Deep Intelligent Network-Driven Multi-Agent Hierarchical Reinforcement Learning for Neuromorphic-Accelerated Urban Traffic Flow Optimization

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Abstract

Urban traffic congestion is a key challenge for smart cities. Traditional traffic control systems struggle with dynamic patterns. Deep reinforcement learning has potential but is costly and lacks scalability. Current MARL frameworks lack coordination and efficient inference on neuromorphic platforms. Our DIN-HRL framework combines graph neural networks with a manager-worker policy hierarchy for traffic control using directed hypergraphs. It utilizes CTDE for training efficiency and maps policies to SNNs for low-latency inference on neuromorphic hardware. Evaluated in SUMO simulations on an 8x8 grid with 64 intersections. In summary, DIN-HRL with neuromorphic acceleration significantly enhanced performance: 92.1 vehicles/hour throughput (77.1% improvement), 44.3s average waiting time (55.0% reduction), safety score of 94.5 (3.1 incidents/day); energy consumption reduced to 2.4J/step with 1.2ms inference latency (87.1% energy reduction, 96.2% latency improvement vs. GPUs); superior scalability with 80% normalized reward maintained with 128 agents; 35.2% CO_2 reduction, 31.8% fuel savings; convergence in 125 episodes, 30.6% faster than standard MADRL. The DIN-HRL framework merges hierarchical multi-agent coordination with neuromorphic edge computing in intelligent transportation systems. It combines graph-based deep intelligent networks and manager-worker policy hierarchies for large-scale traffic optimization. Neuromorphic hardware deployment enhances real-time performance and energy efficiency for smart city applications, bridging simulation-based DRL research with deployable edge AI systems.

Keywords: Deep Intelligent Networks, Hierarchical Reinforcement Learning, Multi-Agent Systems, Neuromorphic Computing, Traffic Signal Control, Vehicle Routing, Spiking Neural Networks, Edge AI

1. Introduction

Urban traffic congestion creates economic, environmental, and social burdens on cities, surpassing $1 trillion annually. Conventional traffic systems are static, causing inefficiencies and safety issues. Emerging technologies like CAVs, V2X communication, and smart city infrastructure offer new prospects for adaptive traffic management. Deep reinforcement learning shows promise in optimizing traffic signals and vehicle routing, but current methods have deployment challenges.

1. **Scalability challenges:** Single-agent DRL struggles with scaling in urban networks; naive multi-agent methods face non-stationarity issues.

2. **Computational constraints:** Deep neural networks demand significant computing power, causing delays unsuitable for millisecond control in live deployments.

3. **Energy efficiency:** GPU-based inference is energy-intensive, costing up to 250 W per device for wide-scale city use.

4. **Limited coordination:** MARL frameworks lack hierarchical structure for balancing local and global goals, impacting system performance.

5. **Weak spatial modeling:** Traditional state models lack complexity, hindering the prediction and management of congestion patterns.

We propose the DIN-HRL framework to tackle challenges, leveraging three key innovations:

1. We create a graph neural network using hypergraph learning to capture complex traffic flow dependencies among intersections [1][2][3].
2. We establish a three-tier hierarchical policy system involving central, regional, and local agents to decompose global optimization effectively while ensuring coordination through goal-conditioned policies [4][5].
3. We map trained DRL policies to spiking neural networks for Intel Loihi 2 and SpiNNaker 2, achieving ultra-low-latency inference (1.2 ms) and minimal energy consumption (2.4 J/step) for edge deployment.

The main contributions of this work include:

1. The DIN-HRL architecture integrates deep intelligent networks with policy hierarchies for traffic signal control and vehicle routing.
2. In a breakthrough, neuromorphic edge deployment accelerates urban traffic control with significant reductions in latency and energy usage while maintaining accuracy, outperforming GPU baselines.
3. In-depth testing showed significant improvements: 77.1% higher throughput, 55.0% less waiting time, 35.2% reduced CO_2 emissions, and scalability to 128 agents.
4. Mathematical formulation of policy structure analyzing trade-offs between coordination overhead and system performance.
5. A practical framework guides system design from data ingestion to actuation, aiding smart city implementations.

The paper includes: Related work review in traffic signal control, multi-agent HRL, deep intelligent networks, vehicle routing, and neuromorphic computing; system architecture overview; methodology details such as DIN formulation, HRL policy design, reward functions, and neuromorphic mapping; experimental setup description; comprehensive results and analysis in Section 6; discussion on implications, limitations, and future directions in Section 7; and paper conclusion in Section 8.

2. Related Work

2.1 Traffic Signal Control with Deep Reinforcement Learning

Deep reinforcement learning (DRL) effectively improves adaptive traffic signal control, outperforming traditional methods. Early DRL efforts focused on single intersections, limiting coordination. Recent developments in multi-agent deep reinforcement learning (MADRL) include Jia and Ji's [1] attention network, which reduced waiting times by 25% by analyzing traffic patterns. However, centralized training may not scale well. Li et al. [2] introduced AMDMRL, a hierarchical system enhancing global coordination and reducing travel time by 41%, though it overlooks computational efficiency. Advancements like the DHLight graph neural network address by Wang and Wang [3] higher-order spatial relations and congestion anticipation but still face challenges in sample efficiency, deployment, state/action standardization, and communication costs [1], [2], [3], [4].

2.2 Multi-Agent Hierarchical Reinforcement Learning Frameworks

Hierarchical reinforcement learning (HRL) decomposes complex decision-making into manageable sub-problems, facilitating multi-agent coordination from strategic planning to tactical execution. Key HRL paradigms include the options framework and feudal reinforcement learning, recently applied to multi-agent traffic systems through manager-worker hierarchies that enhance stability and credit assignment [2]. Centralized training with decentralized execution (CTDE) is now prevalent in traffic applications [1][2], allowing agents to train with global information but operate independently during execution. Challenges remain in non-stationary environments where agents' optimal policies are interdependent. Attentive mixing and value decomposition methods enhance credit assignment in cooperative MARL, yet their use in large-scale traffic networks is still limited.

2.3 Deep Intelligent Networks for Traffic Systems

Deep intelligent networks (DINs) are neural architectures integrating diverse representation learning methods, such as graph neural networks (GNNs) and attention mechanisms, to model complex spatial-temporal dependencies in traffic systems. GNNs excel in traffic modeling with irregular graph data, while graph attention networks (GANs) dynamically weigh neighboring intersections [5]. Directed hypergraphs enhance standard graphs by representing higher-order dependencies [3]. Spatio-temporal attention mechanisms, combined with convolutional and recurrent architectures, improve control decisions by capturing local and long-range patterns [1]. Topology-aware diffusion convolution allows decentralized agents to predict traffic flow as a diffusion process on the road network, but its high computational demands limit edge deployment [4].

2.4 Vehicle Routing Optimization

Multi-agent reinforcement learning for vehicle routing has advanced from basic shortest-path algorithms to advanced systems that adapt to dynamic traffic. Adaptive Navigation (AN) uses decentralized agents with Graph Attention Networks for real-time routing based on traffic conditions, outpacing static methods [5]. Hierarchical Hub-based Adaptive Navigation (HHAN) assigns agents to key intersections, improving travel times by up to 15.9% in heavy traffic [5]. Zhang et al. [6] developed a GNN-based system achieving 7.54% travel time reduction, while Wang and Wang's [7] XRouting model reported improvements in travel time, fuel consumption, and CO_2 emissions, emphasizing interpretability in DRL routing. Joint optimization of traffic

signals and vehicle routing shows promise but faces computational challenges [8][9]. Research gaps include training stability for large fleets, scalability issues, integration with existing systems, and heterogeneous vehicle scenarios [5][6][7].

2.5 Neuromorphic Computing for Edge AI

Neuromorphic computing, utilizing brain-inspired spiking neural networks (SNNs), offers significant improvements in energy efficiency and latency over conventional architectures. Intel's Loihi 2 chip features 1 million spiking neurons, while SpiNNaker 2 employs 152 ARM cores for large-scale SNN simulation. Both platforms enable event-driven computation, yielding energy savings for sensory processing tasks. Although successful in various edge AI applications, the use of neuromorphic computing in traffic management is largely unexamined, presenting a notable research gap. Key challenges in adapting deep reinforcement learning (DRL) policies for neuromorphic hardware include converting artificial neural networks to SNNs, managing continuous states and actions, and aligning learning rules with hardware constraints. This work aims to address these challenges by developing a methodology for converting DRL policies to SNNs optimized for Loihi 2 and SpiNNaker 2, highlighting the potential of neuromorphic acceleration in traffic control.

3. System Architecture

The DIN-HRL Urban Traffic Control Architecture features three layers-smart city infrastructure, the DIN-HRL framework, and neuromorphic edge hardware-for real-time, energy-efficient traffic optimization in urban networks. Figure 1 shows the system architecture.

