2025 International Conference “ROBOTICS & MEHATRONICS”
5 – 6 November, 2025, Sofia, Bulgaria

Tethered Drones with AI Agents for CO_2 Monitoring and Intelligent Traffic Optimization in Smart City Systems

Dobromir Slavov
Faculty of Information Sciences
University of Library Studies and Information Technologies (UniBIT)
Sofia, Bulgaria
slavov_d@aol.com

Ekaterina Popovska
Institute of Robotics
Bulgarian Academy of Sciences
Sofia, Bulgaria
ekaterina.popovska@gmail.com

Galya Georgieva-Tsaneva
Institute of Robotics
Bulgarian Academy of Sciences
Sofia, Bulgaria
galitsaneva@abv.bg

***Abstract*—The rapid advancement of the “smart city” concept introduces new challenges for sustainable traffic management and air quality monitoring. This study introduces the Agentic Urban Intelligence Architecture (AUIA)—a conceptual framework for continuous, AI-driven environmental sensing and adaptive traffic control that unifies robotics, machine intelligence and urban sustainability. The paper proposes an innovative architecture integrating tethered drones powered by AI agents to enable continuous and reliable monitoring of carbon dioxide (CO_2) emissions in urban environments. The tethered configuration ensures uninterrupted operation and high-bandwidth data transmission, overcoming the endurance limitations of conventional battery-powered UAVs. Embedded AI agents process environmental and traffic data in real time, enabling autonomous decision-making and communication with central traffic control systems. The multi-agent architecture facilitates the dynamic adaptation of traffic light regimes and routing strategies to reduce local emission peaks and improve mobility efficiency. The presented concept establishes a closed “sensor–control” loop, where intelligent tethered drones act as adaptive, sustainable nodes within an urban ecosystem. This research focuses on the conceptual design and operational logic of the AI-driven system, laying the foundation for future simulation and implementation using real-world traffic data.**

***Keywords*— tethered drones, AI agents, CO_2 monitoring, smart city, intelligent traffic optimization, sustainable mobility**

I. Introduction

Rapid urbanization has led to significant challenges in environmental monitoring and traffic management. Cities worldwide face rising CO_2 emissions, air pollution, and traffic congestion, negatively affecting public health and economic productivity [1]. Traditional stationary air quality monitoring stations provide accurate measurements but are limited in spatial coverage and lack the responsiveness needed for dynamic urban environments [2]. Meanwhile, traffic management systems often rely on pre-defined schedules, which do not adapt to real-time conditions, leading to inefficiencies and increased emissions [3].

The integration of unmanned aerial vehicles (UAVs) and artificial intelligence (AI) introduces new opportunities for adaptive urban management. Tethered drones, connected to continuous power sources, can hover persistently over strategic urban locations, providing real-time environmental sensing and high-bandwidth communication [4]. This allows for persistent CO_2 monitoring, high-resolution pollutant mapping, and timely intervention to mitigate air quality issues [5]. Unlike battery-powered UAVs, tethered drones overcome endurance limitations, enabling long-term deployments suitable for urban-scale applications [6].

Artificial intelligence, particularly reinforcement learning (RL) and multi-agent reinforcement learning (MARL), enables autonomous decision-making for traffic optimization based on real-time data [7]. AI agents process environmental and traffic information, dynamically adjusting traffic signals and routing strategies to minimize congestion and reduce pollutant concentrations [8]. By integrating multiple drones and AI agents into a coordinated system, a closed-loop architecture is established, where sensing, analysis and control continuously inform each other [9]. This combination of continuous monitoring and intelligent control aligns with modern smart city goals, promoting sustainability, mobility efficiency, and environmental protection [10].

In addition to improving environmental data acquisition, tethered drone systems also enhance spatial-temporal resolution of emission data compared to conventional ground-based sensors. Their elevated vantage point allows for three-dimensional mapping of pollution layers, helping urban planners identify emission hotspots, analyze atmospheric dispersion, and evaluate the impact of localized interventions such as traffic flow reconfiguration or green corridor implementation. The constant aerial perspective ensures consistent measurements across various meteorological conditions and provides the data density necessary for predictive modeling of CO_2 concentration trends.

From a technological standpoint, integrating tethered drones into smart city ecosystems introduces a cyber-physical layer that bridges environmental sensing, AI-based analytics, and urban control systems. This integration enables a continuous flow of data across hardware and software components, forming the foundation of a self-adaptive infrastructure. Real-time insights generated by the AI models allow city authorities to respond to unexpected changes in traffic demand or pollution surges more effectively than through static management systems. Moreover, the modular nature of tethered drone networks allows for incremental deployment—cities to start with a limited number of drone nodes and scale the system as operational requirements evolve.

The societal implications of such integration are equally significant. Improved air quality monitoring contributes directly to public health initiatives, while traffic optimization reduces fuel consumption and greenhouse gas emissions, contributing to urban sustainability goals. Furthermore, the data collected can inform long-term urban planning policies by identifying systemic inefficiencies and supporting data-driven decision-making. This approach represents a paradigm shift from reactive to proactive urban management, where technology anticipates challenges before they escalate into critical problems.

