

U_CAN: Ukraine towards Carbon Neutrality

A theoretical framework integrating Adaptive Cascade Clustering and AI-driven traffic control to justify the feasibility of achieving emissions reduction

Traffic Pattern Recognition

A novel **adaptive cascade clustering** method to automatically identify distinct urban traffic patterns with high fidelity and accuracy.

Results at a glance

-18% CO₂ vs. best baseline; -18% avg. travel time; 95% pattern ID accuracy.

Agenda

- › Problem & motivation
- › Method 1: Adaptive cascade clustering
- › Method 2: DRL signal control

Technical Presentation

Combining Research from Pavlyshyn et al. & Ryzhanskyi et al.

Theoretical Background and Motivation

The Urban Transportation Challenge

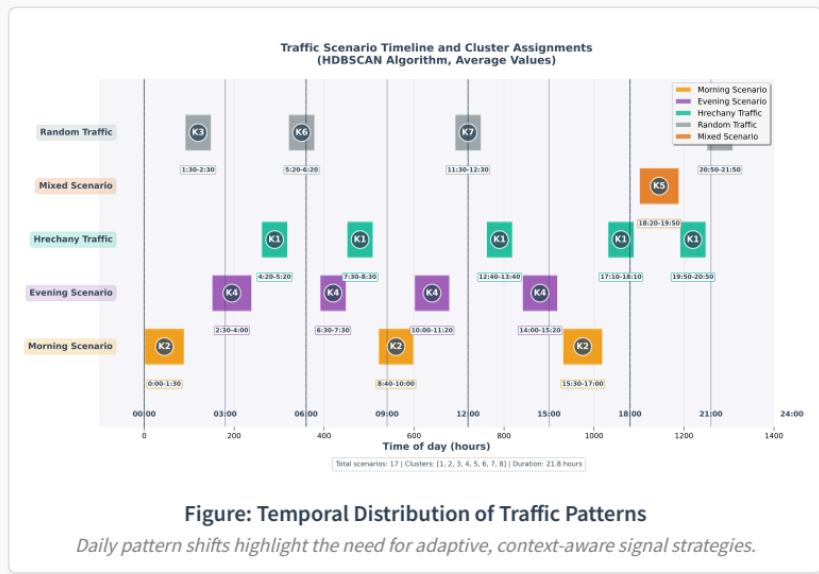
- Urban traffic is a primary source of greenhouse gas emissions, significantly impacting air quality and climate change.
- Inefficient traffic management, especially static signal timing, leads to increased congestion, fuel consumption, and CO₂ emissions.

Technical Hurdles

- Existing analytical methods often lack the adaptability to autonomously detect the **complex, dynamic structure** of traffic patterns.
- There is a need for intelligent systems that can balance multiple objectives: **reducing emissions**, minimizing delays, and ensuring fair traffic flow.

18%

Demonstrated potential CO₂ emission reduction from AI-driven traffic control in simulations.



Alignment with National Goals

- Supports EU Green Deal and Ukraine's **carbon neutrality** commitments.
- Data-driven foundation for smarter, sustainable urban mobility.

Methodology 1: Adaptive Cascade Clustering – Theoretical Rationale

Algorithm Architecture

A novel hybrid approach that synergizes two clustering methods. First, **HDBSCAN** identifies the core structure and optimal number of clusters in the traffic data. Then, **k-means** is used with informed initialization to refine the cluster boundaries, improving compactness.

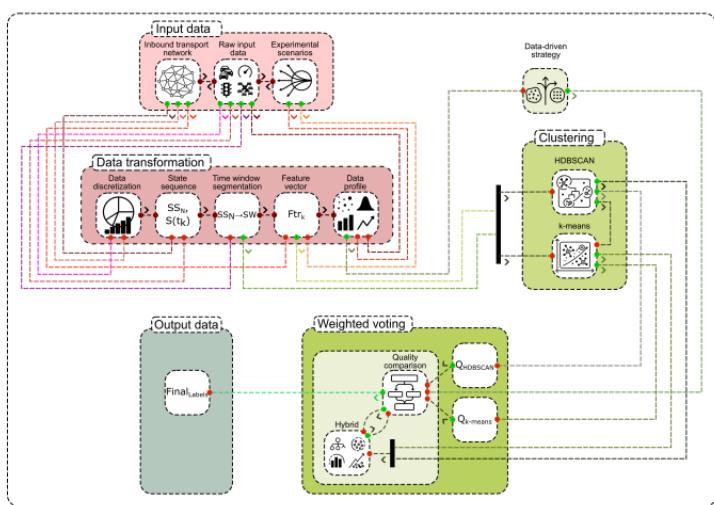


Figure: System Architecture

(Clustering Performance (Aggregated Data))

