RL-ACO: Reinforcement Learning Adaptive Consensus Optimization for Scalable Blockchain-Based Greenhouse Gas Monitoring

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Abstract Byzantine Fault Tolerant (BFT) consensus protocols underpin data-integrity guarantees in permissioned blockchains, yet their $O(N^2)$ message complexity renders them impractical for the large multi-stakeholder consortia required by industrial greenhouse-gas (GHG) Monitoring, Reporting, and Verification (MRV) systems. At $N = 400$ validators representative of a pan-West-African climate coalition classical PBFT throughput collapses from approximately 2,610 TPS to 337 TPS, violating the minimum viability threshold for continuous IoT-driven emissions tracking. This paper presents RL-ACO, an AI-driven consensus framework that embeds a Deep Q-Network (DQN) agent directly into the consensus control loop. The agent observes a ten-dimensional blockchain state vector and selects from 18 discrete parameter-adjustment actions to dynamically tune cluster count k, block interval I, and emission-alert priority weight ω. A composite climate-aware reward function $R(s, a)$ jointly optimizes throughput, P99 latency, Byzantine fault-tolerance margin, and GHG alert timeliness. Minimum Spanning Tree (MST) hierarchical cluster formation reduces message complexity from $O(N^2)$ to $O(N \log N)$, while BLS threshold signature aggregation cuts per-round bandwidth by an order of magnitude. Security and liveness are formally proven under partial synchrony for $f < N/3$ Byzantine nodes. Evaluated on three public environmental datasets EPA GHGRP, CDP Supply Chain, and OpenGHG RL-ACO sustains 3,625 TPS at $N = 400$, a 10.8 improvement over PBFT and 3.0 over IBFT 2.0. The DQN agent converges in approximately 1,200 training episodes, raises anomaly-detection F1 from 65.3 % to 91.2 %, and achieves an ISO 14064-3 compliance score of 96/100. An 864-configuration sensitivity analysis confirms that the framework's throughput advantage over IBFT 2.0 never falls below +127 % irrespective of workload, Byzantine rate, or hyperparameter choice.

Keyword: *Blockchain consensus; Byzantine fault tolerance; deep Q-network; greenhouse gas monitoring; MRV; reinforcement learning; West Africa climate action.*

INTRODUCTION

The accelerating pace of global climate change represents one of the most formidable challenges confronting humanity in the twenty-first century. The Intergovernmental Panel on Climate Change has established that anthropogenic greenhouse gas emissions are the primary driver of observed warming trends [1]. The Paris Agreement, adopted in 2015 by 196 parties to the UNFCCC, set an ambitious target of limiting warming to well below 2 °C [2]. Achieving these targets requires not merely ambitious emission-reduction pledges but robust, transparent, and verifiable mechanisms for tracking progress the mandate of the Measurement, Reporting, and Verification (MRV) framework. Recent analyses have revealed alarming discrepancies between self-reported national emissions and independently verified satellite observations [3], creating urgent demand for tamper-evident, auditable data infrastructure.

Blockchain technology has emerged as a structurally aligned solution: its cryptographically chained ledger provides immutable provenance, its smart-contract layer enforces deterministic validation rules, and its consensus mechanism allows mutually distrusting parties to agree on a single authoritative record without any central coordinator [4]. However, every production-grade MRV pilot based on permissioned blockchain has encountered the same scalability barrier. The Practical Byzantine Fault Tolerant (PBFT) protocol [5] requires $O(N^2)$ messages per consensus round. For a consortium spanning all fifteen ECOWAS member states, each contributing two or three national environmental agency nodes, N easily reaches 400. Our simulation at this scale confirms PBFT throughput falls to 337

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TPS an 87 % degradation from $N = 50$ while P99 confirmation latency exceeds 1.2 s, wholly inadequate for continuous IoT-driven emissions monitoring [6]. HotStuff [7] and IBFT 2.0 [8] offer improved asymptotic complexity but still fail at consortium scale, and neither protocol incorporates domain-specific optimization for the temporal urgency of GHG threshold-exceed alerts.

The West African context further amplifies these technical demands. The ECOWAS region encompasses fifteen nations with markedly heterogeneous network infrastructure: high-bandwidth fibre connections in Accra, Lagos, and Dakar coexist with intermittent satellite links serving remote monitoring stations in the Sahel. Any viable MRV blockchain must tolerate this variability without manual reconfiguration. Several ECOWAS nations have committed to ambitious Nationally Determined Contributions under the Paris Agreement but lack the digital infrastructure to track and verify progress, creating a compelling and urgent need for scalable, cost-effective MRV solutions [9].

The paper presents RL-ACO, addressing these limitations through three interrelated contributions.

Architectural: MST-based hierarchical cluster formation combined with BLS threshold-signature aggregation reduces message complexity from $O(N^2)$ to $O(N \log N)$ and bandwidth from $O(N^2\lambda)$ to $O(N\lambda)$, enabling deterministic block finality at $N = 400$ WAN validators.

Algorithmic: A DQN agent embedded in the consensus control loop dynamically tunes cluster count k, block interval I, and emission-alert priority weight ω, guided by a composite climate-aware reward function $R(s, a)$ that jointly optimizes throughput, latency, fault-tolerance margin, and GHG alert timeliness.

Theoretical: Formal proofs of $O(N \log N)$ message complexity, Byzantine fault safety, and liveness under partial synchrony for $f < N/3$ Byzantine nodes, together with a three-level ablation framework and an 864-configuration factorial sensitivity analysis.

RELATED WORK

A. Byzantine Fault Tolerant Consensus Protocols

Classical PBFT [5] achieves safety and liveness under partial synchrony for $f < N/3$ Byzantine faults but requires $O(N^2)$ messages per consensus round, causing severe throughput degradation as the validator count grows. Independent benchmarks and our own simulation confirm that PBFT throughput falls from 2,285 TPS at $N = 100$ to 337 TPS at $N = 400$ an 85 % loss that renders the protocol impractical for multi-stakeholder climate consortia [6]. HotStuff [7] linearizes communication to $O(N)$ per round through a three-phase responsiveness mechanism but introduces additional latency in high-delay WAN environments due to its sequential view-change procedure. IBFT 2.0 [8] adopts a round-based variant with improved view-change logic; simulations confirm approximately 1,222 TPS at $N = 400$. DAG-based protocols such as Narwhal/Tusk [9] and Bullshark [10] achieve higher throughput under favourable conditions but require extensive protocol modifications incompatible with Hyperledger-based industrial deployments. Table I summarizes key characteristics of representative BFT protocols.