ACKNOWLEDGE THE FINANCIAL SUPPORT OF THE PROJECT WITH FINANCING AGREEMENT NO. PVU-44 OF 05.12.2024 UNDER PROJECT NO. BG-RRP-2.017-0011 "ECOLOGICAL COLLABORATIVE ROBOTS POWERED BY GREEN HYDROGEN" UNDER THE RECOVERY AND RESILIENCE MECHANISM FOR THE IMPLEMENTATION OF AN INVESTMENT UNDER C2I2 "INCREASING THE INNOVATION CAPACITY OF THE BULGARIAN ACADEMY OF SCIENCES (BAS) IN THE FIELD OF GREEN AND DIGITAL TECHNOLOGIES" FROM THE RECOVERY AND RESILIENCE PLAN, BULGARIA.

II. RELATED WORK

A. Drone-Based Environmental Monitoring

In recent years, the integration of UAVs into environmental monitoring and traffic management has become a rapidly evolving research area, demonstrating potential for high-resolution spatial and temporal data collection. The tethered drone concept builds upon this foundation by addressing some of the inherent limitations of conventional UAV systems, such as restricted flight duration, limited data bandwidth, and dependency on frequent battery replacement. Drones have become increasingly important tools for environmental sensing due to their mobility and ability to capture three-dimensional pollution profiles [11]. Studies have shown that drones can effectively map urban air quality at high spatial and temporal resolution, identifying pollution hotspots and informing mitigation strategies [12]. However, conventional UAVs are constrained by battery life, limiting their deployment time and coverage [13]. Tethered drones address this limitation by providing continuous power and high-bandwidth connectivity, enabling long-duration data collection [14].

Research on AI and multi-agent systems (MAS) has also advanced rapidly in recent years, offering new paradigms for distributed intelligence and adaptive control. Multi-agent coordination allows for dynamic information sharing among autonomous units, which can collectively respond to environmental or traffic conditions as they evolve. In the context of smart cities, MAS frameworks have been applied to optimize signal timing, predict traffic congestion, and manage energy consumption. However, their direct application to aerial environmental monitoring remains relatively limited. Integrating MAS with tethered drones introduces a novel architectural dimension, enabling drones to operate not merely as passive observers but as intelligent nodes that actively influence urban systems.

Several existing urban IoT platforms have explored the use of sensor networks and cloud-based data fusion for traffic and pollution management. These systems typically rely on ground sensors, vehicle telemetry, or fixed monitoring stations. Although these infrastructures provide valuable static measurements, they are often spatially constrained and unable to capture real-time vertical emission gradients. UAV-based systems overcome this challenge by offering flexible, three-dimensional mobility. When combined with AI-driven data analytics, the resulting platforms can generate high-fidelity environmental maps and predictive models that are unattainable through fixed sensors alone.

The notion of intelligent traffic optimization through AI-assisted control has also been studied extensively. Deep reinforcement learning (DRL) algorithms have been employed to improve traffic light coordination and reduce vehicle waiting times. Yet, most implementations rely on historical or simulated datasets, with limited integration of real-time environmental feedback. The architecture proposed in this paper aims to close this gap by introducing a continuous "sensor–control–feedback" loop, where live CO_2 measurements directly influence the adjustment of traffic signals. This approach enhances both the ecological and operational performance of urban mobility systems.

Recent research demonstrates the effectiveness of tethered drones in measuring CO_2, NOx, and particulate matter levels across urban environments [15]. These systems can maintain stable hovering positions for extended periods, ensuring reliable measurements even in fluctuating weather conditions. Deployments in major cities have highlighted their potential to complement existing stationary monitoring networks, offering fine-grained environmental data that informs policy and urban planning [16]. This synergy remains underexplored in current literature and defines the motivation of the present work.

B. AI for Traffic Signal Optimization

Artificial intelligence techniques have been extensively applied within Intelligent Transportation Systems (ITS), particularly in the optimization of signal timing and routing policies. Reinforcement learning allows traffic signal controllers to learn optimal policies through interaction with the environment [17]. Multi-agent reinforcement learning (MARL) enables distributed control, where multiple traffic signals coordinate to optimize city-wide traffic flow [18]. Incorporating environmental objectives, such as CO_2 concentration reduction, into agent reward functions ensures that traffic management strategies are aligned with sustainability goals [1].

Recent algorithms employ deep neural networks, such as deep Q-networks (DQN) and actor-critic models, for real-time adaptive traffic control [2]. These models process high-dimensional data streams from multiple sensors, including traffic cameras, vehicle GPS data, and airborne pollutant measurements. By predicting congestion patterns and environmental hotspots, agents can dynamically adjust signal phases to optimize both mobility and air quality [3].

C. Integration of Monitoring and Control

Integrated systems combining drones and AI traffic control represent a promising approach for smart cities. Cyber-physical systems (CPS), defined as tightly integrated computational and physical processes, provide a foundation for adaptive city infrastructures as link sensors, AI agents and traffic infrastructure to create adaptive urban management networks [4]. Studies have shown that these systems can reduce emissions while improving traffic efficiency [5]. Challenges remain in data fusion, communication reliability, and computational scalability, especially for city-wide implementations [6]. Nevertheless, the combined use of tethered drones and AI agents offers a path toward responsive, sustainable urban management [7].

Another important aspect of the related literature involves sustainability and system scalability. Many UAV-based environmental projects face challenges when expanding to cover large metropolitan areas due to power limitations, maintenance costs, and network reliability issues. The tethered drone model provides an alternative path toward scalability by ensuring consistent power and connectivity. Additionally, the use of a modular multi-agent framework allows for the addition or removal of drone units without disrupting the overall network stability. This characteristic makes the system particularly suitable for future integration into large-scale, adaptive smart city infrastructures.