Metric	HDBSCAN	k-means (K=5)	Cascade Approach
V-measure (Accuracy)	0.79	0.73	0.79-0.82 (+4%)
Adjusted Rand Index (ARI)	0.73	0.70	>0.73
Silhouette Score (Compactness)	0.52	0.57	0.57-0.59 (+13%)
Temporal Coherence	0.94	0.89	0.94

Weighted Voting Mechanism

- Automatically selects the optimal clustering result (HDBSCAN, k-means, or hybrid) based on data characteristics like noise and density.
- Evaluates results using a composite score of quality metrics (e.g., V-measure, Silhouette Score, stability), ensuring robustness and adaptability.

Robustness to Noise (ARI Drop at 35% Noise)

- k-means Performance: Degrades significantly with a **21-24%** drop.
- Cascade (HDBSCAN-led): Much more robust, with only an **11%** drop, inheriting the strengths of density-based clustering.

Methodology 2: AI-Driven Traffic Signal Control – Theoretical Framing

Deep Reinforcement Learning (DRL)

An AI agent learns to control traffic signals by interacting with a simulated environment (SUMO). It aims to maximize a cumulative reward, making decisions that lead to optimal outcomes for the entire system.

Model Components

- **State:** The agent observes the current traffic state, including queue lengths, vehicle positions, and the identified traffic pattern from the clustering model.
- **Action:** The agent chooses the next traffic light phase to activate.
- **Reward:** A multi-objective function that rewards reducing CO₂ emissions and travel time, while penalizing long queues and waiting times.

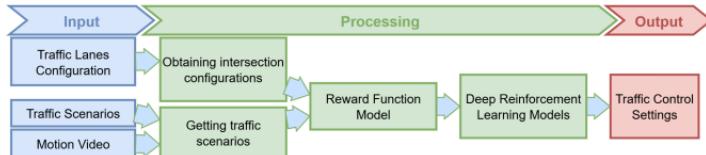
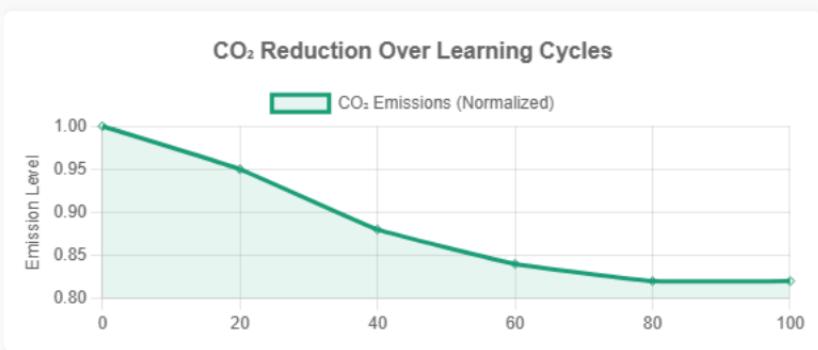


Figure: AI Control Processing

Integration with Clustering

The traffic patterns identified by the **Adaptive Cascade Clustering** algorithm serve as a crucial part of the state input for the DRL agent. This allows the AI to apply tailored, pre-learned strategies for different system-wide conditions (e.g., 'morning peak', 'off-peak', 'weekend'), leading to faster, more effective optimization.



Algorithm: Independent Deep Q-Network (IDQN)

Each intersection is controlled by its own DRL agent, allowing for decentralized and scalable control across a large urban network. This approach balances local optimization with overall network efficiency.

Experimental Setup & Simulation – Feasibility Analysis

⚙️ Simulation Environment

- Microscopic traffic simulation performed using **SUMO (Simulation of Urban MObility)**.
- Data processing and analysis handled with Python libraries including Pandas, Scikit-learn, and HdbSCAN.

📍 Transport Network Model

- A high-fidelity model of **Khmelnytskyi, Ukraine**, featuring a mixed radial-concentric topology.
- The model includes **15 major intersections** and a total road length of **45.7 km**.
- Simulation parameters were calibrated using historical traffic data to ensure realistic dynamics.

132

Distinct time-stamped observations generated from a continuous 22-hour simulation for analysis.