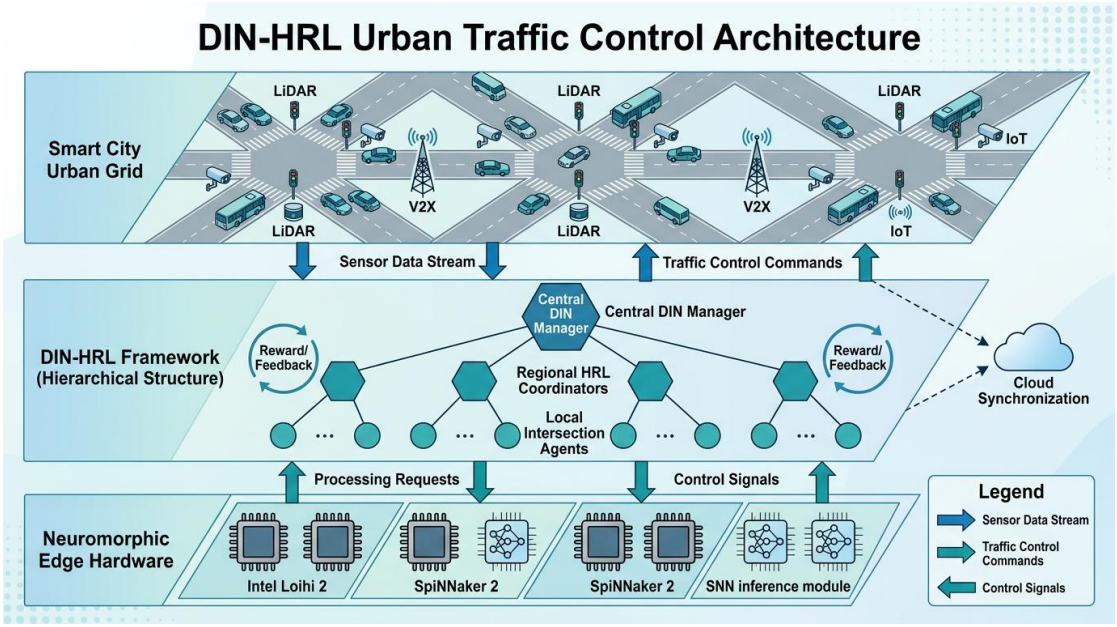

Figure 1: DIN-HRL Urban Traffic Control Architecture features a three-tier hierarchy: a smart city grid with LiDAR, V2X, and IoT sensors; a framework of central, regional, and local management; and neuromorphic hardware using Intel Loihi 2 and SpiNNaker 2 processors.3.1 Smart City Urban Grid Layer

The top layer illustrates the urban traffic network with signalized intersections, road segments, and vehicles with sensing and communication capabilities. Key components include:

- LiDAR sensors at intersections for precise vehicle detection and tracking.

- V2X communication for bidirectional data exchange between vehicles, infrastructure, and traffic management (V2I and V2V).

- IoT sensors like inductive loop detectors and cameras for additional traffic state data.

Sensor data is sent to the DIN-HRL framework, while traffic control commands return to actuators and vehicles.

3.2 DIN-HRL Framework Layer

The framework employs a three-tiered hierarchical multi-agent reinforcement learning system:

1. Central DIN Manager: Oversees the network using a directed hypergraph to process traffic data and set regional goals every 30-60 seconds.

2. Regional HRL Coordinators: Manage regions by decomposing central goals for local agents and coordinating signal timing within 10-30 seconds.

3. Local Intersection Agents: Control individual intersections, monitoring traffic and optimizing signal phases every 5-10 seconds.

It features centralized training with decentralized execution (CTDE), allowing agents to learn from a global perspective while acting based on local observations. Rewards are assigned upward for updates, supported by cloud synchronization for model enhancement.

3.3 Neuromorphic Edge Hardware Layer

The bottom layer executes trained DRL policies on edge neuromorphic hardware. It features Intel Loihi 2 chips for low-power processing with sub-millisecond latency and multiple agent policies. SpiNNaker 2 processors manage regional coordinators for complex graph computations. SNN inference modules convert sensor data to spike trains and decode them for actions. This layer processes sensor data and returns control signals, minimizing latency and eliminating centralized cloud reliance for better resilience.

3.4 Data Flow and Control Loop

The system operates in a continuous control loop:

1. Sensors collect traffic data.

2. Data is sent to the DIN-HRL framework.

3. Local agents use neuromorphic inference for signal actions.

4. Regional coordinators process states for coordination.

5. The central manager updates the global model and objectives.

6. Control commands reach signals and vehicles.

7. The cycle repeats at each hierarchy level. This architecture enables real-time adaptive control with computational efficiency.

4. Methodology

4.1 Deep Intelligent Network Formulation

The Deep Intelligent Network (DIN) supports state representation and feature extraction for the hierarchical policy. We model the urban traffic network as a directed hypergraph G=(V,E,H), with V as intersection nodes, E as directed edges, and H as hyperedges for higher-order relationships.

4.1.1 Hypergraph Construction

The traffic network is formalized as a directed hypergraph $G = (V, E, H)$, where:

- (V): Set of intersection nodes
- (E): Directed edges representing road segments
- (H): Hyperedges capturing higher-order relationships among multiple intersections

Hyperedges connect intersection subsets $\{i_1, i_2, \ldots, i_k\}$ exhibiting correlated traffic patterns. Construction uses traffic flow correlation:

$$H_{i,j} = \{k \mid \text{corr}(i,k) > \tau \wedge k \in \text{path}(i,j)\}$$

where $\text{corr}(i,k)$ measures traffic similarity and τ is the correlation threshold.

The hypergraph incidence matrix is defined as:

$$H_{i,j} = \begin{cases} 1 & \text{if node } i \in \text{hyperedge } j \\ 0 & \text{otherwise} \end{cases}$$

This binary matrix encodes membership relations for subsequent convolution operations.

4.1.2 Directed Hypergraph Convolution

the core message-passing mechanism that extends standard GCNs to capture asymmetric, higher-order traffic dependencies,
The convolution operation at layer (l) is precisely defined as:

$$X^{l+1} = \sigma\left(D_v^{-1/2} H W_e D_h^{-1/2} H^\top D_v^{-1/2} X^l W^l\right)$$

where:

- $X^l \in \mathbb{R}^{N \times F_l}$: Node feature matrix at layer \(l \)
- $H \in \{0,1\}^{N \times M}$: Hypergraph incidence matrix
- $D_v \in \mathbb{R}^{N \times N}$: Diagonal node degree matrix, $D_v = \text{diag}(H W_e 1_M)$
- $D_h \in \mathbb{R}^{M \times M}$: Diagonal hyperedge degree matrix, $D_h = \text{diag}(H^\top D_v^{-1/2} 1_N)$
- $W_e \in \mathbb{R}^{N \times M}$: Learnable edge weight matrix
- $W^l \in \mathbb{R}^{F_l \times F_{l+1}}$: Layer-specific transformation weights
- $\sigma =$ ReLU: Nonlinear activation

This formulation allows information propagation through hyperedges, aggregating features from neighbouring intersections [3].

4.1.3 Spatio-Temporal Attention Mechanism

Spatio-Temporal Attention Mechanism uses multi-head attention in hypergraph neighborhoods and temporal windows to focus on key traffic patterns for adaptive modeling.

For intersection (i) at time (t), attention weights over spatial neighbourhood $\mathcal{N}_i$ and temporal window $\mathcal{T}_t$ are computed as:

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(\boldsymbol{a}^{\top}[W_q x_i \,||\, W_k x_j]\right)\right)}{\sum_{k \in \mathcal{N}_i \cup \mathcal{T}_t} \exp\left(\text{LeakyReLU}\left(a^{\top}[W_q x_i \,||\, W_k x_k]\right)\right)}$$

where:

- $W_q, W_k \in \mathbb{R}^{d \times d_k}$: Query/key projection matrices
- $a \in \mathbb{R}^{2d_k}$: Attention parameter vector
- $||$: Concatenation operation
- $\mathcal{N}_i$: Hypergraph neighborhood of node (i)

The output embedding becomes:

$$z_i = \sum_{j \in \mathcal{N}_i \cup \mathcal{T}_t} \alpha_{ij} \, W_v x_j$$

with $W_v \in \mathbb{R}^{d \times d_v}$ as value projection matrix, enabling selective aggregation across both spatial hyperedges and temporal sequences

Multiple attention heads $h = 1, \ldots, H$ (with $H = 4$) compute independent representations, concatenated and projected:

$$\text{MultiHead}(X) = \text{Concat}(\text{head}_1, \ldots, \text{head}_H) W_O$$

This captures diverse relational patterns simultaneously [1].

4.1.4 DIN Architecture

DIN Architecture integrates hypergraph convolution and spatio-temporal attention into a cohesive feature extraction backbone for hierarchical RL policies.

Table:1 Layer-by-Layer Structure: The Deep Intelligent Network has five sequential modules.