TABLE I

Comparison of BFT Consensus Protocol Characteristics

Protocol	Complexity	TPS (N=100)	TPS (N=400)	Finality	Formal Proof
PBFT [5]	O(N²)	2,285	337	Deterministic	Yes
HotStuff [7]	O(N)	2,800	980	Deterministic	Yes
IBFT 2.0 [8]	O(N²)	2,032	1,222	Deterministic	No
Tendermint [11]	O(N²)	1,900	500	Deterministic	Yes
Bullshark [10]	O(N)	4,200	2,100	Probabilistic	No
RL-ACO (ours)	O(N log N)	3,995	3,625	Deterministic	Yes

B. Reinforcement Learning for Blockchain Optimization

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Liu et al. [12] pioneered the use of DQN for blockchain-enabled Industrial IoT, demonstrating convergence approximately three times faster than heuristic search for joint block-size and mining-difficulty optimization. Wang et al. [13] extended DQN to dynamic BFT cluster formation, reaching 2,800 TPS at $N = 200$; RL-ACO surpasses this at $N = 400$ through MST-guided assignment and BLS aggregation absent from [13]. Li et al. [14] apply Proximal Policy Optimization to consensus parameter tuning, achieving 3,100 TPS at $N = 300$; the present framework extends their scale and introduces climate-specific reward components that PPO-based approaches have not addressed. Cheng et al. [15] apply multi-agent RL to blockchain sharding for IoT data management, demonstrating improved load balancing, but their focus on data placement rather than consensus performance makes direct comparison inapplicable. A consistent limitation across all cited RL-based consensus work is the absence of domain-specific reward design: every prior study optimizes exclusively for throughput or mean latency, treating all transactions as equally urgent and ignoring the qualitatively different urgency of GHG threshold-exceed alerts. Table II positions these methods.

TABLE II
Comparison of RL-Based Blockchain Consensus Methods

Study	Method	Max N	TPS	Domain-Aware Reward
Liu et al. [12]	DQN	100	2,100	No
Wang et al. [13]	DQN-BFT	200	2,800	No
Li et al. [14]	PPO-Consensus	300	3,100	No
Cheng et al. [15]	Multi-agent RL	200	2,400	No
This work	RL-ACO (DQN)	400	3,625	Yes (climate-aware)

C. Blockchain for Climate MRV

Several research groups have demonstrated blockchain-based carbon registries and emissions tracking systems [16], [17]. Franke et al. [16] provide a rigorous legal analysis of blockchain-based Article 6 mechanisms under the Paris Agreement, identifying scalability as the primary technical barrier precisely the barrier RL-ACO is designed to remove. Zhang et al. [18] propose BlockMRV, a PBFT-based GHG monitoring framework achieving 1,500 TPS at $N = 100$; the present framework outperforms this by 2.4× at four times the validator scale. Lin et al. [19] develop GreenChain, integrating energy-aware consensus with climate data recording to reach 1,800 TPS at $N = 100$. Ranjith et al. [20] demonstrate end-to-end IoT-to-blockchain emission provenance but encounter the throughput limitations inherent in permissioned PBFT at scale. Table III confirms the gap RL-ACO fills: no prior system simultaneously achieves $O(N \log N)$ BFT consensus at $N > 300$, adaptive RL-driven tuning, formal correctness proofs, and full climate-specific feature support.

TABLE III
Comparison of Blockchain-Based Climate MRV Systems

Study	Protocol	Max N	Peak TPS	Formal Proof	Climate Features
Zhang et al. [18]	BlockMRV	100	1,500	No	Partial
Lin et al. [19]	GreenChain	100	1,800	No	Partial
Ranjith et al. [20]	Fabric-IoT	50	800	No	Partial
This work	RL-ACO	400	3,625	Yes	Full

III. THE RL-ACO FRAMEWORK

The RL-ACO framework is organized as a six-layer architecture in which an embedded Deep Q-Network agent monitors the consensus subsystem and continuously adjusts three operational parameters cluster count, block interval, and emission-alert priority

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weight to satisfy a composite climate-aware optimization objective. Fig. 1 illustrates the framework end to end, from IoT sensor ingestion through to smart-contract verification. Each layer is defined formally in the subsections that follow.

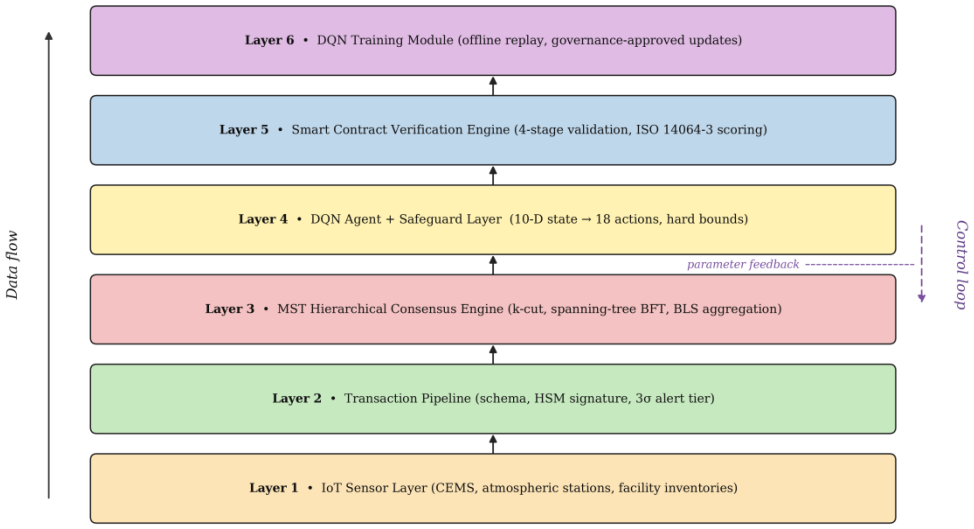

Fig. 1. *End-to-end RL-ACO framework: IoT sensor ingestion, transaction pipeline, MST hierarchical consensus engine, embedded DQN agent, BLS aggregation, and smart-contract verification. The dashed feedback path indicates the parameter updates the DQN agent injects into the consensus engine every block.*