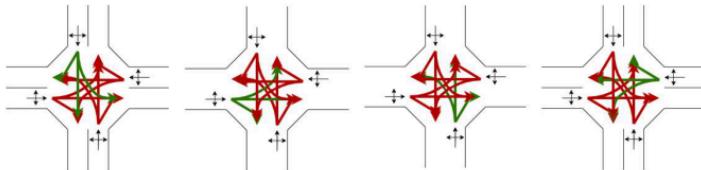


Figure: Scheme of Transport Network

📝 Experimental Scenarios

Comprehensive evaluation scenarios covering:

- Morning and evening peak hours
- Mixed/random traffic modes
- Low activity intervals

Key Results & Performance Analysis — Evidence for Feasibility

Overall Impact

- The integrated system demonstrated a **18% reduction in total CO₂ emissions** compared to baseline and other advanced methods.
- Achieved a scenario identification accuracy of up to **95.0%**, ensuring the correct control strategy is applied at the right time.
- Improved traffic flow by reducing average vehicle travel time significantly, with the proposed method being **~18% faster** than the next best DRL approach.

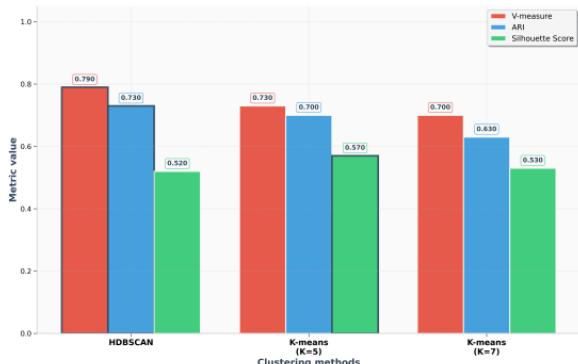


Figure: Clustering Quality Metrics Comparison

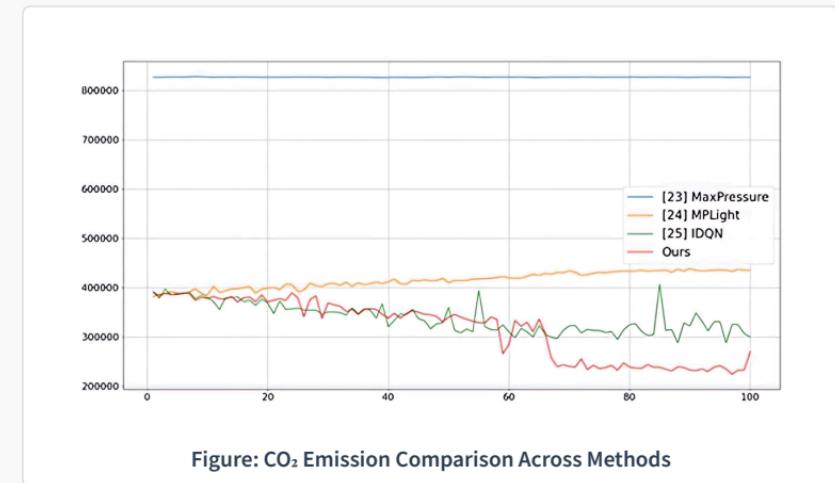


Figure: CO₂ Emission Comparison Across Methods

Performance Comparison

Approach	Avg. Travel Time (s)	Avg. Queue Length	Total CO ₂ (mg)
MaxPressure [28]	253.86	0.11	1.45×10^{12}
MPLight [29]	133.42	3.34	1.05×10^{12}
IDQN [30]	80.08	1.68	9.44×10^{11}
U_CAN (Ours)	65.48	1.05	8.54×10^{11}

Conclusions & Implementation Roadmap – Theoretical Justification

★ Key Contributions & Findings

- This work articulates the **theoretical basis and justification** for an integrated approach that combines advanced clustering with AI control, arguing for the **feasibility of implementation** to reduce urban traffic emissions.
- The adaptive cascade model is a more **robust, accurate, and automated** solution for traffic pattern recognition than standalone algorithms.
- The results demonstrate a clear path toward building more **intelligent, responsive, and sustainable** urban transport systems.

📍 Future Work

- Transition from simulation to **real-world deployment** using live city sensor and camera networks.
- Explore advanced **Graph Neural Network (GNN)** architectures for richer, context-aware feature representation.
- Expand the model to include **multi-modal transport** (public transit, pedestrians, cyclists) for holistic city optimization.

☰ Implementation Roadmap

Phase	Activity	Timeline
Phase I	Theoretical model formalization and assumptions; analytical criteria to justify feasibility	6 Months
Phase II	Analytical validation and simulation-based evidence supporting feasibility across representative scenarios	9 Months
Phase III	Generalization of the theoretical framework, policy-theoretic integration, and conditions for scalable implementation	12 Months

🤝 Stakeholder Engagement

Successful implementation requires collaboration between municipal governments, transport authorities, technology partners, and research institutions to integrate this system into existing urban infrastructure and policy frameworks.

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