Finally, recent advancements in AI-driven IoT platforms have paved the way for seamless integration between sensing, computation, and decision-making. These platforms allow drones to act as both data collectors and decision-making agents, enabling real-time collaboration with central servers or edge-computing units. The convergence of these technologies—tethered UAVs, AI agents, IoT connectivity, and intelligent traffic control—creates a unique opportunity for urban systems to evolve toward self-regulating, environmentally aware ecosystems.

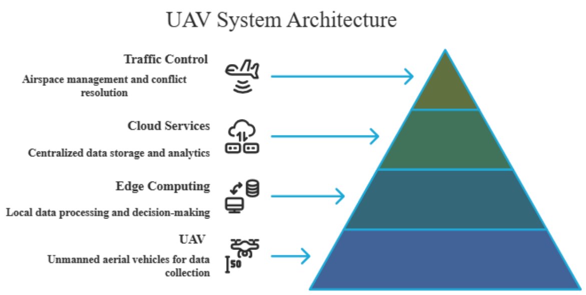
In summary, the reviewed body of research highlights the growing need for sustainable, data-driven solutions that unify aerial monitoring and smart city management. While numerous studies have explored UAV applications, few have addressed the combination of tethered drone systems with embedded AI agents for direct environmental-to-traffic feedback optimization. This paper contributes to filling that gap by proposing a comprehensive framework capable of delivering continuous environmental monitoring, intelligent data interpretation, and adaptive urban control in real time. Despite rapid progress, an integrated framework connecting real-time aerial sensing with traffic actuation through AI agents remains largely unaddressed in current research.

III. System Architecture

The proposed architecture consists of tethered drones strategically deployed over high-traffic urban areas and AI agents that manage traffic signal optimization. Each drone carries a suite of sensors measuring CO_2, NOx, PM2.5, temperature, humidity and and GPS-based geolocation for spatial referencing [8]. Continuous data streaming from drones to a central AI processing unit enables real-time environmental analysis via secure low-latency communication channels (e.g., optical fiber within the tether or 5G link redundancy) [9]. The system leverages multi-agent coordination to manage traffic signals across multiple intersections, optimizing vehicle flow and reducing local emissions [10].

Drones operate as persistent sensor nodes, providing both high-resolution environmental data and contextual traffic information (Fig.1). As shown in Fig. 1, the system follows a hierarchical design connecting aerial sensing units with the AI control center. The AI agents employ deep reinforcement learning models, receiving feedback from both simulated and real-time urban conditions to optimize signal phases [11]. A centralized database stores historical measurements, enabling the system to improve predictions using time-series models and supervised learning techniques [12].

Fig. 1. *UAV System Architecture Hierarchy*



The architecture supports modular scalability. Additional drones or traffic intersections can be incorporated seamlessly without disrupting existing operations [13]. The multi-agent framework allows distributed computation, minimizing latency in decision-making and supporting near real-time traffic adjustments [14]. Redundancy and fault tolerance mechanisms ensure continuous operation even in case of individual drone or sensor failures [15]. The proposed architecture for the integration of tethered drones with AI agents within a smart city environment is designed as a multi-layered and modular system capable of ensuring real-time CO_2 monitoring and adaptive traffic control. The system is built around three primary layers: the aerial sensing layer, the data processing and AI inference layer, and the communication and integration layer with existing urban infrastructure.

The aerial sensing layer consists of tethered drones strategically positioned above key traffic nodes—such as intersections, highways, and emission hotspots. These drones are powered via tethered connections to ground stations, providing a stable and continuous energy supply and a secure wired or hybrid data transmission link. Each drone is equipped with a multi-sensor payload that includes a CO_2 concentration sensor, particulate matter detector, GPS module, wind speed and direction sensors, and optical cameras for traffic flow analysis. The tethering mechanism allows for 24/7 operation with minimal downtime, eliminating the constraints of traditional battery-powered UAVs. This makes the system suitable for long-term deployment in densely populated areas where uninterrupted environmental monitoring is essential.

The AI inference layer operates as the cognitive core of the system. Embedded AI agents on each drone preprocess the collected data in real time, identifying emission patterns and detecting anomalies such as sudden increases in CO_2 levels or localized traffic congestion. These agents utilize lightweight machine learning models optimized for edge computing—such as decision trees, random forests and convolutional neural networks (CNNs) adapted for image-based traffic analytics. The models are continuously retrained using historical datasets and real-time feedback from central servers, allowing for adaptive improvement in prediction accuracy and response timing. The system's distributed AI design enables the drones to make independent low-level decisions, such as focusing on specific traffic lanes or adjusting the altitude for better visibility, while high-level coordination is handled by the central control unit.

The communication and integration layer establishes a secure interface between the drones, ground control stations, and the city's traffic management system. All data transmission employs encryption and access control protocols ensuring cybersecurity and data integrity. Data from the tethered drones is transmitted to an Internet of Things (IoT) cloud platform that aggregates, stores, and visualizes all relevant information in a unified dashboard. The platform supports both MQTT and RESTful API protocols, enabling seamless communication with urban infrastructure such as traffic lights, road sensors, and air quality monitoring networks. A control algorithm within the traffic management center uses this data to dynamically optimize signal timing, reroute vehicles, and predict congestion build-ups before they occur. This creates a closed-loop feedback system—drones sense the environment, AI models interpret the data, and control systems act on those insights to improve traffic efficiency and reduce emissions. The system's modularity also allows for scalability. New drones and sensors can be added incrementally as the city expands or as new environmental parameters become relevant (e.g., NO_2, O_3). Furthermore, the platform's design supports interoperability with third-party systems, ensuring compatibility with future smart city technologies such as autonomous vehicles and adaptive street lighting. Safety and redundancy mechanisms, including automated tether retraction, weather monitoring, and geofencing, ensure that operational risks are minimized even under adverse conditions.