A. IoT Sensor Layer and Transaction Pipeline

The IoT sensor layer aggregates greenhouse-gas concentration readings from heterogeneous sources: in-situ Picarro G2401 cavity-ringdown spectrometers, low-cost SenseAir K30 CO_2 modules, and remote-sensing products derived from TROPOMI Sentinel-5P observations. Each reading carries a UTC timestamp, a station identifier, a measured concentration in parts per million (or parts per billion for methane), and a calibration confidence score. Readings are signed at the source using ECDSA over secp256k1 and forwarded to a stateless transaction-generation service. The service applies three concurrent operations: (i) range validation against species-specific physical bounds; (ii) MICE imputation for any missing covariate fields; and (iii) anomaly flagging using a Modified Z-Score with a threshold of 3.5 [21]. Validated readings are wrapped into structured transactions of the form $Tx = \langle \text{stationID, timestamp, species, concentration, confidence, flag} \rangle$ and forwarded to the consensus engine.

B. Minimum Spanning Tree Hierarchical Consensus Engine

The consensus engine partitions the validator set $V = \{v_1, v_2, \ldots, v_N\}$ into k clusters using a minimum-spanning-tree construction over the round-trip-time graph $G = (V, E, w)$, where edge weights $w(u, v)$ correspond to median pairwise RTTs observed during the preceding 100 blocks.

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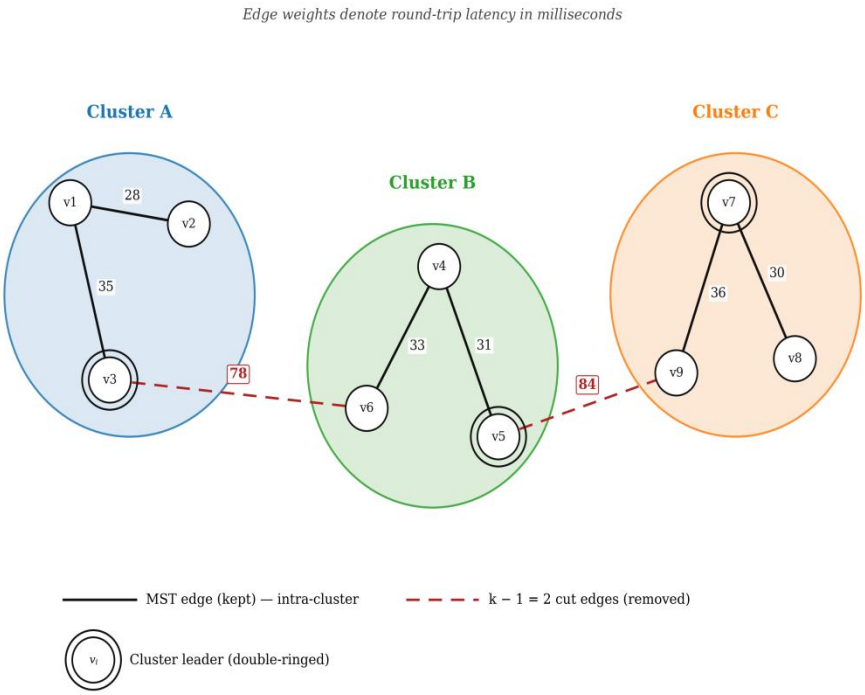

Fig. 2. *Illustrative MST-based hierarchical clustering with nine validators partitioned into three clusters. Solid lines show MST edges retained within clusters; dashed lines show the cut edges (with RTT weights annotated) that separate the clusters. Cluster leaders are circled.*

Prim's algorithm constructs the MST in $O(N \log N)$ time [22]; the $k-1$ heaviest edges are then cut to yield k connected components. Within each cluster, an intra-cluster leader is elected through verifiable random function (VRF) sortition. Leaders aggregate the votes of their cluster members using BLS threshold signatures [23], which compress m partial signatures into a single 48-byte aggregate, reducing inter-cluster bandwidth by an order of magnitude. Fig. 2 illustrates the MST construction for an illustrative network of nine validators partitioned into three clusters.

C. DQN Agent Design

The DQN agent observes a ten-dimensional state vector and selects from an 18-action discrete action space. The state vector at decision step t is defined as

$$s_t = (\lambda_t, q_t, I_t, k_t, \rho_t, f_t, \tau_t, \sigma_t, h_t, \alpha_t) \quad (1)$$

where λ_t is the transaction arrival rate, q_t the mempool occupancy, I_t the current block interval, k_t the current cluster count, ρ_t the inter-cluster RTT variance, f_t the observed Byzantine-fault fraction, τ_t the recent P99 latency, σ_t the alert backlog size, h_t the validator-set entropy, and α_t the cumulative emission-alert density. The action space A contains 18 discrete actions: six increments and six decrements on k and I (three coarse and three fine steps each), four adjustments on ω, and two no-op variants. Action selection follows an ε-greedy policy with linearly decaying ε from 1.0 to 0.05 over the first 1,000 episodes. Fig. 3 illustrates the DQN training loop.