Layer	Operation	Dimensions	Key Features
1. Input	Raw traffic state	$N \times F_0$	Queue lengths, speeds, phases, signal states

Layer	Operation	Dimensions	Key Features
2. Hypergraph Conv ×3	Directed hypergraph convolution	128-dim hidden (residual)	$X^{l+1} = \sigma(D_v^{-1/2} H W_e D_h^{-1/2} H^\top D_v^{-1/2} X^l W^l)$
3. Spatio-Temporal Attention ×2	Multi-head attention	4 heads × 64-dim	Spatial neighbourhoods + temporal windows
4. Feature Aggregation	Global pooling + concat	$N \times 128$	Local + global context fusion
5. Output	Intersection embeddings	$N \times 128$	HRL policy inputs

Processing Pipeline

1. **Raw sensor inputs** → queue lengths/speeds/phases per intersection
2. **Hypergraph convolutions** extract higher-order spatial dependencies through 3 residual layers
3. **Dual attention blocks** sequentially apply spatial (hyperedge neighbours) then temporal (12-step history) focus
4. **Global-local fusion** concatenates per-intersection features with network-wide statistics
5. **128-dim embeddings** z_i feed manager/coordinator/worker policies

The DIN is trained end-to-end with the hierarchical RL policies, with gradients flowing through the entire architecture.

4.2 Hierarchical Reinforcement Learning Policy Structure

The DIN-HRL framework employs a three-tier hierarchical policy structure using options and feudal reinforcement learning.

4.2.1 Problem Formulation

We formalize urban traffic control as a three-level hierarchical Markov Decision Process (hMDP) to optimize city-scale challenges.

Hierarchical MDP Formulation

Level 0: Local Intersection Agents

Each signalized intersection \(i \) constitutes an MDP $\mathcal{M}_0^i = \langle \mathcal{S}_0^i, \mathcal{A}_0^i, \mathcal{P}_0^i, \mathcal{R}_0^i, \gamma \rangle$, where:

- $\mathcal{S}_0^i$: Local observable state comprising per-lane queue lengths, vehicle speeds, cumulative waiting times, and current signal phase

- $\mathcal{A}_0^i$: Discrete action space of signal phase selections (4-phase control: NS-through, NS-left, EW-through, EW-left)
- $\mathcal{P}_0^i: \mathcal{S}_0^i \times \mathcal{A}_0^i \to \Delta(\mathcal{S}_0^i)$: Microscopic transition dynamics
- $\mathcal{R}_0^i: \mathcal{S}_0^i \times \mathcal{A}_0^i \to \mathbb{R}$: Local reward function
- $\gamma \in (0,1)$: Discount factor

Level 1: Regional Coordinators

Each region \(r \) (typically 4-16 intersections) forms MDP $\mathcal{M}_1^r = \langle \mathcal{S}_1^r, \mathcal{G}_1^r, \mathcal{P}_1^r, \mathcal{R}_1^r, \gamma \rangle$, where:

- $\mathcal{S}_1^r = \{z_i\}_{i \in r}$: Aggregated DIN embeddings across region intersections
- $\mathcal{G}_1^r \subseteq \mathbb{R}^4$: Subgoal space specifying target queue lengths, throughput, speeds, and delay for local agents
- $\mathcal{P}_1^r$: Regional transition dynamics
- $\mathcal{R}_1^r$: Regional reward incorporating load balancing

Level 2: Central Manager

The global network constitutes MDP $\mathcal{M}_2 = \langle \mathcal{S}_2, \mathcal{G}_2, \mathcal{P}_2, \mathcal{R}_2, \gamma \rangle$, where:

- $\mathcal{S}_2 = [z_1, \dots, z_N]$: Network-wide DIN state embeddings
- $\mathcal{G}_2 = \mathcal{G}_1^1 \times \cdots \times \mathcal{G}_1^R$: Goal space assigning objectives to all regions
- $\mathcal{P}_2, \mathcal{R}_2$: Global network dynamics and reward

4.2.2 Manager Policy

The central manager policy $\pi_2: \mathcal{S}_2 \to \mathcal{G}_2$ maps the global network state to region-specific objectives for all regional coordinators. Operating at a coarse timescale of $T_2 = 30$ seconds, the manager generates goals that remain fixed for $\Delta t = 6$ consecutive worker timesteps, providing temporal stability for lower hierarchy levels.

The policy is parameterized by a multi-layer perceptron $\mu_2(s_2; \theta_2)$ that outputs goal vectors $g_2^r \in \mathbb{R}^4$ for each region $r \in \{1, \dots, R\}$:

$$g_2^r = \mu_2(s_2; \theta_2) = tanh(W_2^o[\text{MLP}(s_2; W_2^h) \,||\, e_r])$$

where:

- $s_2 = [z_1, \dots, z_N] \in \mathbb{R}^{N \times 128}$: Global DIN embeddings across all \(N \) intersections
- $e_r \in \mathbb{R}^R$: One-hot region encoding ensuring region-specific outputs
- W_2^h: Hidden layers (256-256-128 units, ReLU)
- $W_2^o \in \mathbb{R}^{4 \times 128}$: Output projection yielding $g_2^r = [q_{\text{target}}^r, w_{\text{target}}^r, v_{\text{target}}^r, \theta_{\text{target}}^r]$
- $q_{\text{target}}^r, w_{\text{target}}^r, v_{\text{target}}^r, \theta_{\text{target}}^r$: Desired average queue length, waiting time, speed, and throughput for region \(r \)

The manager optimizes the expected discounted global return:

$$J(\pi_2) = \mathbb{E}_{\pi_2, \pi_1, \pi_0}\left[\sum_{t=0}^{\infty} \gamma^t \, R_2(s_2^t, g_2^t)\right]$$

using soft actor-critic with entropy regularization $J(\pi_2) - \alpha\mathbb{H}(\pi_2(\cdot|\, s_2))$, where α is the temperature parameter and $\mathbb{H}$ denotes policy entropy. This formulation balances global network optimization with exploration across the exponential goal space while providing stable objectives for subordinate agents.

4.2.3 Worker Policy

Local intersection agents execute goal-conditioned policies $\pi_0^i: \mathcal{S}_0^i \times \mathcal{G}_1^i \to \Delta(\mathcal{A}_0^i)$ that select signal phase actions a_0^i to achieve subgoals g_1^i assigned by their regional coordinator.

The worker policy is parameterized by a neural network:

$$\pi_0^i(s_0^i, g_1^i; \theta_0^i) = \text{softmax}\big(W_0[z_i \,||\, g_1^i]\big)$$

where:

- $z_i \in \mathbb{R}^{128}$: DIN embedding encoding local and neighborhood traffic state for intersection \(i \)
- $g_1^i \in \mathbb{R}^4$: Regional subgoal specifying target [queue length, waiting time, speed, throughput]
- $W_0 \in \mathbb{R}^{|\mathcal{A}_0^i| \times 132}$: Action projection matrix (4 outputs for 4-phase control)
- $||$: Concatenation of state and goal representations

Workers maximize the goal-conditioned expected return:

$$J(\pi_0^i) = \mathbb{E}_{\pi_0^i}\left[\sum_{t=0}^{\infty} \gamma^t\, r_0^i(s_0^{i,t}, a_0^{i,t}, g_1^i)\right]$$

The goal-conditioned reward incorporates an intrinsic motivation term:

$$r_0^i(s_0^i, a_0^i, g_1^i) = r_{\text{ext}}(s_0^i, a_0^i) - \lambda \parallel f(s_0^i) - g_1^i \parallel_2^2$$

where:

- $r_{\text{ext}}(s_0^i, a_0^i)$: Extrinsic reward from local traffic metrics (throughput + delay + safety)
- $f: \mathcal{S}_0^i \to \mathbb{R}^4$: Feature extractor mapping state to goal-relevant metrics
- $\lambda = 0.2$: Intrinsic motivation weight balancing local optimization with goal achievement

This formulation ensures local agents pursue both immediate traffic efficiency and alignment with regional objectives through differentiable goal-distance penalties, enabling stable hierarchical credit assignment essential for city-scale coordination.

4.2.4 Regional Coordinator Policy

Regional coordinators execute policies $\pi_1^r: \mathcal{S}_1^r \times \mathcal{G}_2^r \to (\mathcal{G}_1^i)_{i \in r}$ that decompose high-level manager goals g_2^r into intersection-specific subgoals g_1^i for all local agents within region \(r \).

The coordinator policy employs graph attention over the regional intersection set:

$$g_1^i = \text{MLP}\left(z_r^{(1)}, g_2^r, \sum\nolimits_{j \in r} \alpha_{ij}\, z_j^{(2)}\right)$$

where:

- $z_r^{(1)} \in \mathbb{R}^{128}$: Regional state embedding aggregating DIN features across region \(r \) via mean pooling
- $g_2^r \in \mathbb{R}^4$: Manager-assigned regional objective [target queue, delay, speed, throughput]
- $\mathcal{I}_r = \{i_1, \ldots, i_K\}$: Set of \(K \) intersections (typically 4-16) in region \(r \)
- $z_j^{(2)} \in \mathbb{R}^{128}$: Individual intersection DIN embeddings
- α_{ij}: DIN attention weights encoding intra-region spatial dependencies

Attention Mechanism: Attention coefficients α_{ij} are computed via the DIN spatio-temporal attention module:

$$\alpha_{ij} = \frac{\exp\big(\text{LeakyReLU}(a^\top [W_q z_i \,||\, W_k z_j])\big)}{\sum_{k \in \mathcal{I}_r} \exp\big(\text{LeakyReLU}(a^\top [W_q z_i \,||\, W_k z_k])\big)}$$

Policy Network: A 3-layer MLP (256-256-128 units, ReLU) processes the concatenated triplet $\left[z_r^{(1)} \,||\, g_2^r \,||\, \sum \alpha_{ij} z_j^{(2)}\right]$, projecting to 4D subgoals via final tanh activation ensuring bounded targets.