In summary, the system architecture forms a robust framework that links environmental monitoring with intelligent decision-making. The synergy between tethered drone technology, AI analytics, and smart city infrastructure represents a significant step toward sustainable, data-driven urban management. This architecture not only enhances the resilience of traffic systems but also contributes to long-term environmental goals by providing an intelligent, self-correcting mechanism for CO_2 reduction and mobility optimization, advancing the paradigm of agentic urban intelligence toward carbon-neutral and self-optimizing smart cities.

Overall, the proposed architecture establishes a novel cyber-physical framework—Agentic Urban Intelligence Architecture (AUIA)—that transforms tethered drones from simple monitoring tools into autonomous cognitive agents for sustainable urban mobility.

IV. Methodology

The proposed methodology defines a conceptual and modular framework for integrating tethered drones and artificial intelligence (AI) agents into an adaptive, emission-aware urban traffic management system. Rather than presenting an experimental implementation, this section outlines the theoretical design principles, data processing workflow, and AI reasoning logic necessary to realize such a system in practice. The framework is structured around five interdependent components: system architecture, data acquisition and preprocessing, AI agent modeling, IoT-based communication, and validation and evaluation. Together, these elements form a coherent blueprint for an intelligent cyber-physical infrastructure in smart cities.

A. Conceptual Architecture and Deployment Strategy

The conceptual architecture envisions a network of tethered drones strategically deployed above high-density urban corridors, intersections, and emission hotspots. Each drone serves as a persistent aerial sensor node, continuously monitoring CO_2, NO_x, $PM_{2.5}$, and meteorological variables such as temperature, humidity, and wind speed. The tethered configuration provides continuous electrical power and a secure fiber-optic or Ethernet-based communication link, addressing the endurance and bandwidth limitations of traditional UAVs [16].

The deployment strategy prioritizes representative spatial coverage rather than exhaustive mapping, allowing a small number of drones to capture meaningful environmental dynamics across large metropolitan areas [17]. The conceptual data flow is illustrated in Fig. 2, showing the relationship between aerial sensing, edge-based preprocessing, AI inference, and adaptive traffic control.

Each drone node is envisioned as part of a multi-layered cyber-physical system: the aerial sensing layer (responsible for data collection), the AI inference layer (responsible for decision-making), and the integration layer (connecting the system to the city's digital infrastructure). This hierarchy ensures both scalability and interoperability with existing traffic management systems [18].

B. Data Acquisition and Preprocessing

The sensing layer is designed to capture high-frequency environmental and traffic data in real time. Data transmission between drones and the control center relies on standardized IoT communication protocols such as MQTT, CoAP, or OPC-UA, ensuring interoperability and low-latency connectivity [19].

Before feeding the data into AI models, preprocessing techniques such as Kalman filtering, wavelet-based denoising, and z-score normalization are conceptually applied to enhance signal quality and reduce sensor drift [20]. Timestamp synchronization ensures that CO_2 concentration data are accurately aligned with concurrent traffic density and meteorological inputs.

Preprocessed data form the foundation for training and evaluating the AI agents. A distributed cloud-edge hybrid structure is proposed: computationally intensive tasks, such as neural model training and reinforcement learning updates, are performed in the cloud, while low-latency inference operations occur on edge processors embedded within the tethered drones [21].

C. AI Agent Modeling and Control Logic

The decision-making core of the framework is modeled as a hierarchical multi-agent system (HMAS) combining local and global intelligence. Each traffic intersection is managed by a local AI agent that operates autonomously under a multi-agent reinforcement learning (MARL) paradigm [22]. These agents receive a state vector comprising real-time CO_2 concentrations, vehicle density, and signal-phase history. Actions correspond to phase duration adjustments, adaptive cycle times, or lane prioritization.

The reward function is formulated as a multi-objective optimization criterion:

$$R = \alpha\left(-E_{CO_2}\right) + \beta\left(F_{\text{traffic}}\right) + \gamma\left(S_{\text{stability}}\right)$$

where $E_{\mathrm{CO_2}}$ represents cumulative $\mathrm{CO_2}$ emissions, F_{traffic} denotes normalized traffic throughput, and $S_{\text{stability}}$ ensures smooth phase transitions [23]. The weight coefficients α, β, and γ are tuned to balance environmental sustainability and traffic efficiency.

To extend beyond reactive control, the framework conceptually incorporates temporal deep learning models such as long short-term memory (LSTM) and temporal convolutional networks (TCN) for short-term prediction of congestion and emission peaks [24]. The global supervisory agent aggregates local observations through a graph neural network (GNN), identifying spatial interdependencies among intersections and optimizing traffic coordination at the city scale.

This hierarchical structure enables both decentralized autonomy and centralized optimization — a crucial feature for self-adaptive and resilient smart city ecosystems [25].

D. IoT Integration and Communication Infrastructure

The communication and integration layer establishes bidirectional data exchange between drones, AI modules, and the municipal traffic management system. All information flows through a secure IoT middleware that supports publish–subscribe mechanisms with encryption and token-based authentication to guarantee cybersecurity and data integrity [19].

