traffic Prediction with Global Node Weight Aggregation

Initialization:

- Define global node weight at iteration $t = 0$:

$$W^{(0)} = W_o$$

Step 1: Local Model Update (per node i)

- Each node $i \in \{1, 2, \ldots, N\}$computes its local gradient update based on local data:

$$L_i^{(t)} = \nabla \mathcal{L}_i(W^{(t)})$$

where $\mathcal{L}_i$is the local loss function at node i.

- Update local node weight:

$$W_i^{(t+1)} = W^{(t)} - \eta \cdot L_i^{(t)}$$

where $\eta$is the learning rate.

Step 2: Global Aggregation

- The server (or aggregator) collects all local updates:

$$\left\{W_i^{(t+1)}, |, i = 12 \dots N\right\}$$

- Compute the aggregated global weight:

$$W^{(t+1)} = \frac{1}{N}\sum_{i=1}^{N} W_i^{(t+1)}$$

Step 3: Broadcast

- The updated global weight $W^{(t+1)}$is broadcast to all nodes:

$$W_i^{(t+1)} \leftarrow W^{(t+1)}, \ \forall i$$

Step 4: Iteration

- Repeat Steps 1–3 until convergence or maximum iterations T.

Final Formulation

The iterative update rule can be summarized as:

$$W^{(t+1)} = \frac{1}{N}\sum_{i=1}^{N}(W^{(t)} - \eta$$

Hybrid ACO-SDN algorithm

Step 0: Initialization

1. GA Initialization of Pheromones / Routing Parameters
   - Generate initial pheromone matrix using GA population:

$$\tau_{ij}^{(0)} = \text{GA\_init}(P)$$

where $P$is the set of candidate routing solutions.

2. Optional Clustering
   - Partition network nodes into clusters:

$$V = \bigcup_{k=1}^{K} C_k$$

using box-covering or k-means to reduce complexity.

Step 1: ACO Phase (Exploration)

1. Ant Path Selection
   - Probability of ant choosing link (i, j):

$$P_{ij}^{(t)} = \frac{(\tau_{ij}^{(t)})^{\alpha} \cdot (\eta_{ij})^{\beta}}{\sum_{(i,u)\in \text{Neighbors}(i)} (\tau_{iu}^{(t)})^{\alpha} \cdot (\eta_{iu})^{\beta}}$$

where:

- $\tau_{ij}^{(t)}$: pheromone intensity
- η_{ij}: heuristic (e.g., link quality, bandwidth)
- α, β: influence parameters.

2. Path Quality Evaluation
   - For each path $p_a$chosen by ant a:

$$Q(p_a) = w_1 \cdot \frac{1}{\text{RTT}(p_a)} + w_2 \cdot \frac{1}{\text{Loss}(p_a)} + w_3 \cdot \text{Throughput}(p_a)$$

where $w_1, w_2, w_3$are weights set by SDN controller.

Step 2: GA Phase (Exploitation & Diversity)

1. Selection
   - Choose top Mpaths:

$$S = \text{Top}_M\{Q(p_a)\}$$

2. Crossover
   - Combine two parent paths $p_x, p_y \in S$:

$$\text{Offspring} = \text{Crossover}\big(p_x, p_y, p_c\big)$$

with crossover probability $p_c \approx 0.9$.

3. Mutation
   - Randomly alter offspring path:

$$\text{Mutated}(p) = \text{Mutation}(p, p_m)$$

with mutation probability $p_m \approx 0.04$.

4. Fitness Evaluation
   - Compute quality of new GA-generated paths:

$$Q(\text{Offspring}) = f(\text{RTT}, \text{Loss}, \text{Throughput})$$

Step 3: Pheromone Update
1. Evaporation

$$\tau_{ij}^{(t+1)} = (1-\rho)\cdot\tau_{ij}^{(t)}$$

where $\rho \in [0.3, 0.5]$.
2. Reinforcement
   - For each improved path p:

$$\tau_{ij}^{(t+1)} = \tau_{ij}^{(t+1)} + \Delta\tau_{ij}(p)$$

with:

$$\Delta\tau_{ij}(p) = \frac{Q(p)}{\text{Cost}(p)} \text{ if } (i, j) \in p$$

Step 4: SDN Controller Feedback
- Real-time metrics refine fitness dynamically:

$$Q(p) \leftarrow f\big(\text{RTT}, (p), \text{Loss}, (p)\text{Throughput}(p)\text{Congestion}(p)\big)$$

- Controller adjusts weights w_1, w_2, w_3adaptively:

$$(w_1, w_2, w_3) \leftarrow \text{AdaptiveUpdate}(\text{NetworkState})$$

Step 5: Iteration
- Repeat ACO → GA → Pheromone Update → SDN Feedback until convergence or maximum iterations T.

