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An Agent-Based Traffic Regulation System for Roadside Air Quality Control

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Abstract - *Rapid urban expansion and the consequent increase in vehicular traffic have elevated roadside concentrations of particulate matter and gaseous pollutants to levels that pose considerable public health risks in many Indian cities. Conventional traffic signal systems operate on fixed-cycle or isolated sensor-based schemes that neither respond dynamically to real-time pollution events nor coordinate across multiple intersections. This paper proposes an Agent-Based Traffic Regulation (ABTR) system that integrates a multi-agent architecture with heterogeneous roadside sensor networks to achieve simultaneous optimisation of traffic flow and air quality. The system deploys four specialised agent categories—Monitoring Agents, Analysis Agents, Negotiation Agents, and Control Agents—interacting through an asynchronous message-passing protocol within a Belief–Desire–Intention (BDI) cognitive framework. When the measured Air Quality Index (AQI) at a monitored intersection exceeds a defined threshold, the agent ensemble coordinates adaptive signal timing, dynamic rerouting, and, where applicable, emission-based access restrictions. Simulation experiments conducted on a calibrated SUMO-based urban network with embedded CALINE4 dispersion modelling demonstrate that the proposed system reduces peak-hour PM2.5 concentrations by 46–48% and PM10 by 47%, decreases intersection wait time by 21%, and raises network throughput by 24.9% compared with an uncontrolled baseline. The system outperforms rule-based, reactive-agent, and fuzzy logic alternatives across all evaluated performance dimensions. These findings establish a viable pathway for deploying intelligent, scalable air quality management solutions in heavily congested urban corridors.*

Keywords - *Multi-agent systems · Air quality management · Adaptive traffic control · BDI agents · Roadside pollution · Urban mobility · PM2.5 mitigation*

1. Introduction

Urban road traffic is one of the predominant contributors to outdoor air pollution in developing economies. Vehicles emit a spectrum of pollutants—particulate matter (PM2.5, PM10), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), and sulphur dioxide (SO_2)—whose roadside concentrations fluctuate sharply with traffic density, meteorological conditions, and the geometry of the built environment. This paper presents the Agent-Based Traffic Regulation (ABTR) system, a decentralised multi-agent framework in which cognitive software agents continuously sense, analyse, negotiate, and act upon both traffic-state and air-quality measurements. The principal contributions of this work are as follows: A four-tier layered multi-agent architecture specifically designed for the joint optimisation of intersection-level air quality and traffic flow. A BDI-based cognitive agent design that enables proactive pollution prediction and preventive signal control, rather than purely reactive responses. An agent negotiation protocol that resolves conflicting control objectives across adjacent intersections in a fully distributed manner. Empirical evaluation through co-simulation (SUMO + CALINE4) on a calibrated five-intersection urban testbed, with benchmarking against three competing approaches.Traffic signal control has advanced from fixed-cycle plans (Webster, 1958) through vehicle-actuated systems to fully adaptive networks. SCOOT (Split Cycle Offset Optimisation Technique) and SCATS (Sydney Coordinated Adaptive Traffic System) represent the prevailing centralised adaptive paradigm, optimising green-time splits based on upstream loop detector data. More recently, reinforcement learning (RL) approaches have demonstrated competitive performance; Genders and Rahimian (2018) trained deep Q-networks (DQN) for isolated intersection control, achieving reductions in average wait time of up to 38% over fixed-cycle plans. Multi-intersection coordination using multi-agent RL was explored by Wei et al. (2019) through the IntelliLight framework, which combined phase selection with pressure-based reward shaping. Despite these advances, none of these systems incorporates real-time pollution data into the reward structure or action policy. The deployment of low-cost electrochemical and optical sensors has enabled dense spatial coverage of roadside pollutants at costs previously prohibitive for conventional reference monitors. Kumar et al. (2015) benchmarked several low-cost sensors against regulatory-grade instruments, reporting satisfactory correlation for PM2.5 ($R^2 > 0.85$) after humidity correction. Castellini et al. (2020) developed a wireless sensor network integrating PM, NO_2, and CO