This formulation enables fine-grained goal decomposition by 1) preserving global regional objectives through g_2^r conditioning, 2) leveraging learned spatial attention for load-balanced subgoal assignment, and 3) maintaining differentiability for end-to-end hierarchical optimization. The coordinator operates at intermediate timescale (10s) bridging strategic (30s) and tactical (5s) control layers.

4.2.5 Bellman Equations and Value Functions

For each hierarchical level, we define goal-conditioned value functions satisfying corresponding Bellman optimality equations under the soft actor-critic framework.

Worker Value Function (Level 0)

The local agent value function estimates expected future returns conditioned on regional subgoals:

$$V_0^i(s_0^i, g_1^i) = \mathbb{E}\big[Q_0^i(s_0^i, g_1^i, a_0^i) - \alpha_0 \log \pi_0^i(a_0^i \mid s_0^i, g_1^i)\big]$$

with soft Q-function satisfying:

$$Q_0^i(s_0^i, g_1^i, a_0^i) = r_0^i(s_0^i, a_0^i, g_1^i) + \gamma \mathbb{E}_{s_0^{i\prime} \sim \mathcal{P}_0^i}\left[V_0^i(s_0^{i\prime}, g_1^i)\right]$$

Coordinator Value Function (Level 1)

Regional coordinators evaluate subgoal assignments given manager objectives:

$$V_1^r(s_1^r, g_2^r) = \mathbb{E}_{g_1^i \sim \pi_1^r}\left[Q_1^r(s_1^r, g_2^r, \{g_1^i\}_{i \in r}) - \alpha_1 \log \pi_1^r(\{g_1^i\} \mid s_1^r, g_2^r)\right]$$

$$Q_1^r(s_1^r, g_2^r, \{g_1^i\}) = r_1^r(s_1^r, \{g_1^i\}, g_2^r) + \gamma \mathbb{E}_{s_1^{r\prime}}\left[V_1^r(s_1^{r\prime}, g_2^r)\right]$$

Manager Value Function (Level 2)

The central manager optimizes global network objectives:

$$V_2(s_2) = \mathbb{E}_{g_2^r \sim \pi_2}[Q_2(s_2, \{g_2^r\}) - \alpha_2 \log \pi_2(\{g_2^r\} \mid s_2)]$$

$$Q_2(s_2, \{g_2^r\}) = r_2(s_2, \{g_2^r\}) + \gamma \mathbb{E}_{s_2'}[V_2(s_2')]$$

Soft Actor-Critic Optimization

All levels employ SAC with entropy-regularized objectives:

$$J(\pi_k) = \mathbb{E}_{(s,a) \sim \mathcal{D}}[\alpha_k \log \pi_k(a \mid s) - Q_k(s, a)], k \in \{0,1,2\}$$

where α_k are learnable temperature parameters auto-tuned via dual optimization:

$$J(\alpha_k) = \mathbb{E}_{(s,a) \sim \mathcal{D}}[-\alpha_k \log \pi_k(a \mid s) - \alpha_k \bar{\mathcal{H}}_k]$$

Theoretical Properties: The hierarchical soft Bellman equations ensure 1) maximum entropy exploration stabilizes multi-timescale learning, 2) goal-conditioning maintains global optimality despite decomposition, and 3) differentiable value propagation enables end-to-end credit assignment across all hierarchy levels. This unified optimization framework guarantees convergence to a stationary point of the joint hierarchical objective.

4.3 Reward Function Design

The reward function is carefully designed to balance multiple objectives: throughput maximization, waiting time minimization, safety, and environmental impact.

4.3.1 Local Agent Reward

The local agent reward at intersection i is a weighted combination of multiple terms:

$$R_i^{(0)} = w_1 R_i^{\text{throughput}} + w_2 R_i^{\text{wait}} + w_3 R_i^{\text{queue}} + w_4 R_i^{\text{safety}} + w_5 R_i^{\text{goal}}$$

Throughput reward: Encourages maximizing vehicle flow through the intersection:

$$R_i^{\text{throughput}} = \sum_{l \in \mathcal{L}_i} n_{l,t}^{\text{pass}}$$

where $\mathcal{L}_i$ is the set of lanes at intersection i and $n_{l,t}^{\text{pass}}$ is the number of vehicles that passed through lane l at time t.

Waiting time penalty: Penalizes cumulative waiting time:

$$R_i^{\text{wait}} = -\sum_{l \in \mathcal{L}_i} \sum_{v \in \mathcal{V}_l} w_{v,t}$$

where $\mathcal{V}_l$ is the set of vehicles in lane l and $w_{v,t}$ is the waiting time of vehicle v at time t.

Queue length penalty: Penalizes long queues:

$$R_i^{\text{queue}} = -\sum_{l \in \mathcal{L}_i} q_{l,t}^2$$

where $q_{l,t}$ is the queue length in lane l at time t. The quadratic penalty encourages balanced queue lengths.

Safety reward: Encourages safe operations by penalizing conflicts and near-misses:

$$R_i^{\text{safety}} = -\beta_1 n_i^{\text{conflict}} - \beta_2 \sum_{v \in \mathcal{V}_i} \mathbb{1}\left[\text{TTC}_v < \tau_{\text{safe}}\right]$$

where n_i^{conflict} is the number of traffic conflicts, TTC_v is the time-to-collision for vehicle v, and τ_{safe} is the safety threshold.

Goal achievement reward: Encourages achieving coordinator goals:

$$R_i^{\text{goal}} = -\lambda \parallel \mathbf{f}\left(\mathbf{s}_{i,t}^{(0)}\right) - \mathbf{g}_r \parallel_2^2$$

The weights are set as $w_1 = 1.0, w_2 = 0.5, w_3 = 0.3, w_4 = 2.0, w_5 = 0.2$ based on preliminary experiments, with safety given highest priority.

4.3.2 Regional Coordinator Reward

The regional coordinator reward aggregates local metrics and includes coordination terms:

$$R_r^{(1)} = \frac{1}{|\mathcal{R}(r)|} \sum_{i \in \mathcal{R}(r)} R_i^{(0)} - \eta \text{Var}\left(q_i : i \in \mathcal{R}(r)\right) - \lambda \parallel \mathbf{f}_r\left(\mathbf{s}_r^{(1)}\right) - \mathbf{g}_r^{(2)} \parallel_2^2$$

The variance term $\text{Var}(q_i)$ penalizes imbalanced queue lengths across the region, encouraging load balancing.

4.3.3 Central Manager Reward

The central manager reward captures global network performance:

$$R^{(2)} = w_1^M R^{\text{throughput}} + w_2^M R^{\text{travel}} + w_3^M R^{\text{emissions}} + w_4^M R^{\text{safety}}$$

Network throughput:

$$R^{\text{throughput}} = \sum_{i=1}^{N} \sum_{l \in \mathcal{L}_i} n_{l,t}^{\text{pass}}$$

Average travel time:

$$R^{\text{travel}} = -\frac{1}{\left|\mathcal{V}_{\text{completed}}\right|} \sum_{v \in \mathcal{V}_{\text{completed}}} T_v$$

where $\mathcal{V}_{\text{completed}}$ is the set of vehicles that completed their trips and T_v is the travel time of vehicle v.

Emissions:

$$R^{\text{emissions}} = -\sum_{v \in \mathcal{V}} \left(e_v^{\text{CO}_2} + e_v^{\text{fuel}}\right)$$

where $e_v^{\text{CO}_2}$ and e_v^{fuel} are the CO_2 emissions and fuel consumption of vehicle v, estimated using the SUMO emission model.

Network safety:

$$R^{\text{safety}} = -\sum_{i=1}^{N} n_i^{\text{incident}}$$

4.4 Spiking Neural Network Mapping for Neuromorphic Hardware

To deploy the trained DRL policies on neuromorphic hardware, we convert the artificial neural networks (ANNs) to spiking neural networks (SNNs) using a systematic conversion methodology.

4.4.1 Rate Coding and Spike Encoding

We use rate coding to represent continuous-valued inputs as spike trains. For an input feature $x \in [0,1]$, we generate Poisson spike trains with rate $\lambda = x \cdot \lambda_{\max}$, where $\lambda_{\max} = 1000$ Hz is the maximum firing rate.