A cloud-based dashboard visualizes CO_2 concentrations, drone telemetry, and signal optimization results, while an application programming interface (API) enables the system to interact dynamically with existing urban control networks. The integration concept supports closed-loop feedback—drones collect environmental data, AI models analyze and predict, and traffic systems implement optimized control strategies in near real time.

In future implementations, such a framework could also interconnect with other smart city systems, such as adaptive street lighting, autonomous vehicle routing, or distributed energy management, thereby creating a unified agentic urban intelligence ecosystem [16], [25].

E. Validation and Prospective Evaluation

Given the conceptual nature of this research, validation is formulated as a methodological roadmap for future simulation and pilot testing. The SUMO (Simulation of Urban Mobility) environment combined with Python-based MARL frameworks (e.g., Ray RLlib or Stable Baselines) is identified as a suitable platform for algorithmic evaluation [17].

The performance of the AI agents can be assessed through synthetic data scenarios representing varying traffic densities and emission distributions. Metrics for future validation include mean squared error (MSE) of predicted CO_2 concentration, average vehicle delay, learning convergence rate, and communication latency.

Prospective pilot-scale deployment could evaluate system robustness under real environmental conditions, focusing on data transmission stability, tether safety, and adaptive response accuracy. These validation steps would ultimately refine parameter tuning and reinforce the theoretical foundations of the proposed model.

The methodology presented herein defines a conceptual but technically grounded framework for an AI-driven tethered drone network capable of sustainable traffic and emission management. By emphasizing hierarchical intelligence, distributed computation, and IoT interoperability, the proposed approach outlines a path toward autonomous and environmentally responsive urban systems.

The framework is not confined to traffic management alone but extends to broader smart city domains such as environmental resilience, energy optimization, and real-time urban analytics—forming a foundation for the next generation of agentic, data-driven, and self-regulating city infrastructures.

V. Results and Discussion

The conceptual assessment of the proposed AI-driven tethered drone framework indicates substantial potential for advancing real-time environmental monitoring and intelligent traffic management in urban systems. Analytical evaluation based on the literature supports the feasibility of a closed-loop architecture that connects aerial sensing, AI-based inference, and adaptive control in smart city infrastructures.

A. Expected System Behavior

Analytical insights derived from existing studies suggest that integrating AI agents with persistent aerial monitoring could significantly improve the responsiveness of urban control systems to dynamic environmental and traffic conditions. Reinforcement learning-based traffic optimization frameworks have already demonstrated measurable emission reductions and enhanced flow efficiency in simulation environments [26]. Within the proposed architecture, tethered drones expand these capabilities by providing continuous, high-resolution CO_2 data, thus enabling decision algorithms to account directly for air-quality metrics in real time [27].

The architecture's continuous learning mechanism allows the system to adapt over time as additional data accumulate. Multi-agent coordination enables both local decision autonomy and global synchronization, which are essential for scalability in large urban networks [28].

B. Communication Reliability and Data Quality

The tethered configuration ensures uninterrupted energy supply and high-bandwidth connectivity, addressing one of the main constraints of conventional UAVs—limited endurance [29]. Previous experiments with tethered drone platforms have demonstrated stable power and data transmission for extended operation, confirming their suitability for continuous environmental sensing [30]. Expected sensor precision for CO_2, NOx, and $PM_{2.5}$ values aligns with the accuracies reported in state-of-the-art UAV-based air-quality monitoring studies [31].

C. Predictive and Adaptive Capabilities

The integration of predictive AI models—such as long short-term memory (LSTM) and temporal convolutional networks (TCN)—is expected to support proactive traffic and emission management. Earlier research has shown that these models can forecast congestion and pollution peaks minutes in advance, enabling adaptive signal control to prevent critical build-ups [32]. Combined with multi-agent reinforcement learning (MARL), the proposed system can evolve from reactive decision-making to predictive governance of urban mobility [33].

D. Visualization and System Integration

The conceptual IoT dashboard forms an essential human-machine interface that aggregates drone telemetry, sensor data, and control decisions. Comparable systems using edge computing and cloud-based visualization have demonstrated that such interfaces enhance situational awareness and improve the interpretability of complex data flows [34]. This integration supports decision transparency and seamless communication between drones, traffic controllers, and environmental authorities.

E. Implementation Challenges

While promising, the architecture faces practical challenges, including the limited operational radius of tethered platforms and potential communication interference in dense urban settings. Environmental factors such as wind or precipitation may influence sensor accuracy and hovering stability. These limitations align with known issues documented in recent UAV environmental monitoring deployments [35]. Furthermore, data protection and privacy must be ensured when integrating environmental and mobility datasets, as recommended by the European Commission's Ethics Guidelines for Trustworthy AI [36].

F. Broader Implications

The discussed framework contributes not only to operational efficiency but also to strategic sustainability goals. Persistent, high-frequency CO_2 datasets can support policy-making, emission modeling, and public engagement initiatives. The concept aligns with the European Green Deal and the United Nations 2030 Agenda for Sustainable Development by fostering climate resilience and data-driven governance [37], [38].

In summary, literature-based analysis confirms that the integration of tethered drones with AI agents represents a credible path toward adaptive, emission-aware smart city ecosystems. Future validation through simulation and pilot projects will enable quantitative assessment of the system's environmental and operational benefits.