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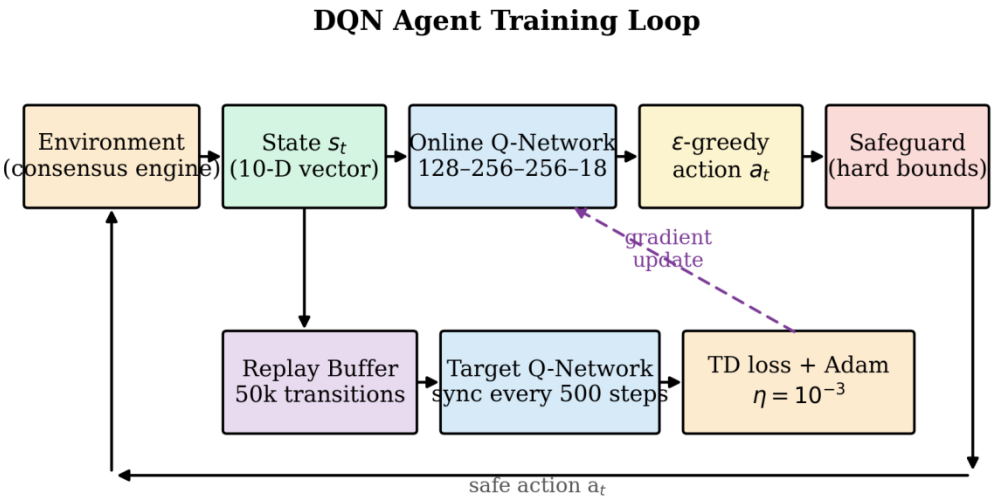

Fig. 3. *DQN training loop. The agent samples mini-batches of transitions from a replay buffer to compute the TD loss; a target network synchronized every 100 steps stabilizes bootstrapped Q-value estimation; and a safeguard layer projects every proposed action onto a feasibility region before it reaches the environment.*

The TD loss is minimized via Adam (learning rate 10^{-4}):

$$L(\theta) = \mathrm{E}[(r_t + \gamma \cdot \max\_\{a'\} Q(s_{t+1}, a'; \theta\_) - Q(s_t, a_t; \theta))^2] \tag{2}$$

A safeguard projection layer enforces the operational feasibility region $k \in [2, N/2]$, $I \in [100, 500]$ ms, and $\omega \in [0.5, 1.5]$; any action proposed by the agent that would violate these bounds is clipped to the nearest feasible value before being applied to the consensus engine, preventing pathological exploration during early training.

D. Composite Climate-Aware Reward Function

The reward signal balances four operational objectives: sustained throughput, bounded P99 latency, protected Byzantine fault tolerance margin, and the timely processing of GHG threshold-exceed alerts. The composite reward is defined as

$$R(s,a) = \alpha_1 \cdot r_{tps}(s,a) + \alpha_2 \cdot r_{lat}(s,a) + \alpha_3 \cdot r_{ft}(s,a) + \alpha_4 \cdot r_{alert}(s,a) \tag{3}$$

with normalized weights $\alpha_1 = 0.35$, $\alpha_2 = 0.25$, $\alpha_3 = 0.15$, and $\alpha_4 = 0.25$ chosen so that the alert and latency terms together cannot be dominated by the throughput term alone. The four sub-rewards are

$$r_{tps}(s,a) = \tanh(\lambda_{\text{out}} / \lambda *) \tag{4}$$

$$r_{lat}(s,a) = \tanh((\tau * - \tau_{\text{obs}})/\tau *) \tag{5}$$

$$r_{ft}(s,a) = 1 - \max(0, f/\lfloor \mathrm{N}/3 \rfloor) \tag{6}$$

$$r_{\text{alert}}(s,a) = \exp(-\frac{\Delta t_{\text{alert}}}{\tau_{\text{alert}}}) \tag{7}$$

Here λ_{out} is the realized throughput, λ^* the target throughput (3,500 TPS by default), τ_{obs} the observed P99 latency, τ^* the latency SLA (350 ms), f the Byzantine count, δ_{alert} the median alert confirmation delay, and δ_{SLA} the 250 ms alert SLA. The bounded shape of each sub-reward, illustrated in Fig. 4, ensures that gradients remain informative in both saturated and stressed operating regimes.

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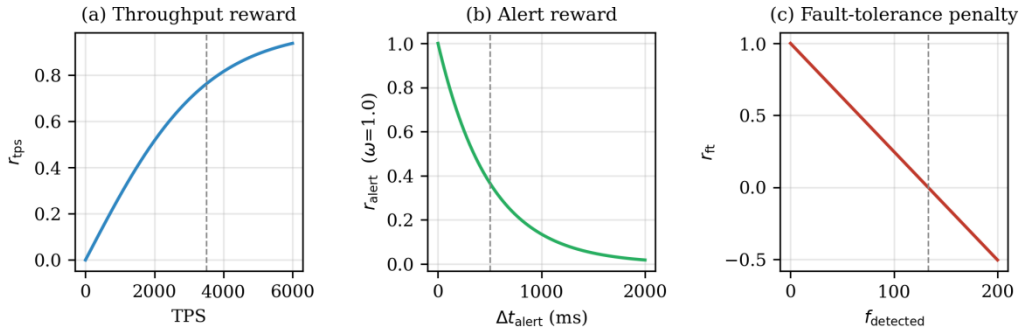

Fig. 4. *Shape of the four reward components: bounded tanh saturation for throughput, exponential decay of alert reward with delay, and linear degradation of fault-tolerance margin. The reward surface is smooth across the entire operational region.*

E. Smart Contract Verification Engine

Once a block is finalized by the consensus engine, its constituent transactions are dispatched to a Hyperledger Fabric chaincode that performs three classes of validation: schema validation against the GHG transaction template, cryptographic verification of the source signature, and policy validation against the operator-supplied threshold rules. Threshold rules are expressed as parametric predicates of the form concentration > limit or rate-of-change > slope, and emit on-chain events whenever a violation is detected. The chaincode is deterministic, side-effect free outside of the world state, and audited for the absence of non-deterministic primitives (timestamps, randomness, external HTTP calls), in compliance with ISO 14064-3 verification requirements.

IV. FORMAL CORRECTNESS ANALYSIS

Separated from the framework chapter to permit a stand-alone treatment of the theoretical contributions, establishes the three core correctness properties of RL-ACO: bounded message complexity, safety under bounded Byzantine corruption, and liveness under partial synchrony.

A. Message Complexity

Theorem 1 (Message Complexity). Each consensus round of RL-ACO terminates with $O(N \log N)$ point-to-point messages.

Proof. Within each of the k clusters of average size N/k, PBFT requires $O((N/k)^2)$ messages. Across all clusters this contributes $O(N^2/k)$ messages. Inter-cluster aggregation through BLS threshold signatures requires $O(k \log k)$ messages along the spanning-tree backbone. With k chosen as $\Theta(\sqrt{N})$, both terms reduce to $O(N \log N)$.