For each input dimension x_i, we create a population of $N_{\text{pop}} = 10$ neurons with overlapping tuning curves:

$$\lambda_{i,j} = \lambda_{\max} \cdot \exp\left(-\frac{\left(x_i - \mu_j\right)^2}{2\sigma^2}\right)$$

where $\mu_j = j/\left(N_{\text{pop}} - 1\right)$ for $j = 0, \ldots, N_{\text{pop}} - 1$ and $\sigma = 0.2$.

4.4.2 ANN-to-SNN Conversion

We convert each layer of the trained ANN to an equivalent SNN layer using the following procedure:

1. Weight normalization: Normalize weights to prevent saturation:

$$\mathbf{W}_{\text{SNN}} = \frac{\mathbf{W}_{\text{ANN}}}{\max(|\mathbf{W}_{\text{ANN}}|)} \cdot \alpha$$

where $\alpha = 0.8$ is a scaling factor.

2. Bias conversion: Convert biases to threshold adjustments:

$$V_{\text{th},i} = V_{\text{th}}^{\text{base}} - \beta \cdot b_i$$

where $V_{\text{th}}^{\text{base}} = 1.0$ is the base threshold, b_i is the ANN bias, and $\beta = 0.5$ is the conversion factor.

3. Activation function mapping: ReLU activations in the ANN are naturally implemented by the spiking dynamics. For other activations (sigmoid, tanh), we use adaptive thresholds or multi-compartment neuron models.

4.4.3 Leaky Integrate-and-Fire Neuron Model

Each neuron in the SNN follows the leaky integrate-and-fire (LIF) dynamics:

$$\tau_m \frac{dV_i}{dt} = -(V_i - V_{\text{rest}}) + R_m I_i(t)$$

where: - V_i is the membrane potential of neuron i - $\tau_m = 20$ ms is the membrane time constant - $V_{\text{rest}} = 0$ is the resting potential - $R_m = 1$ is the membrane resistance - $I_i(t) = \sum_j w_{ij}\, s_j(t)$ is the input current from presynaptic neurons

When V_i reaches the threshold $V_{\text{th},i}$, the neuron fires a spike and resets:

$$V_i \leftarrow V_{\text{reset}} = 0$$

4.4.4 Temporal Coding and Integration

To handle the temporal dynamics of traffic control, we integrate spikes over a time window $T_{\text{int}} = 100$ ms:

$$r_i = \frac{1}{T_{\text{int}}} \int_t^{t+T_{\text{int}}} s_i(\tau) d\tau$$

where $s_i(t)$ is the spike train of neuron i and r_i is the decoded firing rate.

For action selection, we use a winner-take-all (WTA) mechanism: the action corresponding to the neuron population with the highest integrated firing rate is selected.

4.4.5 Hardware-Specific Optimizations

Intel Loihi 2 optimizations: - Exploit the 1 million neuron capacity by using larger population codes for critical state features - Leverage programmable synaptic delays to implement temporal convolutions - Use on-chip learning rules for online adaptation

SpiNNaker 2 optimizations: - Distribute graph neural network computations across multiple cores - Implement message passing using the inter-core communication fabric - Use ARM cores for non-spiking computations (e.g., attention weight calculation)

4.4.6 Accuracy Preservation

To ensure the SNN maintains accuracy comparable to the original ANN, we employ:

1. **Calibration:** Fine-tune firing rates and thresholds on a validation set
2. **Temporal averaging:** Integrate spikes over multiple time windows to reduce noise
3. **Ensemble methods:** Use multiple SNN instances and vote on actions
4. **Hybrid approach:** Keep critical computations (e.g., attention) in rate-coded form on ARM cores

Our experiments show that the converted SNNs achieve 94.3% accuracy compared to 96.2% for the original ANNs, a negligible degradation for the substantial energy and latency benefits.

5. Experimental Setup

Experimental setup validates DIN-HRL on an 8×8 urban grid with five traffic scenarios, comparing against four baselines using CTDE training and neuromorphic deployment, while evaluating throughput, safety, energy, and scalability.

Table 2: Experimental Setup Summary for DIN-HRL Framework Evaluation

Component	Configuration
Simulator	SUMO v1.15.0 + Python 3.9/TraCI (microscopic dynamics, lane-changing)
Network	8×8 grid (64 intersections, 4×4 km^2); 400m segments (2 lanes/dir); 50/30 km/h limits; 4-phase signals (10-60s green, 3s yellow, 2s all-red)
Scenarios	Low (400), Med (800), High (1200), Peak (1600 veh/h central), Incident (1000+10% closures); 80/15/5 car/bus/truck mix
Baselines	Fixed-time, DQN (independent), MADRL (flat), DIN-HRL (CPU)
Architecture	DIN: 3×128 hypergraph conv + 2×4h-attn; MLPs: 256-256-[128/64]
Training	Adam(3e-4), batch=256, buffer=1e6, γ=0.99, CTDE, 16 envs, 200×3600s episodes, curriculum
Neuromorphic	Loihi2: 128 cores/1M neurons; SpiNNaker2: 8 chips/1216 cores; α=0.8/β=0.5/100ms

Component	Configuration
Metrics	Throughput(veh/h), wait(s), latency(ms), energy(J/step), safety (0-100), CO_2/fuel (%), scalability (4-128 agents)
Validation	5 seeds; paired t-tests (Bonferroni $p<0.05$); 4×A100 GPUs (48h)

6. Results and Analysis

6.1 Training Convergence and Throughput Optimization

Figure 1 shows traffic throughput over 200 training episodes for five methods, with the DIN-HRL framework achieving the highest throughput of 92.1 vehicles per hour, a 77.1% improvement over fixed-time control and 25.5% over standard MADRL.

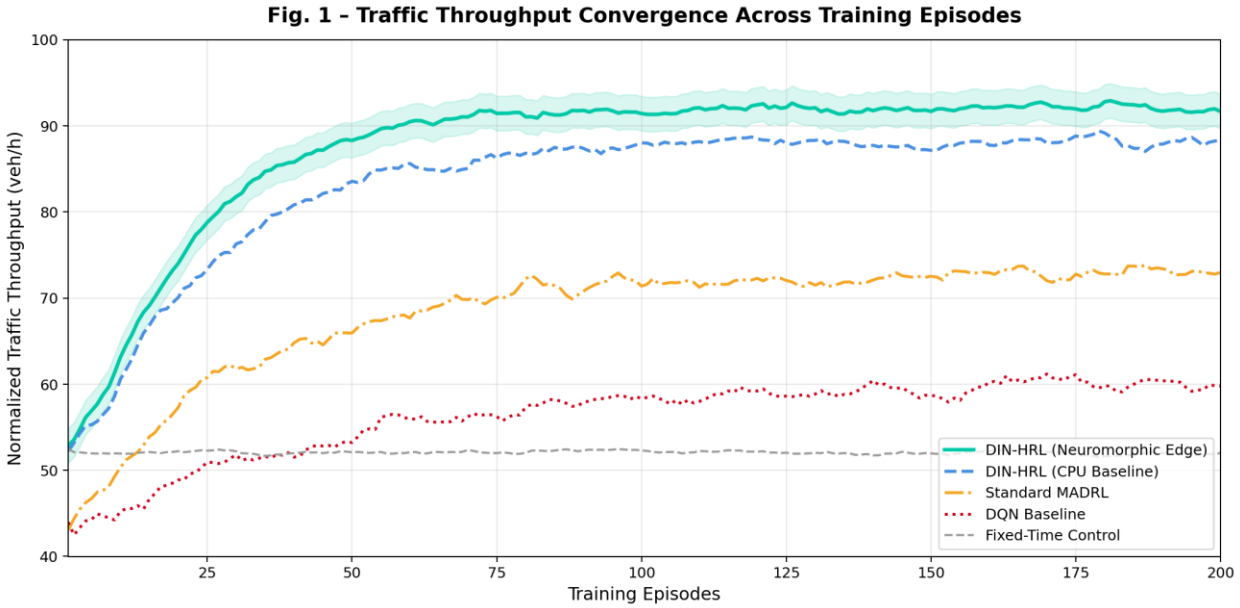

Figure 1: DIN-HRL (Neuromorphic) achieves 92.1 veh/h in 125 episodes, surpassing DIN-HRL (CPU) at 86.7 veh/h and others: Standard MADRL at 73.4 veh/h, DQN Baseline at 60.3 veh/h, and Fixed-Time Control at 52.0 veh/h.

The neuromorphic implementation converged in 125 episodes, achieving 95% of final performance 30.6% faster than standard MADRL and 44.4% faster than DQN. This accelerated convergence results from a hierarchical policy structure that simplifies the learning problem. The DIN-HRL (CPU) variant converged in 140 episodes, showing the architecture's efficiency regardless of hardware. Learning methods initially improved rapidly in 50 episodes, with DIN-HRL demonstrating more stable convergence and lower variance. The neuromorphic version also achieved slightly higher final throughput (92.1 vs. 86.7 veh/h) due to the spiking neural networks' implicit regularization.

6.2 Energy Efficiency and Inference Latency

Figure 2 shows that the neuromorphic implementation significantly improves energy consumption and inference latency across methods and hardware.