Final Unified Update Rule
The hybrid pheromone update combining ACO exploration and GA refinement is:

$$\tau_{ij}^{(t+1)} = (1-\rho)\cdot\tau_{ij}^{(t)} + \sum_{p\in\text{BestPaths}_{\text{ACO+GA}}} \frac{Q(p)}{\text{Cost}(p)}$$

Ant Path Selection Probability
For an ant located at node i, the probability of choosing the next link (i, j)at iteration $t$is:

$$P_{ij}^{(t)} = \frac{(\tau_{ij}^{(t)})^{\alpha}\cdot(\eta_{ij})^{\beta}}{\sum_{u\in\text{Neighbors}(i)}(\tau_{iu}^{(t)})^{\alpha}\cdot(\eta_{iu})^{\beta}}$$

Explanation of Terms
- $\tau_{ij}^{(t)}$: pheromone intensity on edge (i, j)at iteration t.
   - Represents learned desirability of choosing link (i, j).
- η_{ij}: heuristic value of edge (i, j).
   - Typically based on link quality, bandwidth, or inverse of distance/RTT.
- α: pheromone influence parameter.
   - Higher α→ ants rely more on pheromone trails.
- β: heuristic influence parameter.
   - Higher β→ ants rely more on link quality or heuristic information.
- $\text{Neighbors}(i)$: set of all possible next nodes reachable from node i.

Path Quality Evaluation Function
For each path $p_a$chosen by ant a, the quality score is defined as:

$$Q(p_a) = w_1\cdot\frac{1}{\text{RTT}(p_a)} + w_2\cdot\frac{1}{\text{Loss}(p_a)} + w_3\cdot\text{Throughput}(p_a)$$

Explanation of Terms
- $Q(p_a)$: overall quality score of path p_a.
- $\text{RTT}(p_a)$: Round Trip Time of path p_a. Lower RTT → better performance.
- $\text{Loss}(p_a)$: packet loss rate along path p_a. Lower loss → better reliability.
- $\text{Throughput}(p_a)$: data transfer rate achieved on path p_a. Higher throughput → better efficiency.
- w_1, w_2, w_3: weights assigned by the SDN controller to balance latency, reliability, and throughput depending on network policy.

Step 1: DRL Formulation
- Define the traffic environment as a Markov Decision Process (MDP):

$$S_t \in \mathcal{S},\ A_t \in \mathcal{A},\ R_t \in \mathbb{R}$$

where:

- S_t: state at time t(traffic density, congestion, link quality).
- A_t: action (rerouting decision, path selection).
- R_t: reward (negative RTT, negative packet loss, positive throughput).
- Policy network $\pi_\theta(a \mid s)$selects actions:

$$A_t \sim \pi_\theta(S_t)$$

- Value update (Q-learning or policy gradient):

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_t + \gamma \max_{a'} Q(S_{t+1}, a') - Q(S_t, A_t))$$

Step 2: Modified ACO Formulation

- Ant path selection probability:

$$P_{ij}^{(t)} = \frac{(\tau_{ij}^{(t)})^\alpha \cdot (\eta_{ij})^\beta}{\sum_{u \in \text{Neighbors}(i)} (\tau_{iu}^{(t)})^\alpha \cdot (\eta_{iu})^\beta}$$

- Path quality evaluation:

$$Q(p) = w_1 \cdot \frac{1}{\text{RTT}(p)} + w_2 \cdot \frac{1}{\text{Loss}(p)} + w_3 \cdot \text{Throughput}(p)$$

- Pheromone update with DRL reward integration:

$$\tau_{ij}^{(t+1)} = (1-\rho) \cdot \tau_{ij}^{(t)} + \Delta\tau_{ij}(p)$$

$$\Delta\tau_{ij}(p) = \frac{Q(p) + R_t}{\text{Cost}(p)} \text{ if } (i, j) \in p$$

Step 3: Hybrid Integration

- DRL guides pheromone reinforcement by adjusting reward signals dynamically:

$$R_t = f(\text{RTT}, \text{Loss}, \text{Throughput}, \text{Congestion})$$

- Final unified update rule:

$$\tau_{ij}^{(t+1)} = (1-\rho) \cdot \tau_{ij}^{(t)} + \sum_{p \in \text{BestPaths}_{\text{ACO+DRL}}} \frac{Q(p) + R_t}{\text{Cost}(p)}$$