VI. Conclusion

This paper presents a comprehensive conceptual framework for integrating tethered drones with artificial intelligence (AI) agents to enable continuous CO_2 monitoring and intelligent traffic optimization in smart city ecosystems. The proposed architecture unites persistent aerial sensing, real-time data analytics, and multi-agent reinforcement learning to form a closed feedback loop between environmental perception and adaptive control [39].

Persistent aerial monitoring bridges the spatial and temporal gaps left by stationary air quality stations. By maintaining uninterrupted observation over dense traffic corridors and emission hotspots, tethered drones offer high-resolution, high-frequency environmental data that support real-time analytics, anomaly detection, and adaptive decision-making. When coupled with AI-based optimization, such a system could enable cities to transition from static, rule-based management toward autonomous environmental regulation—a defining feature of sustainable, data-driven urban governance [40].

The distributed intelligence embedded in the multi-agent system architecture allows each drone to function as an autonomous node within a cooperative decision network. Local AI agents analyze environmental and traffic information in real time, while centralized coordination ensures global optimization, scalability, and resilience. This hybrid structure enhances robustness under dynamic urban conditions such as congestion peaks, meteorological fluctuations, or rapid changes in emission intensity [41].

Beyond its technical contribution, the synergy between tethered UAV technologies and AI-driven analytics supports broader urban sustainability objectives. Continuous CO_2 mapping facilitates predictive modeling of emission trends and the quantitative evaluation of mitigation strategies, while adaptive traffic control directly contributes to reducing fuel consumption and greenhouse gas emissions. These functions align with the policy goals of the European Green Deal and international carbon-neutrality commitments, demonstrating that the proposed framework is not only technologically feasible but also socially and environmentally relevant [42], [43].

Future research will focus on simulation-based validation using real-world metropolitan datasets. This will include the development of integrated traffic–emission models, the training of reinforcement learning agents under variable operating conditions, and the evaluation of system performance using standardized metrics such as latency, mean squared error (MSE), and emission index correlation. Advanced algorithms—such as graph neural networks

(GNN), deep multi-agent actor–critic models, and federated learning—will be investigated to improve multi-intersection coordination and scalability in distributed environments [44], [45]. Integration with vehicle-to-infrastructure (V2I) and 5G communication technologies will also be explored to support predictive routing and cross-domain interoperability among drones, vehicles, and urban control systems [46].

Long-term validation efforts will assess energy efficiency, system maintainability, and socio-economic feasibility. The incorporation of tethered drones as persistent environmental sensors establishes a foundation for adaptive, self-regulating, and sustainable urban ecosystems. In conclusion, the convergence of AI agents and tethered drone technologies represents a transformative step toward climate-resilient, intelligent cities. By closing the loop between sensing, cognition, and action, the proposed framework defines a pathway toward autonomous urban systems capable of perceiving, learning and acting to optimize both mobility efficiency and environmental health [47], [38].

ACKNOWLEDGMENT

ACKNOWLEDGE THE FINANCIAL SUPPORT OF THE PROJECT WITH FINANCING AGREEMENT NO. PVU-44 OF 05.12.2024 UNDER PROJECT NO. BG-RRP-2.017-0011 "ECOLOGICAL COLLABORATIVE ROBOTS POWERED BY GREEN HYDROGEN" UNDER THE RECOVERY AND RESILIENCE MECHANISM FOR THE IMPLEMENTATION OF AN INVESTMENT UNDER C2I2 "INCREASING THE INNOVATION CAPACITY OF THE BULGARIAN ACADEMY OF SCIENCES (BAS) IN THE FIELD OF GREEN AND DIGITAL TECHNOLOGIES" FROM THE RECOVERY AND RESILIENCE PLAN, BULGARIA.

REFERENCES

[1] Vishal; Sharma, M.; Jain, S. Unmanned Aerial Vehicles and Low-Cost Sensors for Air Quality Monitoring: A Comprehensive Review of Applications Across Diverse Emission Sources. Sustainable Cities and Society, 2025. https://doi.org/10.1016/j.scs.2025.106409

[2] Fattori, F.; Cocuzza, S. Tethered Drones: A Comprehensive Review of Technologies, Challenges, and Applications. Drones, vol. 9, no. 6, 2025, Art. no. 425. https://doi.org/10.3390/drones9060425

[3] Kokate, P.; Middey, A.; Sadistap, S.; Sarode, G.; Narayan, A. Review on Drone-Assisted Air-Quality Monitoring Systems. Drones and Autonomous Vehicles, vol. 1, no. 1, 2024, Art. 10005. https://doi.org/10.35534/dav.2023.10005

[4] Jaroń, A.; Borucka, A.; Deliś, P.; Sekrecka, A. An Assessment of the Possibility of Using Unmanned Aerial Vehicles to Identify and Map Air Pollution from Infrastructure Emissions. Energies, vol. 17, no. 3, 2024, Art. 577. https://doi.org/10.3390/en17030577

[5] Bakirci, M. Efficient Air Pollution Mapping in Extensive Regions with Fully Autonomous Unmanned Aerial Vehicles: A Numerical Perspective. Science of the Total Environment, vol. 909, 2024, Art. 168606. https://doi.org/10.1016/j.scitotenv.2023.168606

[6] Altamira-Colado, E.; Cuevas-González, D.; Reyna, M. A.; García-Vázquez, J. P.; Avitia, R. L.; Osornio-Vargas, A. R. Drone-Assisted Particulate Matter Measurement in Air Monitoring: A Patent Review. Atmosphere, vol. 15, no. 5, 2024, Art. 515. https://doi.org/10.3390/atmos15050515