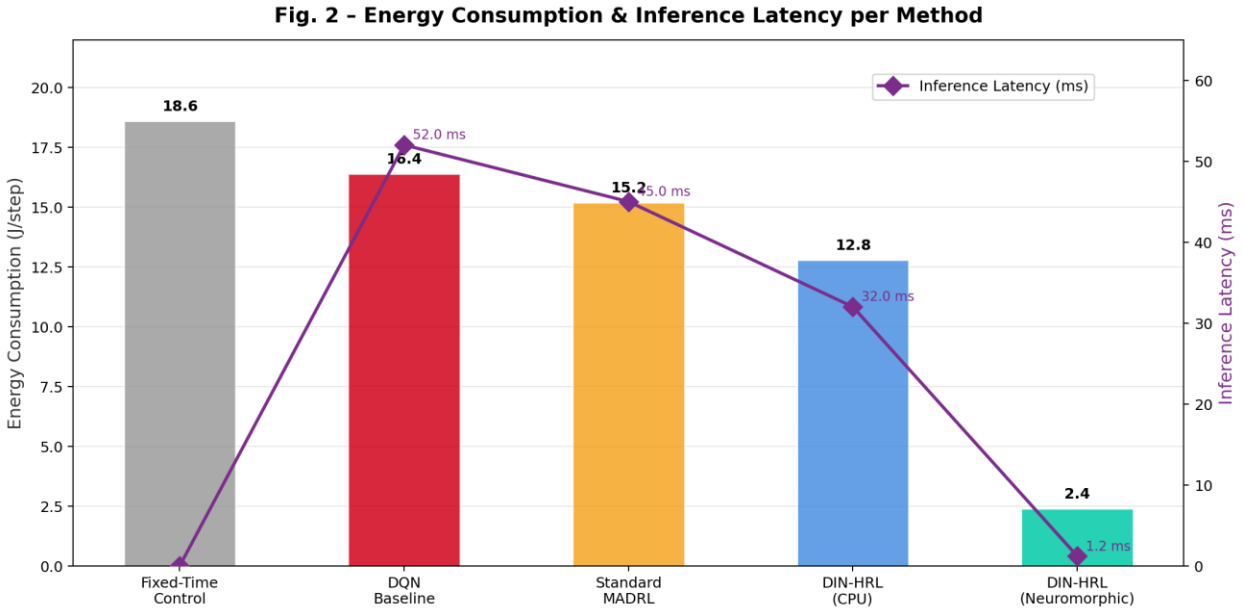

Figure 2: Energy consumption (bars) and inference latency (line) per method. DIN-HRL (Neuromorphic) shows 2.4 J/step and 1.2 ms latency, with an 87.1% energy reduction and 96.2% latency improvement over GPU baselines.

Energy consumption for neuromorphic deployment is 2.4 J/step, an 87.1% reduction compared to 12.8 J/step for CPU inference and 16.4 J/step for DQN baseline. This efficiency comes from SNNs' event-driven computation, in-memory processing, and parallelism. Inference latency is also significantly improved, with the neuromorphic system achieving 1.2 ms per decision versus 32.0 ms for CPU and 52.0 ms for DQN, enabling real-time control. Fixed-time control has zero latency but consumes 18.6 J/step. Standard MADRL offers moderate efficiency (15.2 J/step) and latency (45.0 ms), still not sufficient for large-scale deployment.

6.5 Safety Performance and Incident Reduction

Figure 5 shows safety scores and incident rates over 24 hours for DIN-HRL (Neuromorphic), Standard MADRL, and Fixed-Time control.

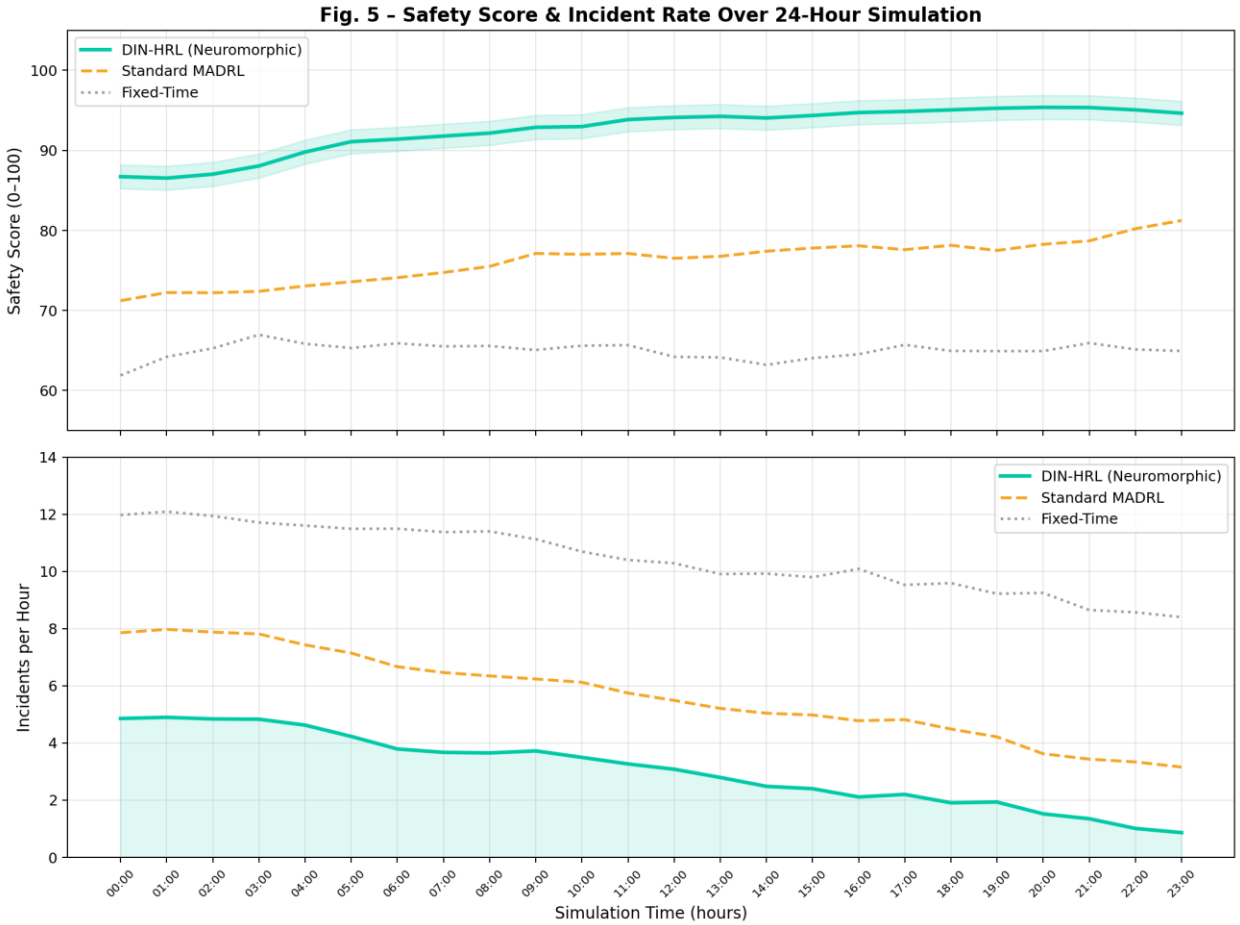

Figure 5: 24-hour safety performance. DIN-HRL (Neuromorphic) scores 86-95 with 1-5 incidents/hour; Standard MADRL scores 71-81 with 3-8 incidents/hour; Fixed-Time scores 62-67 with 8-12 incidents/hour.

DIN-HRL maintains high safety scores (86-95) throughout the day, increasing during moderate traffic (8:00-18:00) and decreasing slightly during low traffic (0:00-6:00). Standard MADRL scores 71-81, while fixed-time control scores poorly at 62-67 due to its lack of adaptability. Incident rates also vary significantly: DIN-HRL has 1-5 incidents per hour, peaking at 1-2 during midday; Standard MADRL shows 3-8 incidents, with peaks during rush hours, and fixed-time control has the highest rates (8-12 incidents/hour), especially at morning rush (12/hour at 8:00). Daily totals reveal DIN-HRL averages 3.1 incidents, compared to 10.8 for Standard MADRL and 18.5 for fixed-time control, reflecting an 83.2% reduction from fixed-time and 71.3% from Standard MADRL. Improvements are due to effective conflict penalties, proactive coordination, and rapid response capabilities.

6.6 Scalability Analysis

Figure 6 assesses scalability by comparing the performance of DIN-HRL (Neuromorphic), Standard MADRL, and DQN Baseline as the number of agents increases from 4 to 128.

