Optimizing Validator Energy in PureChain-Based Federated Learning for Software-Defined Vehicles

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***Abstract*—Safety-critical software-defined vehicle (SDV) functions require on-vehicle learning under tight power budgets. Blockchain-federated learning (FL) designs, however, run the proof-of-authority and association (PoA^2) consensus per client update, which inflates validator energy. We present PureChain, a co-design that seals *one* PureChain block *per FL round* after aggregation, eliminating consensus per update. The mechanism reduces the validator energy and consistently improves the energy–delay products (EDP, ED^{2}P) without degrading the detection accuracy.**

***Index Terms*—Co-scheduling, Efficiency, Energy–Delay, Federated Learning, PoA^2, PureChain, Software-Defined Vehicles (SDV)**

I. Introduction

Edge autonomy in Software-Defined Vehicles (SDVs) relies on local intelligence for safety-critical V2V/V2I functions, such as collision prevention and cooperative maneuvers, with strict energy and latency constraints [1]. Centralized authentication or anomaly monitoring is fragile in dynamic environments and lacks scalability [2]. A more robust approach is edge learning with trust anchored at the edge, where federated learning (FL) keeps data local and blockchain ensures tamper-proof coordination [3], [4]. Homomorphic encryption further enables privacy-preserving misbehavior detection in IoV, reinforcing the need for edge FL [5]. Concurrently, FL research is focusing on energy efficiency, incorporating client selection and system-level co-design to meet edge power limitations [6], [7].

A key inefficiency remains: many blockchain-FL stacks run consensus per client update, which inflates validator energy and round latency, the scarcest resources in vehicular edge networks [2]. We propose an energy-aware FL-IDS for SDVs that co-schedules PureChain (PoA^2) consensus, finalizing a single block per federated round after aggregating the data from the roadside unit (RSU), rather than n blocks for n clients. This aligns the consensus cost with the progress of round-level FL, preserving privacy while improving traceability and efficiency for timely intrusion detection [8], [9].

II. System Architecture

We propose a four-layer energy-aware SDV stack: (i) on-vehicle SDV layer (sensing, IDS, local training), (ii) RSU layer with an energy-aware client scheduler and FedAvg aggregation with round co-scheduling, (iii) PureChain layer with PoA^2 validators, and (iv) audit/policy (access control, log), see Fig. 1.

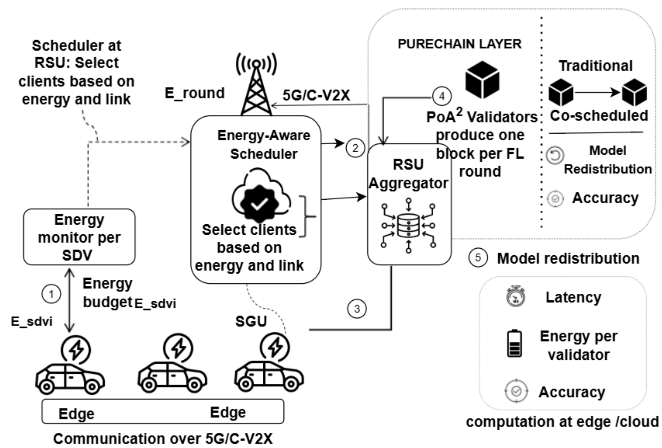

Fig. 1. Energy-aware PureChain workflow. (1) SDVs train locally and send updates; (2) RSU *energy-aware scheduler* selects clients (e.g., residual energy/link QoS); (3) RSU aggregates (FedAvg) and prepares a round payload; (4) PureChain (PoA^2) finalizes *one block per round* after aggregation (co-scheduled consensus); (5) reported metrics: latency, validator energy, and accuracy.