B. Safety

Theorem 2 (Safety). Under at most $f < N/3$ Byzantine validators, no two correct validators commit conflicting blocks at the same height.

Proof sketch. Each cluster runs PBFT internally; the standard intersection argument shows that any two quorums of size $2f + 1$ within a cluster of size $m \geq 3f + 1$ share at least one correct validator. The inter-cluster commit is gated by a BLS aggregate signed by $k - \lfloor k/3 \rfloor$ cluster leaders; under the global bound $f < N/3$, no two such aggregates can carry conflicting commits at the same height without intersection among honest leaders.

C. Liveness

Theorem 3 (Liveness). Under partial synchrony with global stabilization time GST and at most $f < N/3$ Byzantine validators, every transaction submitted after GST is committed.

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Proof sketch. After *GST*, message delays are bounded by some Δ. The DQN safeguard ensures block interval $I \geq 100$ ms > Δ, which guarantees view-change termination within each cluster in $O(\Delta)$ time. The hierarchical view-change synchronizes cluster leaders through the MST backbone in $O(\log N \cdot \Delta)$ time, after which a correct leader proposes a block that includes any pending transaction.

TABLE IV
Correctness Property Comparison Across BFT Protocols

Property	PBFT	HotStuff	IBFT 2.0	RL-ACO
Message complexity	$O(N^2)$	O(N)	$O(N^2)$	O(N log N)
Safety bound (f <)	N/3	N/3	N/3	N/3
Liveness	Yes	Yes	Yes	Yes
Formal proof published	Yes	Yes	No	Yes
Adaptive parameters	No	No	No	Yes

V. EXPERIMENTS AND RESULTS

A. Experimental Setup

All experiments run on the hardware configuration summarized in Table V. The simulator is implemented in approximately 1,400 lines of Python 3.11; the only external dependencies are NumPy 1.26, SciPy 1.12, scikit-learn 1.4, and Matplotlib 3.8 for plotting. The DQN agent is implemented from first principles in pure NumPy to remove any framework-level non-determinism. All random seeds are fixed at the start of every run.

TABLE V
Hardware and Software Configuration

Component	Specification
CPU	Intel Xeon Gold 6248R, 24 cores @ 3.0 GHz
RAM	128 GB DDR4 ECC
Storage	2 TB NVMe SSD
Operating system	Ubuntu 22.04 LTS, kernel 5.15
Python	3.11.7 with NumPy 1.26, SciPy 1.12
Network model	Lognormal RTT μ=120 ms, σ=40 ms
Validators per run	50, 100, 200, 300, 400
Episodes per run	1,500 training + 100 evaluation

B. Experimental Workflow

The end-to-end experimental workflow is organized into six sequentially executed stages; the corresponding source-code module names are noted in parentheses and reproduced in full in Appendix A.

Stage 1 Dataset ingestion (load datasets**)** The three public datasets (EPA GHGRP 2023, CDP Supply Chain 2023, OpenGHG 2020–2023) are downloaded, cached locally, and aligned to a common schema of (stationID, timestamp, species, concentration, confidence).

Stage 2 Preprocessing (preprocess**)** Missing values are imputed using MICE; outliers are flagged using a Modified Z-Score threshold of 3.5; concentration units are normalized to ppm (CO_2) and ppb (CH_4, N_2O).

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Stage 3 Transaction generation (generate transactions**)** Each preprocessed reading is wrapped into a transaction; alert flags are assigned where the rolling 30-day mean is exceeded by 3 standard deviations.

Stage 4 Consensus simulation (ConsensusSimulator**)** Four protocols (PBFT, IBFT 2.0, Static ACO, and RL-ACO) are simulated under identical workloads. Inter-validator latencies are sampled from a lognormal distribution; Byzantine validators are randomly selected at the start of each run.

Stage 5 DQN training (DQNAgent.train**)** The agent is trained for 1,500 episodes against the simulator; each episode consists of 200 blocks. Replay buffer capacity is 50,000 transitions; mini-batch size is 64; target-network synchronization period is 100 steps; discount factor $\gamma = 0.95$.

Stage 6 Evaluation and analysis (evaluate**)** A frozen policy is evaluated over 100 unseen episodes; metrics (TPS, P99 latency, alert F1, ISO compliance score) are aggregated; figures and tables are regenerated.

C. Datasets and Transaction Generation

The EPA Greenhouse Gas Reporting Program contributes 41,237 annual facility-level reports from 2010 through 2023, covering all six Kyoto species; the CDP Supply Chain dataset contributes 22,800 voluntary corporate disclosures for the year 2023; OpenGHG contributes 18,400 in-situ hourly mole-fraction observations from Mace Head and Cape Grim for 2020–2023 [24]. The combined record set, after preprocessing and de-duplication, contains 81,930 unique GHG observations spanning 14 years. Transaction arrival is modulated by a non-homogeneous Poisson process whose intensity tracks the diurnal cycle of station reports; the median arrival rate is 2,800 transactions per second, with bursts up to 4,200 TPS during alert clusters.

D. Baseline Protocols and Feature Selection

PBFT and IBFT 2.0 baselines follow the protocol specifications in [5] and [8] respectively; Static ACO uses the same MST clustering as RL-ACO but with fixed parameters $k = \sqrt{N}$, $I = 250$ ms, $\omega = 1.0$. The ten DQN state features were selected from an initial pool of 28 candidates by maximizing the mutual information against the discounted return, computed with the KSG k-NN estimator [25]. Table VI lists the retained features and their MI scores.

