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% CO_2 vs. best baseline; −18% avg. travel time; 95% pattern ID accuracy.

Agenda

- Problem & motivation
- Method 1: Adaptive cascade clustering

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 CO_2 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 CO_2 emission reduction from AI-driven traffic control in simulations.

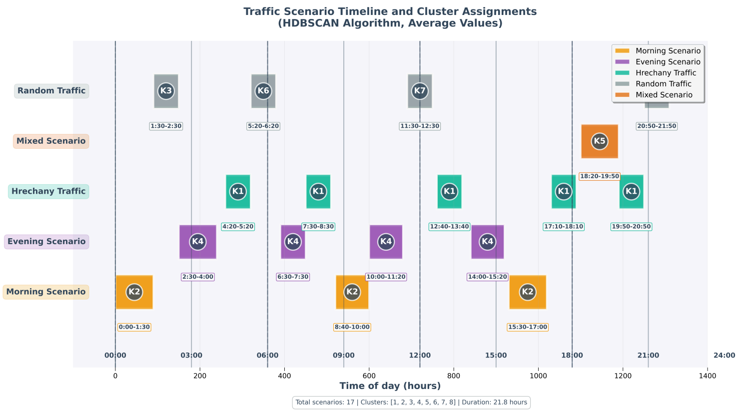


Figure: Temporal Distribution of Traffic Patterns

Daily pattern shifts highlight the need for adaptive, context-aware signal strategies.

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.

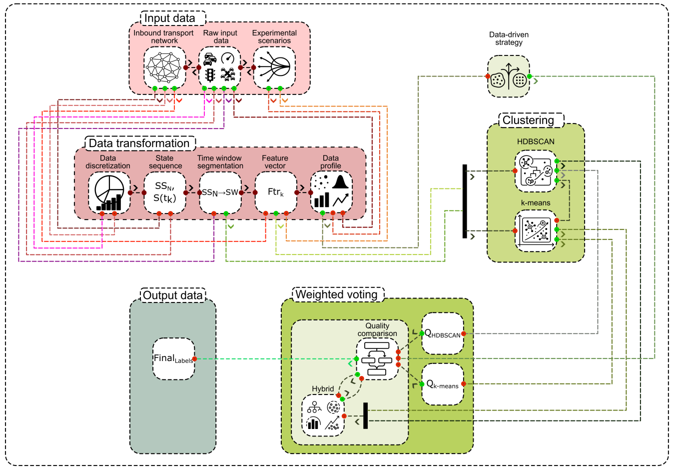


Figure: System Architecture

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 CO_2 emissions and travel time, while penalizing long queues and waiting times.

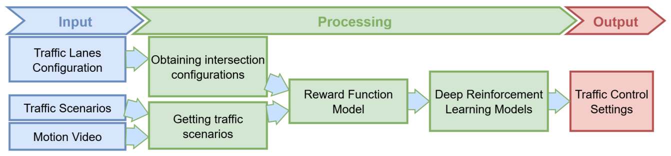
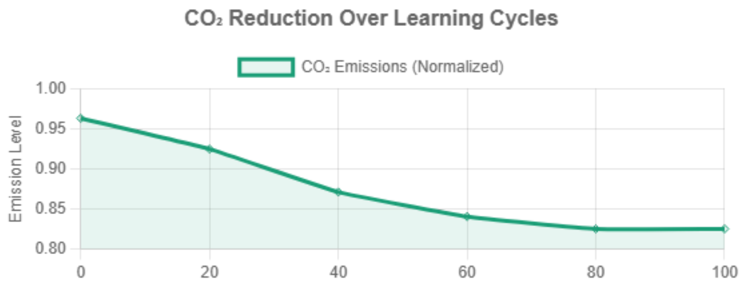


Figure: AI Control Processing

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.

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

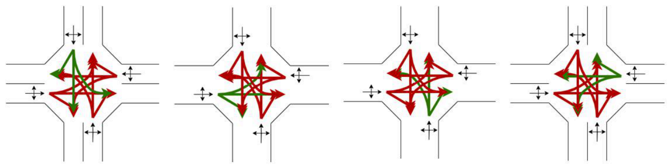

Figure: Scheme of Transport Network

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 CO_2 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.

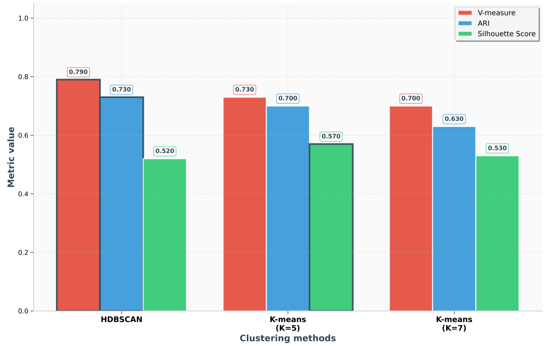

Figure: Clustering Quality Metrics Comparison

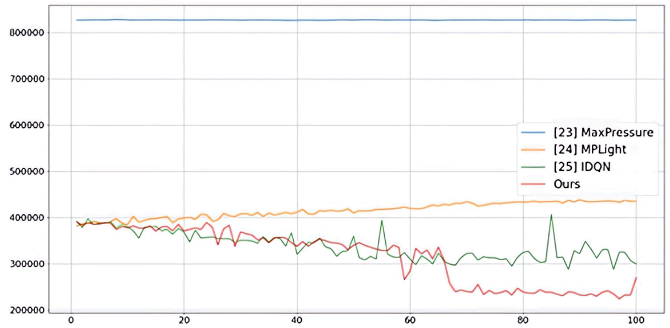

Figure: CO_2 Emission Comparison Across Methods

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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