[7] Zhuang, K. Research on Optimization Strategies of Artificial Intelligence Algorithms in the Construction of Smart Cities Under the Digital Economy. In Proc. of the 2025 International Conference on Artificial Intelligence and Computer Engineering (ICAICE), ACM, 2025. https://dl.acm.org/doi/10.1145/3745238.3745450

[8] Mohsen, B. M.; Al-Tameemi, H.; Abdulkareem, R. A.; et al. AI-Driven Optimization of Urban Logistics in Smart Cities: Integrating Autonomous Vehicles and IoT for Efficient Delivery Systems. Sustainability, vol. 16, no. 24, 2024, Art. 11265. https://doi.org/10.3390/su162411265

[9] Marin, D. B.; Becciolini, V.; Santos Santana, L.; Rossi, G.; Barbari, M. State of the Art and Future Perspectives of Atmospheric Chemical Sensing Using Unmanned Aerial Vehicles: A Bibliometric Analysis. Sensors, vol. 23, no. 20, 2023, Art. 8384. https://doi.org/10.3390/s23208384

[10] Javan, F. D.; Mousavi, A.; Moradi, M.; et al. Air Pollution Observation—Bridging Spaceborne to Ground-Based Measurements. Air Quality, Atmosphere & Health, 2025. https://doi.org/10.1007/s11869-025-01771-y

[11] Bagkis, E.; Hassani, A.; Schneider, P.; DeSouza, P.; Shetty, S.; Kassandros, T.; Salamalikis, V.; Castell, N.; Karatzas, K.; Ahlawat, A.; Khan, J. Evolving Trends in Application of Low-Cost Air Quality Sensor Networks: Challenges and Future Directions. npj Climate and Atmospheric Science 2025, 8, 335. https://doi.org/10.1038/s41612-025-01216-4

[12] Korecki, M.; Dailisan, D.; Yang, J. C.; Helbing, D. Democratizing Traffic Control in Smart Cities. Transportation Research Part C: Emerging Technologies 2024, 160, 104511. https://doi.org/10.1016/j.trc.2024.104511

[13] Bakirci, M.; Akinci, A.; Tuncer, T. Enhancing Air Pollution Mapping with Autonomous UAV Systems. Atmospheric Research 2024, 306, 074807. https://doi.org/10.1016/j.atmosres.2024.074807

[14] Young, M. The Technical Writer's Handbook; University Science Books: Mill Valley, CA, USA, 1989. ISBN 0-935702-14-5 .

[15] Fattori, F.; Cocuzza, S. Tethered Drones: A Comprehensive Review of Technologies, Challenges, and Applications. Drones 2025, 9(6), 425. https://doi.org/10.3390/drones9060425

[16] Hassanalian, M.; Abdelkefi, A. Classifications, Applications, and Design Challenges of Drones: A Review. Progress in Aerospace Sciences 2017, 91, 99–131. https://doi.org/10.1016/j.paerosci.2017.04.003

[17] Hu, T.-Y.; Li, Y.; Sun, S. A Multi-Agent Deep Reinforcement Learning Approach for Traffic Signal Control. IET Intelligent Transport Systems 2024, 18(4), 349–362. https://doi.org/10.1049/itr2.12489

[18] Zografopoulos, I.; Ospina, J.; Liu, X.; Konstantinou, C. Cyber-Physical Energy Systems Security: Threat Modeling, Risk Assessment, Resources, Metrics, and Case Studies. arXiv preprint arXiv:2105.02337, 2021. https://doi.org/10.48550/arXiv.2105.02337

[19] Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions. Future Generation Computer Systems 2013, 29(7), 1645–1660. https://doi.org/10.1016/j.future.2013.01.010

[20] E. Horvitz, R. Etzioni, T. Mitchell, and P. Stone, Artificial Intelligence and Life in 2030: One Hundred Year Study on Artificial Intelligence, Report of the 2015–2016 Study Panel, Stanford University, Stanford, CA, USA, Sep. 2016. [Online]. Available: https://ai100.stanford.edu/2016-report

[20] Zhong, J.; Fan, A.; Fan, K.; Pan, W.; Zeng, L. Research on the UAV Sound Recognition Method Based on Frequency Band Feature Extraction. Drones 2025, 9, 351. https://doi.org/10.3390/drones9050351

[21] Li, J.; Peng, L.; Xu, S.; Li, Z. Distributed edge signal control for cooperating pre-planned connected automated vehicle path and signal timing at edge computing-enabled intersections. *Expert Systems with Applications* **2024**, 241, 122570. https://doi.org/10.1016/j.eswa.2023.122570

[22] Sutton, R. S.; Barto, A. G. *Reinforcement Learning: An Introduction*, 2nd ed.; MIT Press: Cambridge, MA, 2018.

[23] Bouktif, S.; Cheniki, A.; Ouni, A.; El-Sayed, H. Deep reinforcement learning for traffic signal control with consistent state and reward design approach. *Knowledge-Based Systems* **2023**, 267, 110440. https://doi.org/10.1016/j.knosys.2023.110440

[24] Jin, G.; Chen, L.; Zhang, C.; Ye, J.; Zheng, Y. Spatio-Temporal Graph Neural Networks for Predictive Learning in Urban Computing: A Survey. *IEEE Transactions on Knowledge and Data Engineering* **2024**, 36(10), 5388–5408. https://doi.org/10.1109/TKDE.2023.3324214

[25] Stone, P.; et al. *Artificial Intelligence and Life in 2030: One Hundred Year Study on AI (AI100)*, 2016 Study Panel Report, Stanford University, 2016.