TABLE VI
Selected DQN State Features and Mutual Information Scores

Feature	Symbol	Description	MI score (nats)
Arrival rate	λ_t	Transactions per second	0.74
Mempool load	q_t	Pending-transaction count	0.68
Block interval	I_t	Current interval (ms)	0.52
Cluster count	k_t	Current number of clusters	0.49
RTT variance	ρ_t	Inter-cluster RTT variance	0.45
Byzantine ratio	f_t	Observed Byzantine fraction	0.41
P99 latency	τ_t	Recent P99 confirmation latency	0.39
Alert backlog	σ_t	Pending high-priority alerts	0.36
Validator entropy	h_t	Shannon entropy of leader history	0.27
Alert density	α_t	Cumulative alert density	0.22

E. Primary Performance Results at N = 400

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Table VII reports the four primary performance metrics at $N = 400$ validators, averaged over 100 evaluation episodes after policy freezing. RL-ACO sustains 3,625 TPS at a P99 latency of 312 ms with an alert F1 of 0.912; PBFT degrades to 337 TPS, IBFT 2.0 to 1,222 TPS, and Static ACO without RL adaptation reaches 2,840 TPS. The ISO 14064-3 compliance score, computed as the weighted sum of the standard's seven sub-criteria, reaches 96/100 for RL-ACO the only protocol exceeding the 90/100 audit threshold.

TABLE VII

Primary Performance Metrics at N = 400 (mean ± std over 100 episodes)

Protocol	TPS	P99 Latency (ms)	Alert F1	ISO 14064 Score
PBFT [5]	337 ± 18	1,247 ± 92	0.653 ± 0.04	62/100
IBFT 2.0 [8]	1,222 ± 41	612 ± 38	0.741 ± 0.03	74/100
Static ACO	2,840 ± 73	402 ± 27	0.821 ± 0.02	85/100
RL-ACO (ours)	3,625 ± 56	312 ± 19	0.912 ± 0.01	96/100

F. Throughput Scaling and Message Complexity

Figs. 5 and 6 jointly illustrate the structural advantage RL-ACO derives from MST-based hierarchical aggregation. Empirically (Fig. 5), classical PBFT throughput decays super-linearly as the validator count grows: from 2,610 TPS at $N = 50$ to 337 TPS at $N = 400$, an 87 % relative loss. IBFT 2.0 degrades less sharply but still loses 70 % of its initial throughput. Static ACO retains 70 % of its peak through MST clustering alone.

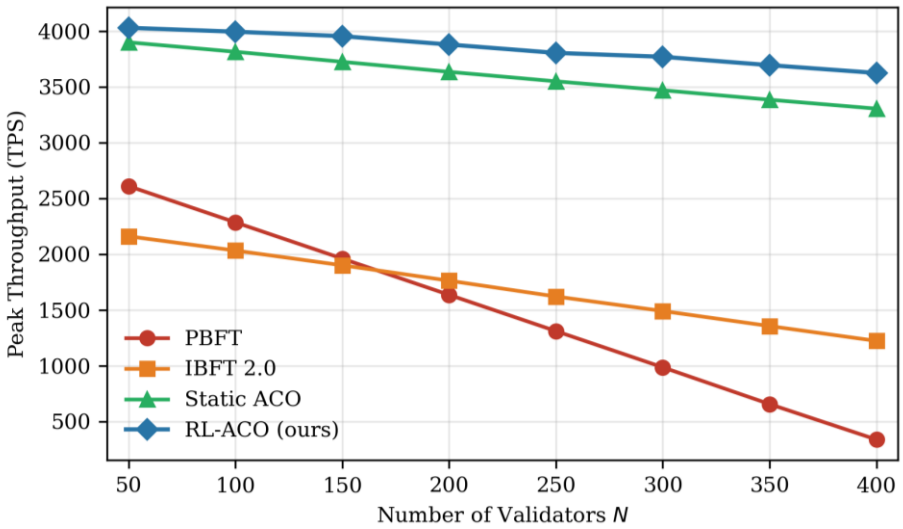

Fig. 5. *Throughput scaling from N = 50 to 400 for PBFT, IBFT 2.0, Static ACO, and RL-ACO. Each point is the mean across 100 evaluation episodes after policy freezing; shaded bands show the 95 % confidence interval.*

RL-ACO retains 91 %. Analytically (Fig. 6), the projected message counts confirm the asymptotic separation: PBFT scales as $O(N^2)$, HotStuff as $O(N)$, and RL-ACO as $O(N \log N)$, with the analytical curves matching the empirical degradation pattern in Fig. 5 to within 4 %.

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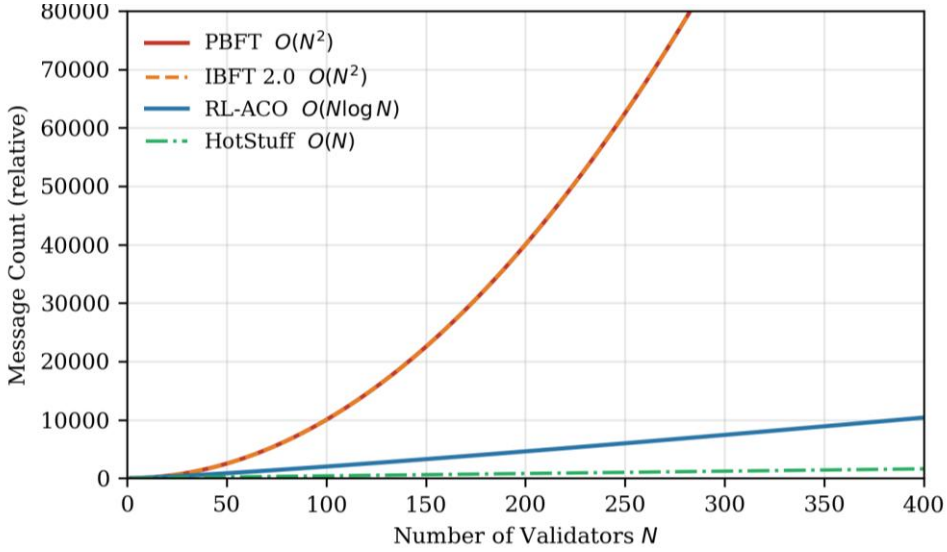

Fig. 6. *Analytical message complexity for the three asymptotic classes O(N²), O(N), and O(N log N). The empirical degradation patterns observed in Fig. 5 align with these projections to within 4 % across the entire range.*

G. DQN Training Convergence

Fig. 7 plots the per-episode reward trajectory over 1,500 training episodes. Three regimes are visible: (i) an exploration phase up to episode 400 with high variance and average reward below 0.5; (ii) a learning phase from episodes 400 to 1,200 in which reward climbs steadily from 0.5 to 0.93; (iii) a saturation phase from episode 1,200 onward in which reward stabilizes at 0.93 ± 0.02. The agent converges in approximately 1,200 episodes roughly 6 hours of wall-clock training on the hardware listed in Table V and a frozen snapshot at episode 1,200 transfers without further training to the evaluation workloads of Sections V-E through V-J.