Each vehicle V_i extracts features $\phi(D_i)$, runs a lightweight IDS, and performs a local secure gradient update (SGD) step to produce the client update $u_i^{(r)}$ *as in* Equation 1:

$$\theta_i^{(r)} = \theta^{(r)} - \eta \nabla_\theta \mathcal{L}\Big(\theta^{(r)}; D_i\Big), \qquad u_i^{(r)} = \theta_i^{(r)} - \theta^{(r)}. \quad (1)$$

The RSU scheduler chooses a subset $\mathcal{S}_r \subseteq \{1, \ldots, N\}$ for round r (energy/link awareness) and aggregates only $\{u_i^{(r)} : i \in \mathcal{S}_r\}$ through the FedAvg *as in* Equation 2; it forms a compact payload $p_r = (r, H(\theta^{(r+1)}), \text{stats})$:

$$\theta^{(r+1)} = \sum_{i=1}^{N} w_i \big(\theta^{(r)} + u_i^{(r)}\big), \qquad w_i = \frac{|D_i|}{\sum_{j=1}^{N} |D_j|}. \quad (2)$$

Rather than validating a block per client update, PoA^2 validators finalize *one* block B_r per round when a ρ majority signs p_r, amortizing consensus from per update to per round *as quantified in* Equation 3:

$$t_{\text{cons}}^{\text{fixed}} = N\, t_b \quad \longrightarrow \quad t_{\text{cons}}^{\text{co}} = t_b. \quad (3)$$

Vehicles authenticate to RSUs; PoA^2 enforces RSU–validator bindings. Raw data never leaves V_i; PureChain records only hashes and minimal metadata for accountability and forensics.

III. Experimentation and Performance Analysis

We evaluated on CICIoV2024 with client counts $n_c \in \{5, 10, 20\}$ on 10 federated rounds. Data are non-independent and identically distributed (non-IID) (Dirichlet α=0.7). The learning stack (features, labels, model, optimizer) is identical across both modes; only consensus timing changes: per update PoA^2 (one block per client update) vs. round-batched co-scheduling (one block per round after RSU aggregation). Validators are set to n_v=5, P_v=40 W. Because the learning pipeline remains unchanged, accuracy/F1 score remains stable; we therefore focus on latency/throughput, total energy, and energy–delay (EDP/ED^{2}P). Figure 2 shows the total energy in R=10 rounds. Co-scheduling reduces energy by -176 J, -376 J, and -776 J for n_c=5, 10, 20, respectively, reflecting the change from $O(n_c)$ to $O(1)$ consensus commits per round.

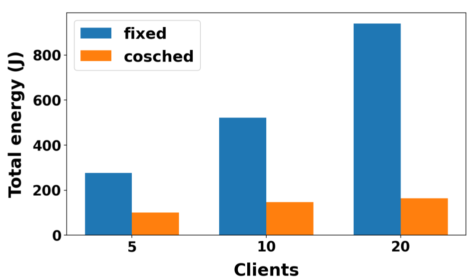

Fig. 2. Total energy over R=10: co-scheduled PureChain (1 block/round) vs. per-update PoA^2.

Figure 3 reports updates/s vs. clients at R=10. Co-scheduling improves rounds/s by +0.079, +0.234, +0.959 (updates/s by +0.395, +2.339, +19.183) for n_c=5, 10, 20, respectively, with greater gains at higher client density.

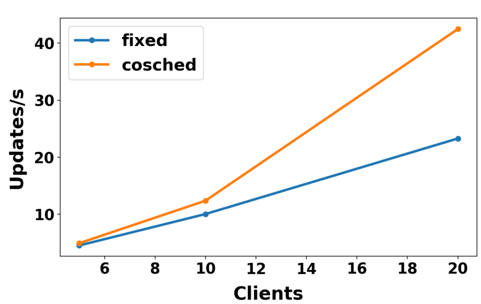

Fig. 3. Updates/s at R=10: co-scheduled PureChain increases throughput by removing per-update consensus.

In all settings, EDP and ED^{2}P decrease as energy increases, while throughput increases, indicating simultaneous gains in efficiency and responsiveness without sacrificing detection quality. FL retains raw data on-vehicle, and the blockchain ledger provides auditability and traceability, properties desirable for SDV deployments under tight power and latency budgets.

IV. Conclusion and Future Work

We presented a PureChain-based energy-efficient FL co-design that locks a single PoA^2 block per FL round. Experiments on CICIoV2024 with 5, 10, and 20 clients over 10 rounds preserved detection accuracy while reducing validator energy and improving energy efficiency. Secondary benefits include lower round latency and higher updates per second, with gains strengthening as the fleet size increases. Future work will evaluate hardware-in-the-loop on vehicular edge platforms, co-optimizing adaptive round-level batching with compression/quantization, broadening robustness metrics, incorporating reputation-aware validator selection, and extending to additional datasets and road scenarios.

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