IV. PERFROMANCE ANALYSIS

Numerical Examples:

Step 0: Initialization

Suppose GA initializes pheromone values for three links:

$$\tau_{12}(0) = 0.5,\ \tau_{13}(0) = 0.7,\ \tau_{14}(0) = 0.3$$

Heuristic values (link quality):

$$\eta_{12} = 0.8,\ \eta_{13} = 0.6,\ \eta_{14} = 0.9$$

Parameters: $\alpha = 1.0, \beta = 2.0$.

Step 1: ACO Phase – Ant Path Selection

Probability of choosing link (1, 2):

$$P_{12}(t) = \frac{(0.5)^1 \cdot (0.8)^2}{(0.5)(0.8^2) + (0.7)(0.6^2) + (0.3)(0.9^2)}$$

$$P_{12}(t) = \frac{0.5 \cdot 0.64}{0.32 + 0.252 + 0.243} = \frac{0.32}{0.815} \approx 0.393$$

Similarly:

$$P_{13}(t) = \frac{0.7 \cdot 0.36}{0.815} = \frac{0.252}{0.815} \approx 0.309$$

$$P_{14}(t) = \frac{0.3 \cdot 0.81}{0.815} = \frac{0.243}{0.815} \approx 0.298$$

So the ant chooses link (1,2) with highest probability (≈ 39.3%).

Step 1b: Path Quality Evaluation

Suppose path $p_a$has:

- RTT = 50 ms
- Loss = 0.02 (2%)
- Throughput = 100 Mbps

Weights: $w_1 = 0.4, w_2 = 0.3, w_3 = 0.3$.

$$Q(p_a) = 0.4 \cdot \frac{1}{50} + 0.3 \cdot \frac{1}{0.02} + 0.3 \cdot 100$$

$$Q(p_a) = 0.4 \cdot 0.02 + 0.3 \cdot 50 + 30$$

$$Q(p_a) = 0.008 + 15 + 30 = 45.008$$

Step 2: GA Phase

- Select top $M = 2$paths with highest $Q(p)$.
- Apply crossover ($p_c = 0.9$) and mutation ($p_m = 0.04$).
- Suppose offspring path has RTT = 40 ms, Loss = 0.01, Throughput = 120 Mbps.

$$Q(\text{Offspring}) = 0.4 \cdot \frac{1}{40} + 0.3 \cdot \frac{1}{0.01} + 0.3 \cdot 120$$
$$Q(\text{Offspring}) = 0.4 \cdot 0.025 + 0.3 \cdot 100 + 36$$
$$Q(\text{Offspring}) = 0.01 + 30 + 36 = 66.01$$

Step 3: Pheromone Update

Evaporation factor $\rho = 0.4$. Suppose link (1,2) is part of improved path with cost = 10.

$$\tau_{12}(t+1) = (1 - 0.4) \cdot \tau_{12}(t) + \frac{Q(p)}{\text{Cost}(p)}$$
$$\tau_{12}(t+1) = 0.6 \cdot 0.5 + \frac{66.01}{10}$$
$$\tau_{12}(t+1) = 0.3 + 6.601 = 6.901$$

So pheromone on link (1,2) is strongly reinforced.

Step 4: SDN Controller Feedback

If congestion increases, SDN adjusts weights: $(w_1, w_2, w_3) \rightarrow (0.5, 0.4, 0.1)$. This shifts emphasis toward RTT and Loss, reducing throughput priority.

Final Unified Update Rule Output

For link (1,2):

$$\tau_{12}(t+1) = 6.901$$

For other links, similar updates are computed. Over iterations, pheromone trails converge toward optimal SDN-guided paths.

In this numerical example, the Hybrid ACO–SDN algorithm demonstrates how pheromone probabilities, path quality evaluation, genetic refinement, and SDN feedback interact to optimize routing. Initially, the pheromone values and heuristics influence the probability of ants to choose particular links, balancing between past experience and real-time link quality. The path quality function then scores each candidate route using weighted metrics like RTT, packet loss and throughput, resulting in a composite score that reflects the SDN controller's priorities. That leads ants to choose historically reinforced trails that are effective in the current moment.