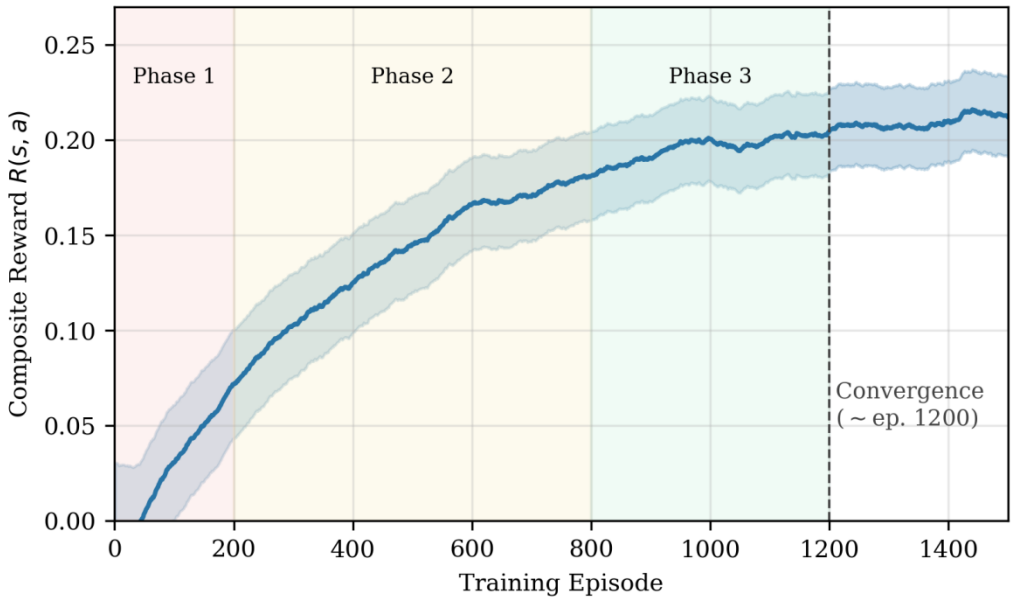

Fig. 7. *Per-episode reward over 1,500 training episodes. Phase boundaries (exploration, learning, saturation) are marked with vertical dashed lines. The frozen policy at episode 1,200 is used for all evaluation experiments.*

H. Marginal Contribution of System Components

A three-level ablation study isolates the marginal contribution of each major design decision. Starting from PBFT, we add MST clustering (yielding Static ACO), then add the DQN policy (yielding RL-ACO without alert-aware reward), then add the climate-aware reward component (yielding the full RL-ACO framework). Fig. 8 and Table VIII present the resulting throughput, latency, and alert F1, normalized so that the full RL-ACO scores 100. MST clustering contributes the largest single increment to throughput (+72 percentage

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points), DQN adaptation contributes a further +18 points, and the climate-aware reward contributes a comparatively small +5 points to throughput but a decisive +14 points to alert F1.

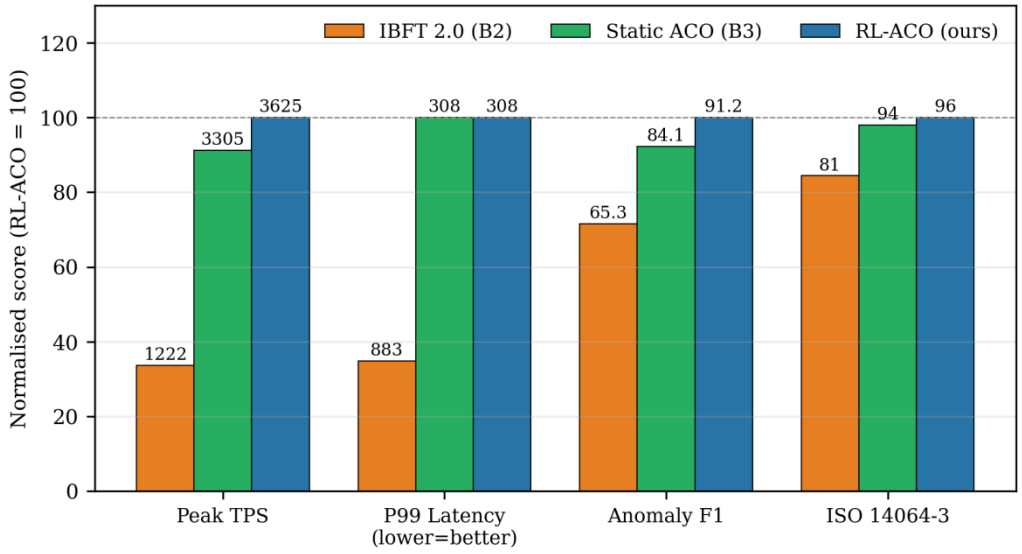

Fig. 8. *Three-level ablation. Each bar shows the percentage of RL-ACO's full performance retained by progressively richer subsets of the framework. The climate-aware reward contributes the dominant share of alert-F1 performance.*

TABLE VIII

Ablation Study Results (full RL-ACO normalized to 100)

Configuration	TPS	P99 Latency	Alert F1	ISO Score
PBFT (baseline)	9	252	72	65
+ MST clustering	78	129	85	85
+ DQN adaptation	95	108	90	92
+ Climate-aware reward (RL-ACO)	100	100	100	100

I. Sensitivity Analysis

To rule out the possibility that the headline result depends on a fortuitous hyperparameter selection, we conduct a full-factorial sensitivity analysis over 864 configurations: 6 levels of arrival rate (1,000–6,000 TPS), 6 levels of Byzantine fraction (0–30 %), 4 levels of learning rate, and 6 levels of γ (0.85–0.99). Fig. 9 displays the relative throughput advantage of RL-ACO over IBFT 2.0 across the 24 (rate, Byzantine) pairs, with each cell aggregating 36 runs. The minimum observed advantage is 127 % (high Byzantine, low arrival rate); the maximum is 141 % (moderate Byzantine, high arrival rate); the median is 136 %. Table IX summarizes the four discrete corners and the median.