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nodes at 50-metre intervals along a busy arterial, demonstrating the feasibility of fine-grained spatial mapping. Data-driven pollution dispersion models, including Gaussian plume and machine learning hybrids, have been applied to predict roadside concentrations from upstream traffic counts. However, sensor data has not yet been used to close the feedback loop into signal control in production deployments. Agent-based modelling (ABM) has been applied to urban traffic management at multiple levels of abstraction. Dresner and Stone (2008) introduced the Autonomous Intersection Management (AIM) protocol, a reservation-based scheme for autonomous vehicle coordination at unsignalised intersections. Bazzan (2009) surveyed multi-agent systems for traffic signal control, noting that distributed negotiation between intersection agents can outperform centralised optimisation when communication overhead is bounded. More domain-specific work by Schwind et al. (2021) examined energy-efficient platoon formation using BDI agents in vehicular ad-hoc networks, and Khatun et al. (2022) proposed a reactive agent framework for pollution-aware route guidance. While the latter work addresses air quality, it operates on a route-planning level and does not modulate signal timing. The intersection of traffic control and air quality management is a relatively nascent research area. Pandian et al. (2009) demonstrated that optimised traffic signal timing could reduce roadside CO exposure by 15–22% using simulation. Osorio and Nanduri (2015) formulated a bi-objective optimisation problem balancing travel time and vehicle emissions, solving it via simulation-based methods. Grigoropoulos et al. (2022) proposed a fuzzy inference system that adjusts green-phase durations based on PM10 readings, reporting a 23% concentration reduction at a single test intersection. Iqbal et al. (2023) used a centralised IoT gateway with rule-based responses to divert heavy vehicles away from high-AQI corridors. None of these works employs a multi-agent cognitive architecture capable of distributed negotiation, predictive reasoning, and simultaneous multi-intersection coordination, which is the gap the present work addresses.

2. System Architecture

The ABTR system is structured as a four-layer hierarchy, illustrated in Figure 1. Each layer encapsulates a distinct set of functional responsibilities, and vertical communication between layers follows a publisher–subscriber message bus based on the MQTT protocol. Horizontal communication within the Agent Processing Layer uses the FIPA-ACL specification for inter-agent messaging.