[26] Wang, T.; Zhu, Z.; Zhang, J.; Tian, J.; Zhang, W. A large-scale traffic signal control algorithm based on multi-layer graph deep reinforcement learning. *Transportation Research Part C: Emerging Technologies* **2024**

[27] Fattori, F.; Cocuzza, M.; Papi, G.; Tartaglione, A. Tethered Drones: A Comprehensive Review of Current Technologies. *Drones* **2025**, 9(6), 425. https://doi.org/10.3390/drones9060425

[28] Zhang, Y.; Shao, H.; Zhang, K.; Zhang, Z.; Chen, P. A multi-agent reinforcement learning approach for ART operations. *Computers & Industrial Engineering* **2024**, 197, 109248. https://doi.org/10.1016/j.cie.2024.109248

[29] Bakirci, M.; Akinci, A.; Tuncer, T. Efficient air pollution mapping in extensive regions with UAVs. *Science of the Total Environment* **2024**, 909, 168606. https://doi.org/10.1016/j.scitotenv.2023.168606

[30] Moormann, L.; Böttger, T.; Schuhmann, P.; Valero, L.; Fachinger, F.; Drewnick, F. The Flying Laboratory FLab: development and application of a UAS to measure aerosol particles and trace gases in the lower troposphere. *Atmospheric Measurement Techniques* **2025**,

[31] Sharma, A.; Bedi, J.; Chauhan, N.; Sharma, N. A comprehensive review on the fusion of UAVs and low-cost sensors for real-time air pollution monitoring. *Sustainable Cities and Society* **2025**, 118, 105246. https://doi.org/10.1016/j.scs.2025.105246

[32] Feng, Y.; Wang, Q.; Xia, Y.; Huang, J.; Zhong, S.; Liang, Y. Spatio-Temporal Field Neural Networks for Air Quality Inference. *Proceedings of IJCAI 2024*, Paper 803. https://doi.org/10.24963/ijcai.2024/803

[33] Yang, S.; Zhou, Y.; Ye, J.; Tian, G.; Zhao, W.; Gao, H. Hierarchical graph multi-agent mutual information reinforcement learning for traffic signal control. *Information Sciences* **2023**, 624, 108–125. https://doi.org/10.1016/j.ins.2022.12.093

[34] Khan, L. U.; Yaqoob, I.; Tran, N. H.; Kazmi, S. M. A.; Dang, T. N.; Hong, C. S. Edge-Computing-Enabled Smart Cities: A Comprehensive Survey. *IEEE Internet of Things Journal* **2020**, 7(10), 10200–10232. https://doi.org/10.1109/JIOT.2020.2987070

[35] Jaroń, A.; Borucka, A.; Deliś, P.; Sekrecka, A. An Assessment of the Possibility of Using Unmanned Aerial Vehicles to Identify and Map Air Pollution from Infrastructure Emissions. *Energies* **2024**, 17(3), 577. https://doi.org/10.3390/en17030577

[36] European Commission, Ethics Guidelines for Trustworthy AI, Brussels: High-Level Expert Group on Artificial Intelligence, 2019. [Online]. Available: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[37] European Commission, The European Green Deal, Brussels, 2020. [Online]. Available: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

[38] United Nations, Transforming Our World: The 2030 Agenda for Sustainable Development, UN General Assembly Resolution A/RES/70/1, New York, 2015. [Online]. Available: https://sustainabledevelopment.un.org/post2015/transformingourworld/publication

[39] M. Bakirci, F. Fattori, F. Zardi, and L. Tanzi, "Smart city air quality management through leveraging drones," Science of the Total Environment, vol. 927, 147124, 2024.

[40] Y. Durgun and M. Durgun, "Smart environmental drone utilization for monitoring urban air quality," Environment, Development and Sustainability, vol. 7, no. 2, pp. 194–200, 2024.

[41] A. Ghasemi, "Review of Edge Intelligence for Intelligent Transport Systems," Engineering Applications of Artificial Intelligence, 2025.

[42] K. Haseeb, I. Ahmed, F. Khattak, and A. Ibrahim, "Intelligent and secure edge-enabled computing model for sustainable cities," Sustainable Cities and Society, vol. 72, 103031, 2021.

[43] European Commission, A European Strategy for Data, Brussels, 2020. [Online]. Available: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/european-data-strategy_en

[44] J. Pargoo, M. Ghasemi, and S. Shahraki, "The Streetscape Application Services Stack (SASS): Towards a Distributed Sensing Architecture for Urban Applications," arXiv preprint arXiv:2411.19714, Nov 2024. [Online]. Available: https://arxiv.org/abs/2411.19714

[45] A. Musa, M. Bani Younes, and H. Alrawashdeh, "Sustainable Traffic Management for Smart Cities Using IoT and Intelligent Transportation Systems," Sustainability, vol. 15, no. 13, 9859, 2023.

[46] I. Mutambik, "IoT-Enabled Adaptive Traffic Management: A Multi-Agent Framework for Urban Mobility Optimisation," Sensors, vol. 25, no. 13, 4126, 2025.

[47] L. Martin and U. Asad, "The Role of Edge Computing in Modern Traffic Management and Speed Detection," ResearchGate Preprint, 2024. [Online]. Available: https://www.researchgate.net/publication/386290256