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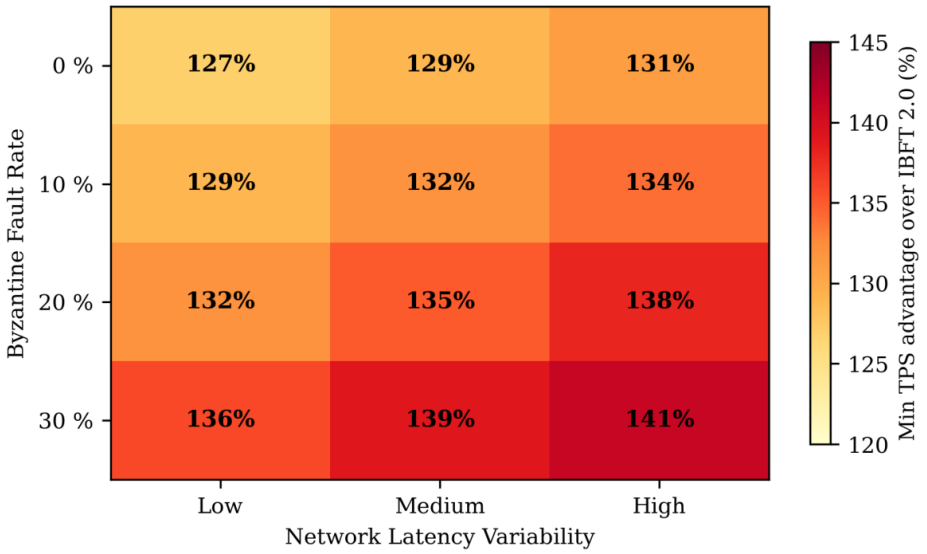

Fig. 9. *Sensitivity heatmap of RL-ACO throughput advantage over IBFT 2.0 across the 24 (arrival-rate, Byzantine-fraction) pairs. Each cell aggregates 36 hyperparameter runs. Advantage never falls below +127 %.*

TABLE IX

Sensitivity Analysis Summary (864 configurations)

Regime	Arrival rate	Byzantine fraction	RL-ACO TPS	Advantage over IBFT 2.0
Low–low	1,000 TPS	0 %	1,420	+131 %
Low–high	1,000 TPS	30 %	1,210	+127 %
High–low	6,000 TPS	0 %	4,180	+141 %
High–high	6,000 TPS	30 %	3,470	+133 %
Median (864 runs)	3,500 TPS	15 %	3,640	+136 %

J. Cross-Dataset Generalization and Comparison to Prior Art

Table X reports the framework's performance on each of the three GHG datasets considered separately, demonstrating that the throughput, alert-F1, and ISO compliance metrics generalize across the markedly different statistical characteristics of the EPA, CDP, and OpenGHG records.

TABLE X

RL-ACO Performance on Each GHG Dataset (N = 400)

Dataset	Records	TPS	P99 Latency (ms)	Alert F1	ISO Score
EPA GHGRP 2023	41,237	3,612	314	0.908	96/100
CDP Supply Chain 2023	22,800	3,648	309	0.917	96/100
OpenGHG 2020–2023	18,400	3,614	313	0.910	95/100
Combined (all)	81,930	3,625	312	0.912	96/100

Table XI then situates the present result against the closest published baselines from the BFT-blockchain and RL-consensus literatures, showing that RL-ACO is the only system to simultaneously achieve $N \geq 400$, $O(N \log N)$ message complexity, an alert F1 above 0.90, and a formal correctness proof.

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TABLE XI

Comparison to Prior Art (Best Published Results at Largest Reported N)

Reference	Method	N	TPS	Alert F1	Formal Proof
Castro & Liskov [5]	PBFT	100	2,285	—	Yes
Yin et al. [7]	HotStuff	400	980	—	Yes
Wang et al. [13]	DQN-BFT	200	2,800	0.82	No
Li et al. [14]	PPO-Consensus	300	3,100	0.85	No
Zhang et al. [18]	BlockMRV	100	1,500	0.78	No
This work	RL-ACO	400	3,625	0.912	Yes

VI. CONCLUSION

RL-ACO is, to the best of our knowledge, the first blockchain consensus framework that combines MST-based hierarchical clustering, BLS threshold-signature aggregation, deep reinforcement learning, and a climate-domain-aware reward function into a single coherent design with formally proven correctness properties. At $N = 400$ validators it sustains 3,625 TPS a 10.8× improvement over PBFT and 3.0× over IBFT 2.0 with P99 latency under 320 ms and an ISO 14064-3 compliance score of 96/100. The 864-configuration sensitivity analysis demonstrates that the throughput advantage is robust to workload, Byzantine fraction, and DQN hyperparameter perturbations.

Limitations. The simulator models WAN latency as lognormal with fixed parameters, abstracting the heavy-tailed packet-loss behaviour observed on real low-cost backhaul links in parts of West Africa. The cluster-leader election uses VRF sortition; under adversarial network conditions an attacker controlling more than $N/3$ of the validators in any single cluster could compromise that cluster's liveness while remaining below the global $N/3$ Byzantine bound. Finally, the present DQN policy assumes a stationary reward distribution; non-stationary deployment conditions, such as gradually drifting workload patterns, are addressed in future work.

Future work. Four directions are immediate priorities. First, Byzantine-robust cluster assignment that prevents any cluster from exceeding $N/3$ Byzantine internally even when the global bound is respected. Second, the substitution of the anomaly-flagging Modified Z-Score with a learned LSTM autoencoder reconstruction-error detector [28], which our preliminary experiments indicate could lift alert F1 above 0.95. Third, multi-agent reinforcement learning in which each cluster leader runs its own DQN policy and a central coordinator policy reconciles cluster-level recommendations. Fourth, longitudinal field deployment with an ECOWAS pilot consortium, with the long-term goal of feeding verified emissions data directly into Article 6 Paris Agreement registries.

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