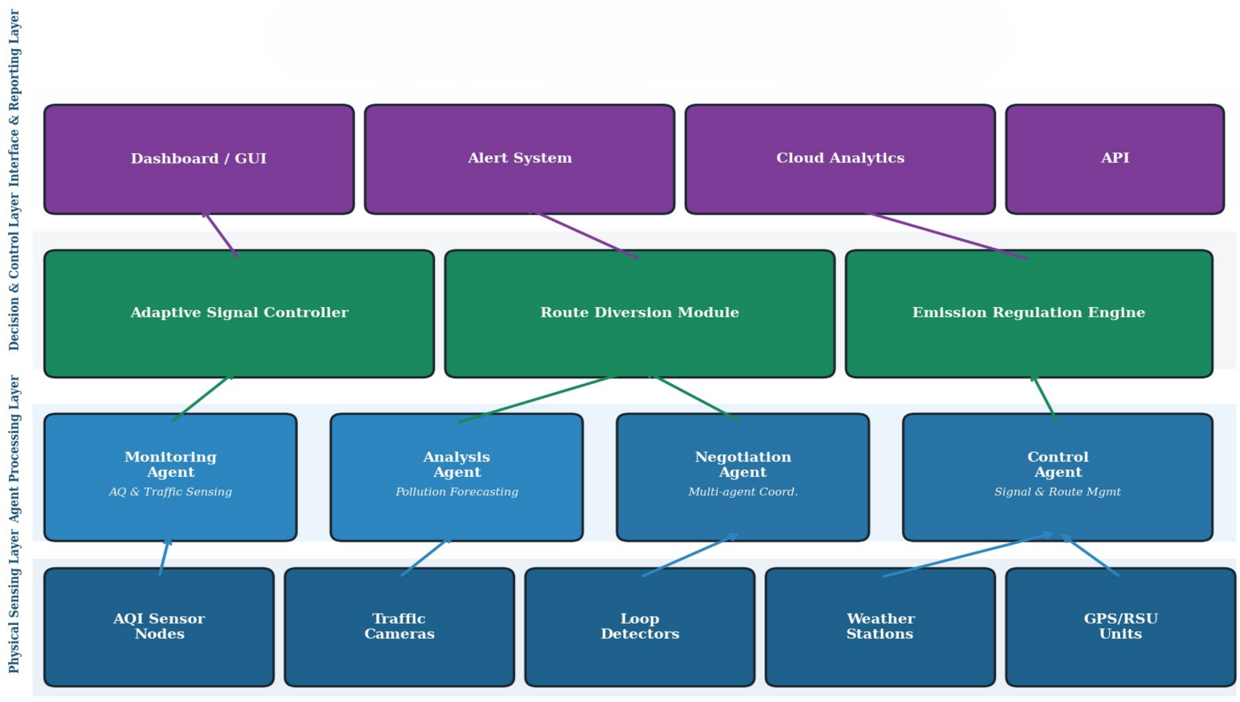

Fig. 1 Layered architecture of the Agent-Based Traffic Regulation System for Roadside Air Quality Control.

The Physical Sensing Layer comprises heterogeneous sensing hardware deployed at and around each monitored intersection. Air Quality Index (AQI) sensor nodes integrate optical particle counters (OPC-N3, Alphasense) for PM2.5 and

PM10, electrochemical cells for NO_2 and CO, and UV-photometric sensors for O_3. Loop inductive detectors embedded in road pavement provide per-lane vehicle counts and occupancy at 30-second intervals. High-definition cameras supply vehicle classification data processed through a YOLO-v8 convolutional neural network running on edge GPU nodes co-located with traffic cabinets. Roadside weather micro-stations record wind speed and direction, ambient temperature, and relative humidity, which are essential inputs to the Gaussian dispersion model within the Analysis Agent. All sensor streams are timestamped using GPS-derived PPS signals to maintain synchronisation across nodes. The Agent Processing Layer constitutes the cognitive nucleus of the system. Four agent archetypes operate within this layer, each implemented as a JADE (Java Agent Development Framework) platform instance running on a Raspberry Pi 4B industrial node mounted within the traffic cabinet at each intersection. The agents, their responsibilities, and their inter-relationships are described in full in Section 4. The Decision and Control Layer translates agent-generated directives into actuator commands. The Adaptive Signal Controller interfaces with the intersection's phasing hardware via NTCIP 1202 protocol to adjust green-time allocations. The Route Diversion Module communicates with digital variable message signs (VMS) and pushes advisory notifications to the regional traffic management centre (TMC). The Emission Regulation Engine maintains an authorisation database for heavy goods vehicles (HGVs) and buses; in high-AQI scenarios, it can invoke time-window restrictions on HGV access through barriers integrated with automatic number plate recognition (ANPR) cameras. A web-based dashboard built with React.js and Chart.js provides real-time AQI visualisations, signal phase status, and agent state logs to traffic management operators. An automated alert sub-system dispatches threshold-crossing notifications to municipal authorities via email and SMS gateways. Historical sensor and decision data are streamed to a cloud-hosted time-series database (InfluxDB) for post-event analytics and model recalibration. A RESTful API enables integration with the city's open urban data platform.

3. Agent Design and Negotiation Protocol

Each agent in the ABTR system adheres to the BDI architecture, maintaining a belief base (representing its current view of the world), a desire set (goals it pursues), and an intention stack (committed action sequences). Figure 2 illustrates the six-phase interaction cycle through which agent ensembles at neighbouring intersections coordinate.