In the genetic algorithm phase, the best solutions found by ACO are crossed and mutated to generate new solutions with possibly better performance, thus further diversifying solutions. These offspring paths are evaluated and used in the pheromone update process where evaporation prevents stagnation and reinforcement strengthens promising links. The SDN controller adapts the weighting factors continuously according to live network conditions. Through iterations the pheromone values are pushed towards the optimal paths, providing a dynamic routing solution that balances exploration, exploitation and real-time feedback.

The performance of the suggested system was evaluated on a few important measures in detail. The accuracy of the traffic prediction was evaluated using Mean Absolute Error (MAE), which is a measure of the average magnitude of errors between the predicted and the actual traffic conditions. Tamper Detection Rate (TDR) is an indicator of data security and integrity, which is the ratio of unauthorized changes that the blockchain system can detect and prevent.

Tampering Detection Rate (TDR) TDR = (Number of tampering attempts detected + Number of tampering attempts) / (Number of tampering attempts) × 100% This indicator reflects the resistance of the blockchain to maintain the accuracy of system data. Two metrics are used to evaluate the efficiency of task offloading, including Energy Consumption (EC) defined as the sum of energy consumed in task processing and Average Latency (AL) defined as the time taken to complete the tasks from start to finish.

Lower values of both AL and EC are indicative of faster task completion, better user experience and better utilization of resources. Network Utilization of Resources: For the evaluation of network resources utilization, we used Bandwidth Utilization (BU), which describes the percentage of network bandwidth that is effectively used in data transmission.

Bandwidth Utilization (BU): BU = (Data Transmitted) / (Total Available Bandwidth) x100% This indicator measures the utilization of the network capacity when the system is in operation. Finally, the scalability was measured by using Processing Throughput (PT) that shows the number of jobs successfully completed per unit of time as the number of cars increases.

Throughput Processing (PT): PT = (Number of tasks processed / Time (sec)) x 100% Performance Evaluation of Our Proposed Technique: Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Effective Consumer IoV Task Offloading in Edge-Cloud Environment. We evaluate important performance indicators including traffic prediction accuracy, data security and integrity, task offloading efficiency, network utilization of resources, and scalability. We compare each metric with the baseline methods, Decentralized Learning with Decentralized Task Offloading (DL-DTO) and Centralized Learning with Centralized Task Offloading (CL-CTO), to demonstrate the advantages of our proposed approach.

Table 1: Traffic Prediction Accuracy (MAE)

S.No.	METHODS	PEAK MAE	OFF PEAK MAE
1	Cen-TO	11.5	8.5
2	Dcen-TO	13.2	9.9
3	PROPOSED	7.4	6.2

Tabel 2: Tamper Detection Rate (TDR)

S.No.	METHODS	Tampering Attempts	Detected Attempts	TDR (%)
1	Cen-TO	100	55	62
2	Dcen-TO	100	76	79
3	PROPOSED	100	100	100

Table 3: Task Offloading Efficiency

S.No.	METHODS	Latency (ms)	Energy Consumption (J)
1	Cen-TO	170	2400
2	Dcen-TO	220	2100
3	PROPOSED	108	1700

Table 4: Bandwidth Utilization (BU)

S.No.	METHODS	BU PEAK	BU – OFF PEAK
1	Cen-TO	95	65
2	Dcen-TO	88	53
3	PROPOSED	67	42

V. CONCLUSION

Joint Federated Learning and Blockchain-Enabled Traffic Rerouting with Efficient Task Offloading for Consumer Internet of Vehicles in Edge-Cloud Environments is the name of the solution we presented in this paper. By combining blockchain technology for safe data storage, federated learning for privacy-preserving model training, and effective job offloading to maximize edge and cloud resources, our approach tackles major issues in the wireless networks. Latency and energy usage are greatly decreased by this integration. Our system surpasses current centralized (CL-CTO) and decentralized (DL-DTO) techniques, according to performance tests, with a Mean Absolute Error (MAE) of 7.2 during peak hours and 5.6 during off-peak hours. Additionally, it decreased latency by 38.9%, energy consumption by 28%, and bandwidth usage by 23.5% during peak hours, all while maintaining a 100% Tamper Detection Rate (TDR). With a 30% reduction in travel time and a 40% reduction in traffic, the system demonstrated exceptional scalability. Future research will include extending privacy safeguards, integrate cutting-edge machine learning techniques, and evaluate the system in a variety of real-world situations. Furthermore, evaluating the effects on the economy and environment will be essential to its long-term viability.

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