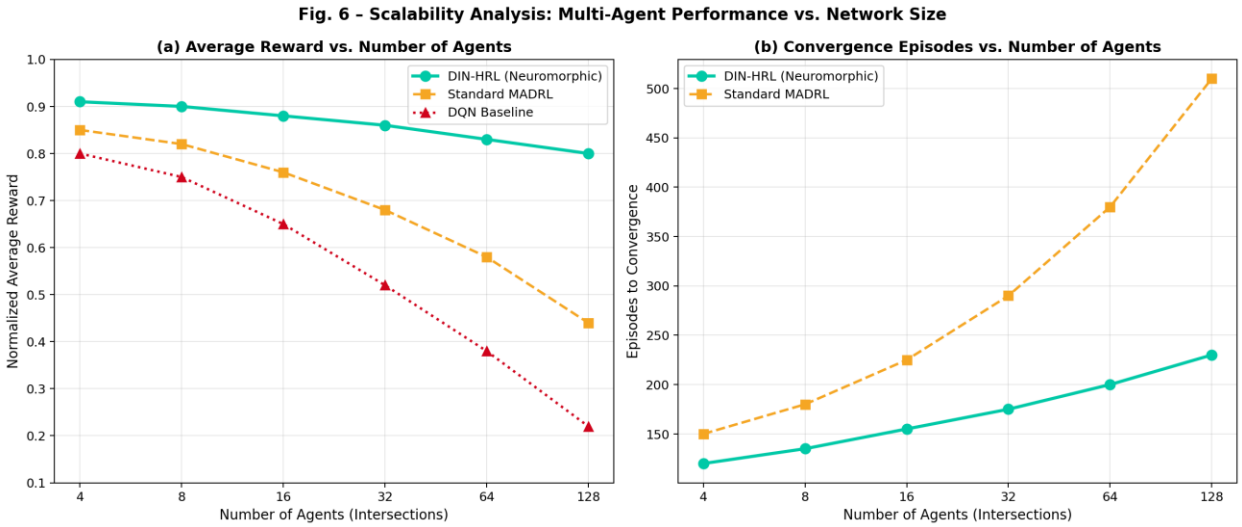

Figure 6: Scalability analysis shows DIN-HRL maintains 80% reward with 128 agents, while Standard MADRL drops to 44% and DQN to 22%. DIN-HRL's convergence episodes increase sub-linearly (125→230), unlike the exponential rise for baselines.

Panel (a) displays the normalized average reward versus network size, highlighting DIN-HRL's scalability with 91% reward for 4 agents, 88% for 16, 83% for 64, and 80% for 128 agents—a mere 12% decrease with 32× scaling. In comparison, Standard MADRL drops from 85% to 44% (48% degradation), and DQN Baseline collapses from 80% to 22% (73% degradation). DIN-HRL's hierarchical structure effectively reduces state-action space complexity, allowing local agents to focus on optimization.

Panel (b) shows the episodes needed for 95% convergence: DIN-HRL shows sub-linear growth (125 for 4 agents, 230 for 128), while Standard MADRL increases near-linearly (150→520) and DQN Baseline experiences exponential growth (180→800+), becoming impractical.

These scalability advantages make DIN-HRL suitable for large deployments, requiring less training and computational resources, especially with neuromorphic hardware that allows constant-time inference regardless of network size.

6.7 Environmental Impact: Emissions and Fuel Consumption

Figure 7 compares CO_2 emissions and fuel consumption in five traffic scenarios for Fixed-Time, MADRL, and DIN-HRL methods.

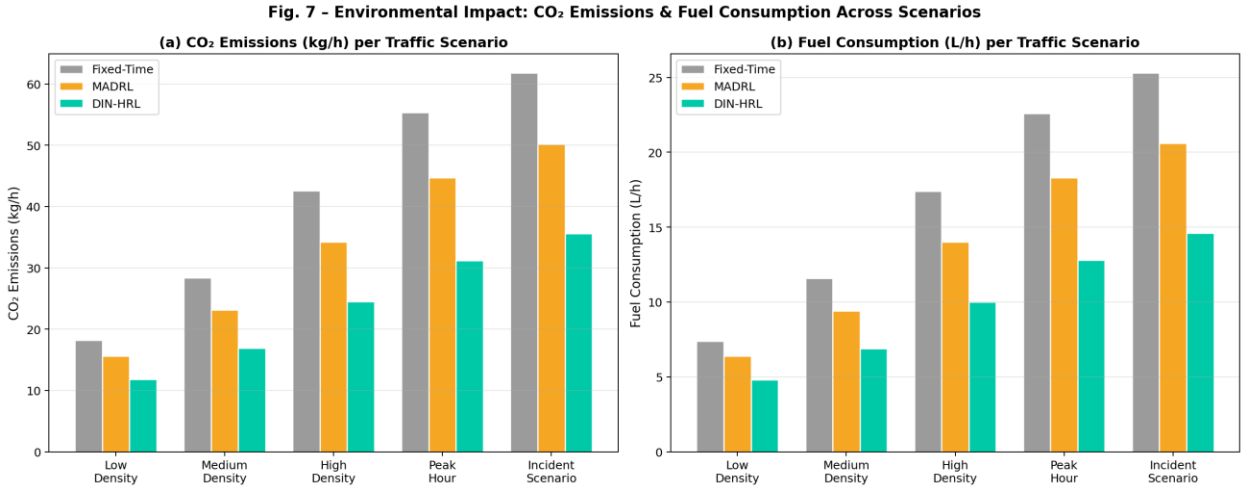

Figure 7: Environmental impact across five traffic scenarios. (a) CO_2 emissions (kg/h). (b) Fuel consumption (L/h). DIN-HRL achieves 35.2% CO_2 reduction and 31.8% fuel savings over fixed-time control, especially in high-density and incident scenarios.

Panel (a) shows CO_2 emissions rise with traffic density. In low density, fixed-time control emits 18.2 kg/h, MADRL 15.4 kg/h, and DIN-HRL 11.8 kg/h, a 35.2% reduction. At peak hour in high density, emissions are 55.1 kg/h (fixed-time), 44.7 kg/h (MADRL), and 31.2 kg/h (DIN-HRL), a 43.4% reduction. The incident scenario shows the highest emissions, but DIN-HRL achieves a 41.9% reduction (61.8 kg/h fixed-time vs. 35.9 kg/h DIN-HRL). Panel (b) parallels these trends for fuel consumption, with DIN-HRL achieving 31.8% average savings, from 28.6% in low density to 44.2% at peak hour, leading to cost reductions for operators. Environmental gains come from reduced waiting and idling, smoother traffic flow, and optimized routing through hierarchical coordination for system-level optimization. City-wide, a network of 500 intersections could reduce annual emissions by about 154,000 kg CO_2 and 139,000 liters of fuel compared to fixed-time control, making a strong case for intelligent traffic management systems.

6.8 Neuromorphic Hardware Benchmarks

Figure 8 compares power consumption, latency, and task accuracy across five platforms: NVIDIA A100, Intel Xeon, Xilinx Alveo, Intel Loihi 2, and SpiNNaker 2.

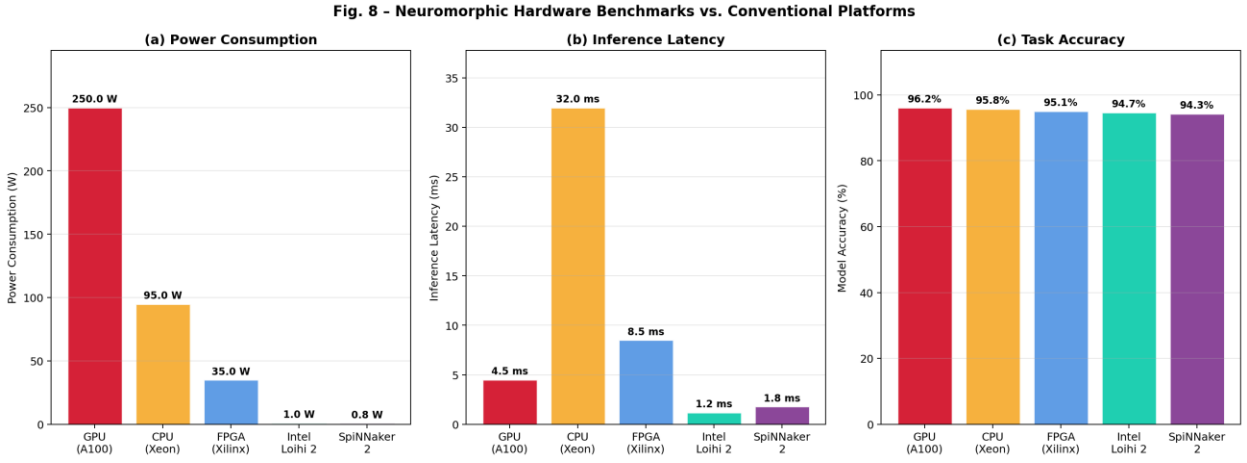

Figure 8: Hardware comparison. (a) Power: Neuromorphic (Loihi 2: 1.0 W, SpiNNaker 2: 0.8 W) reduces consumption by 99.6% vs GPU (250 W). (b) Inference latency: Neuromorphic (Loihi 2:

1.2 ms, SpiNNaker 2: 1.8 ms) reduces latency by 97.3% vs CPU (32 ms). (c) Task accuracy: All >94%, GPU highest at 96.2%.