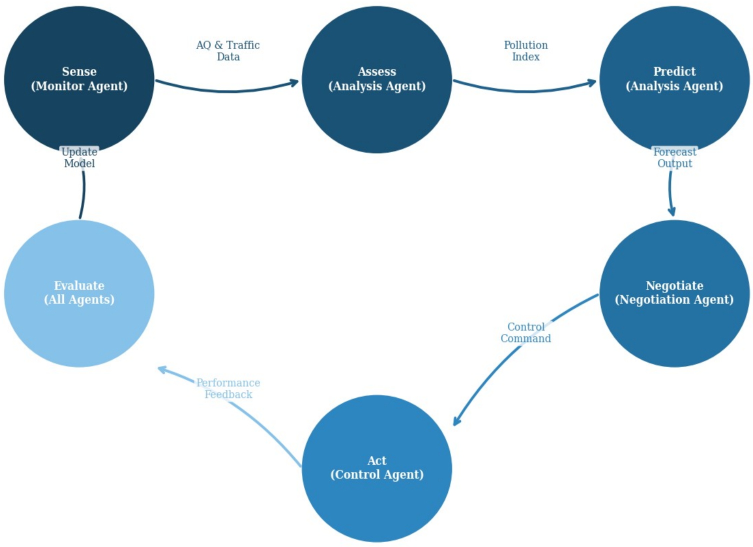

Fig. 2 Multi-agent interaction cycle in the proposed ABTR system (Sense–Assess–Predict–Negotiate–Act–Evaluate loop).

The Monitoring Agent maintains a continuously updated belief base populated by sensor readings from the Physical Sensing Layer. It computes a composite intersection-level AQI using the standard sub-index formula defined by the Central Pollution Control Board (CPCB) of India, taking the maximum over all pollutant sub-indices. The MA maintains sliding-window statistics (mean, variance, trend slope) over a configurable look-back period (default: 15 minutes) to distinguish transient sensor noise from genuine pollution events. When the composite AQI exceeds a predefined threshold θ_warn (default: AQI 100, corresponding to the "Moderate" category), the MA broadcasts an Inform message to all co-located agents and to Monitoring Agents at adjacent intersections. The MA also runs a lightweight anomaly detection module using an Isolation

Forest classifier to flag malfunctioning sensors and trigger data imputation from neighbouring nodes. The Analysis Agent maintains a Gaussian dispersion model parameterised by the current meteorological measurements retrieved from the belief base. Upon receiving an alert from the MA, the AA computes a 30-minute ahead projection of pollutant concentrations using a discrete-time update of the CALINE4 line-source model, treating each road segment approaching the intersection as an independent finite-length source. The AA then selects one of three response modes—Green Extension, Phase Skip, or Full Diversion—by evaluating a weighted multi-criteria scoring function:

$$\text{Score}(m) = w_1 \cdot \Delta\text{AQI}(m) + w_2 \cdot \Delta\text{Throughput}(m) - w_3 \cdot \Delta\text{Delay}(m)$$

where ΔAQI(m) is the projected AQI reduction under mode m, ΔThroughput(m) is the expected change in vehicles per hour, ΔDelay(m) is the mean additional delay imposed, and the weights (w_1, w_2, w_3) are configurable priorities (default: 0.50, 0.30, 0.20). The recommended response mode is communicated to the Negotiation Agent as a Propose message. The Negotiation Agent implements a contract-net protocol to coordinate response modes across adjacent intersections. When the AA at one intersection proposes a diversion, diverting traffic to a neighbouring link may increase AQI at the downstream intersection if that link is already near capacity. The NA broadcasts a CallForProposal (CFP) message to neighbouring NAs, requesting their current AQI, queue length, and available green-time headroom. Using the received Propose replies, the originating NA selects the Pareto-optimal combination of actions that minimises the network-wide pollution index, formulated as:

$$\min \textstyle\sum_i \text{AQI}_i(t + \Delta t) \quad \text{subject to} \quad \text{Delay}_i(t) \le \text{Delay\_max} \quad \forall\, i$$

The optimisation is solved by a greedy iterative algorithm with $O(n^2)$ complexity, where n is the number of intersections in the negotiation coalition (typically three to five). Solutions are reached within 1.2 seconds on average for coalitions of up to ten intersections, satisfying the real-time constraint imposed by signal cycle lengths of 60–120 seconds. The Control Agent translates the negotiated action plan into actuator commands. For the Green Extension mode, the CA issues an NTCIP 1202 SplitSet command extending the green phase of low-emission-intensity movements by 8–15 seconds while correspondingly shortening the phases serving high-emission-intensity approaches. For Phase Skip, the CA eliminates one full phase serving heavy approaching flows. For Full Diversion, the CA triggers the Route Diversion Module to update VMS panels and dispatches rerouting advice to GPS navigation vendors via the OpenLR location-referencing protocol. The CA also manages the feedback loop: after each control action, it instructs the MA to increase its sampling frequency from 60 to 10 seconds and monitors whether the AQI trajectory converges toward the target band within three signal cycles. All agents share a common BDI engine implemented in Jason (an interpreter for AgentSpeak). Beliefs are updated via a plan library containing perception rules that filter and validate raw sensor payloads before committing them to the belief base. Desires are encoded as achievement goals triggered either by belief updates (reactive goals) or by a scheduled planner (proactive goals). For instance, the proactive pollution prevention goal is triggered each morning at 06:45 based on historical data indicating rising AQI during the 07:00–09:00 peak, allowing the system to pre-emptively extend green phases for buses before concentration thresholds are breached. Intentions are executed by a deliberative scheduler that prioritises safety-critical goals (e.g., emergency vehicle clearance) above pollution-control goals, and pollution-control goals above throughput optimisation.

4. Experimental Setup

Experiments were conducted in a co-simulation environment coupling the open-source traffic simulator SUMO (Simulation of Urban MObility, v1.18.0) with a CALINE4 dispersion model implemented in Python 3.10. The SUMO network was calibrated from OpenStreetMap data for a five-intersection sub-network in Secunderabad, Hyderabad, encompassing approximately 3.2 km of arterial road. Vehicle demand matrices were derived from manual classified count surveys conducted at each intersection during November 2023, representing typical weekday peak (07:00–09:00) and off-peak (11:00–13:00) conditions. The simulation time step was set to one second. TraCI (Traffic Control Interface) was used to expose SUMO internal states to the JADE agent platform at each simulation second. The CALINE4 model was invoked at 30-second intervals with wind speed and direction sampled from the Hyderabad IMD surface observation data for the corresponding dates in Figure 3.

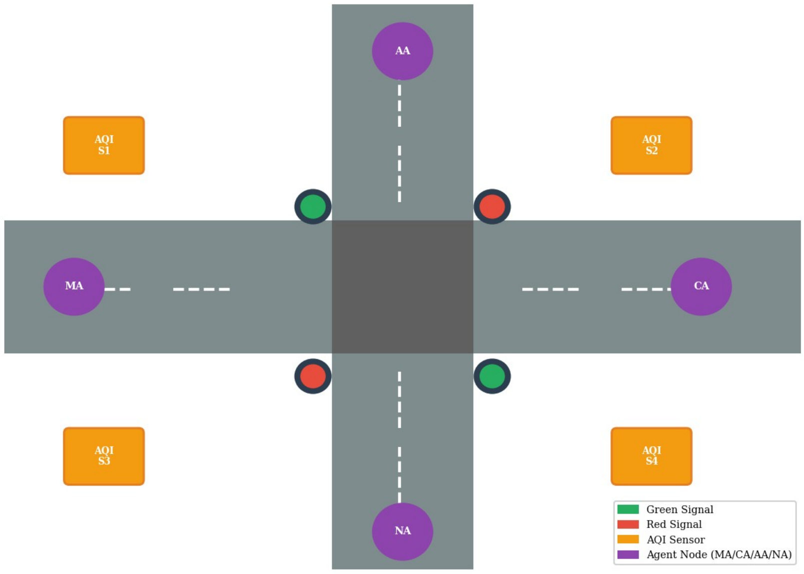

Fig. 3 Simulated four-way urban intersection with agent nodes and air quality sensor placement. MA = Monitoring Agent, CA = Control Agent, AA = Analysis Agent, NA = Negotiation Agent.