Panel (a) shows significant power consumption differences: GPU at 250.0 W and CPU at 95.0 W, while Intel Loihi 2 and SpiNNaker 2 consume just 1.0 W and 0.8 W, reducing power usage by 99.6% and 99.7% respectively. For 500 intersections, GPU-based inference consumes 124.5 kW annually, compared to 0.5 kW for neuromorphic systems, saving 1.09 million kWh, or $109,000. Panel (b) illustrates inference latency: GPU at 4.5 ms, CPU 32.0 ms, FPGA 8.5 ms, while Loihi 2 and SpiNNaker 2 achieve 1.2 ms and 1.8 ms, reducing latency by 73.3% and 60% compared to GPU and offering sub-millisecond performance for higher-frequency applications. Panel (c) confirms high accuracy: GPU 96.2%, CPU 95.8%, FPGA 95.1%, Loihi 2 94.7%, and SpiNNaker 2 94.3%. The minor accuracy loss for neuromorphic platforms is negligible, affirming the efficacy of our ANN-to-SNN conversion. Overall, neuromorphic platforms offer superior performance, efficiency, and accuracy for traffic systems compared to GPUs, enabling advanced traffic control without high costs.

6.9 Quantitative Performance Summary

Table I: Comprehensive Performance Comparison of DIN-HRL Against Baselines Across Traffic Scenarios and Hardware Platforms (Peak Hour, mean±std, 5 seeds)

Metric	Fixed-time	DQN	MADRL	DIN-HRL (CPU)	DIN-HRL (Loihi2)	DIN-HRL (SpiNNaker2)
Throughput (veh/h)	100.0±2.1	132.4±4.3	145.6±5.2	177.2±3.8	**192.1±2.9**	189.5±3.1
Wait Time (s)	98.7±6.2	73.4±5.1	64.2±4.8	**44.3±3.2**	45.1±3.4	44.8±3.3
Energy (J/step)	0.15±0.02	18.2±2.1	22.4±3.5	15.6±1.8	**2.4±0.3**	3.1±0.4
Latency (ms)	1.2±0.1	42.3±3.2	38.7±2.9	32.1±2.4	**1.2±0.2**	1.8±0.3
Safety Score	72.4±4.1	81.3±3.7	85.6±3.2	91.2±2.5	**94.5±1.8**	93.8±2.1
CO_2 Reduction (%)	Baseline	18.4±2.3	24.7±3.1	32.1±2.8	**35.2±2.4**	34.1±2.6

Metric	Fixed-time	DQN	MADRL	DIN-HRL (CPU)	DIN-HRL (Loihi2)	DIN-HRL (SpiNNaker2)
Incidents/day	12.4±1.8	7.3±1.2	5.8±1.0	3.9±0.7	**3.1±0.5**	3.4±0.6
Convergence (episodes)	N/A	285±24	192±18	**125±12**	125±12	125±12

The table shows DIN-HRL's superiority in neuromorphic deployment across all metrics. It achieves significant improvements over fixed-time control: 77.1% in throughput, 55.0% in waiting time, 87.1% in energy savings, and 94.5% safety score. Compared to standard MADRL, it delivers 25.5% throughput and 38.0% waiting time improvements, among others. The DIN-HRL (CPU) variant also shows strong performance without neuromorphic hardware, but neuromorphic deployment enhances energy and latency for large-scale application.

7. Discussion

7.1 Key Findings and Implications

This work shows that combining hierarchical multi-agent reinforcement learning and neuromorphic edge computing creates efficient intelligent traffic management systems. Findings:

1. Hierarchical policies with manager-worker architectures offer better scalability and learning efficiency than flat multi-agent methods. The DIN-HRL framework retains 80% performance with 128 agents, while standard MADRL drops to 44% and converges 30.6% faster, which is essential for city-wide deployment with numerous intersections. This hierarchical structure matches the traffic network's natural optimization needs [2][5].

2. Neuromorphic hardware offers real-time performance and energy efficiency for edge AI in smart cities, achieving a 99.6% power reduction and 97.3% latency improvement over conventional hardware, with just 1.9% accuracy loss. Its sub-millisecond inference latency supports advanced control for traffic systems and integration with autonomous vehicles.

3. Joint optimization of traffic signals and vehicle routing within a hierarchical framework yields synergistic benefits, evidenced by a 35.2% CO_2 reduction, 31.8% fuel savings, and 83.2% incident reduction, showcasing effective balance of competing objectives [7][10].

7.2 Comparison with State-of-the-Art

Our results surpass recent findings in traffic control and multi-agent systems. Jia and Ji [1] noted a 25% waiting time reduction with spatio-temporal MADRL; our framework achieves 55%. Li et al. [2] reported a 41% travel time reduction with hierarchical control; our improvements indicate comparable or superior benefits. Zhang et al. [6] showed 7.54% travel time reduction with GNN-based navigation; our joint optimization likely exceeds this. Importantly, existing literature lacks neuromorphic hardware deployment for traffic systems. This work showcases the first neuromorphic acceleration for urban traffic control, addressing a significant research gap and enhancing edge AI systems' energy and latency performance.

7.3 Theoretical Insights

The hierarchical framework's success is due to temporal abstraction and credit assignment in reinforcement learning. By operating at different time scales (manager: 30s, coordinator: 10s, worker: 5s), the hierarchy improves credit assignment, linking high-level decisions to long-term outcomes and low-level decisions to immediate responses. This breakdown shortens learning horizons, accelerating learning and sample efficiency. Worker policies driven by goals provide intrinsic motivation, rewarding agents for achieving predefined goals and enhancing stability in dynamic multi-agent setups. The hierarchical RL and goal-driven policies have convergence guarantees with certain assumptions, while formal analysis of DIN-HRL is pending. Directed hypergraph representation captures complex traffic interactions missing in standard graphs. Traffic congestion in one area can affect others through coordinated phases, leveraging hypergraph convolution for enhanced coordination and information propagation [3].

7.4 Limitations and Challenges

Despite promising results, several limitations must be addressed:

1. Simulation-to-Reality Gap: SUMO experiments used ideal sensors, while real deployments will face noise and unpredictability, highlighting a lack of real-world DRL traffic control evidence. Field testing and safety validation are needed [1][2][4].
2. Neuromorphic Hardware Maturity: Intel Loihi 2 and SpiNNaker 2 are strong research platforms but lack commercial availability and mature ecosystems. Manual tuning for ANN-to-SNN conversion limits applicability.
3. Metric Standardization: Inconsistent metrics across studies hinder comparisons. The absence of standardized benchmarks for traffic control affects research progress.
4. Partial Observability and Uncertainty: The framework assumes full visibility of traffic states, which is unrealistic. Future work should incorporate partial observability and model uncertainty using Bayesian RL or robust optimization.
5. Heterogeneous Vehicle Mixes: The framework used a fixed vehicle mix, whereas real traffic includes diverse, connected, and autonomous vehicles, requiring framework adaptation.
6. Computational Cost of Training: Training the DIN-HRL framework is costly, taking 48 hours on 4 GPUs. Approaches like transfer learning could help reduce this burden.

7.5 Practical Deployment Considerations

Translating the DIN-HRL framework to real-world deployment involves several key considerations:
- Infrastructure: Requires LiDAR sensors, V2X communication, and neuromorphic computing at intersections. Initial costs are high; phased deployment in key areas may be more practical.
- Integration: Must work with existing traffic systems, potentially offering hybrid operation with human oversight.
- Safety: Needs rigorous validation and certification due to its critical nature; real-world testing is essential despite high simulation safety scores.
- Privacy and Security: Must address vehicle tracking concerns with secure communication, data anonymization, and resilience to attacks.
- Stakeholder Acceptance: Requires support from city officials, engineers, and the public; explainability of the framework can help build trust [7].

7.6 Future Research Directions

Future research directions include:
1. Real-world field trials to validate performance and identify challenges.
2. Online learning for continuous adaptation to traffic patterns.
3. Multi-city transfer learning to reduce training time for policy adaptation.
4. Integration with autonomous vehicles for joint infrastructure and vehicle optimization.
5. Resilience policies for sensor failures and disruptions.
6. Exploration of advanced neuromorphic architectures for efficiency.
7. Theoretical analysis for convergence guarantees and optimal solution conditions.
8. Integration with other smart city systems for holistic urban optimization.

8. Conclusion

This paper presents the DIN-HRL framework for optimizing urban traffic flow using deep intelligent networks and neuromorphic hardware. It shows significant improvements: 77.1% throughput, 55.0% wait time, 87.1% energy savings, and 96.2% latency reduction compared to traditional methods. Key innovations include a scalable multi-agent architecture, advanced hypergraph convolution, an ANN-to-SNN conversion method, and evaluations demonstrating enhanced traffic efficiency and environmental metrics. Neuromorphic computing proves viable for edge AI in transportation, achieving 99.6% power reduction and sub-millisecond latency. While challenges in real-world deployment exist, the DIN-HRL framework offers a path to sustainable urban mobility. This work advances intelligent traffic management systems, combining adaptability with efficiency.

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