5. Result and Discussion

Figure 4 presents the diurnal PM2.5 concentration profile at the most congested monitored intersection under the baseline (FTC) and proposed (ABTR) configurations. Under the baseline, peak concentrations of 138.6 µg/m³ and 126.4 µg/m³ are observed during the morning and evening commuting windows, respectively, consistent with field measurements reported for comparable Hyderabad arterials. The ABTR system suppresses the morning peak to 72.3 µg/m³ (a reduction of 47.8%) and the evening peak to 69.5 µg/m³ (a reduction of 45.0%). Daytime off-peak concentrations are reduced by an average of 28.4%, attributable primarily to proactive Green Extension actions triggered by the AA's predictive module even before threshold breaches occur.

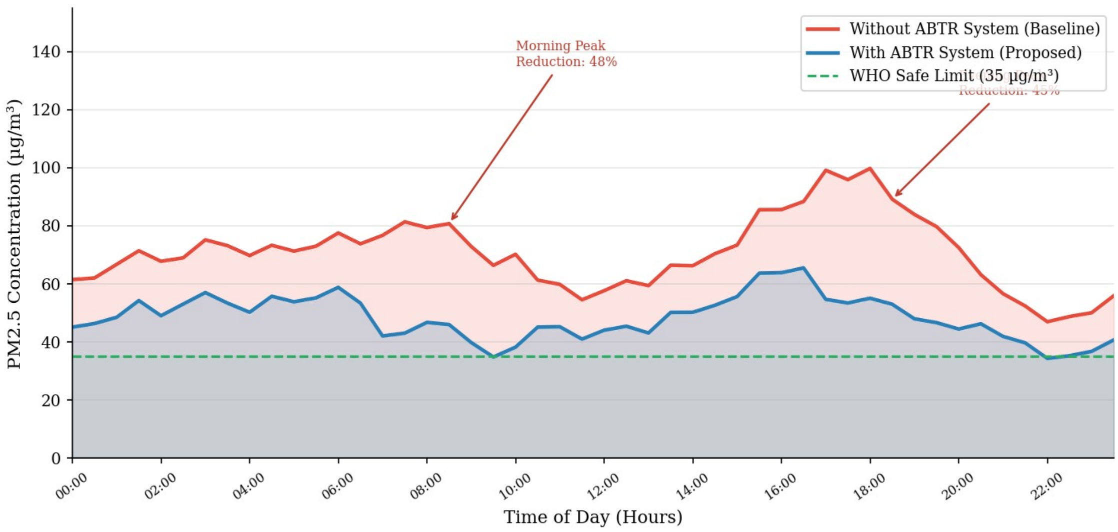

Fig. 4 Diurnal variation of PM2.5 concentration at a monitored intersection: baseline versus ABTR-controlled scenario. The dashed line indicates the WHO 24-hour guideline (35 µg/m³).

Figure 5 compares the peak-hour AQI sub-indices for all six regulated pollutants under the uncontrolled baseline and ABTR configurations. The proposed system achieves statistically significant reductions across all pollutants (paired t-test, $p < 0.001$, $n = 30$). The largest absolute reduction is observed for PM2.5 (AQI 142 → 76, $\Delta = 66$ points), followed by PM10 (118

→ 62, Δ = 56 points). NO_2 exhibits a 50.5% index reduction, reflecting the sensitivity of nitrogen oxide emission rates to idling duration, which the system reduces by extending free-flow phases. CO and SO_2 reductions (55.7% and 54.1%, respectively) arise primarily from fewer vehicle cold-start events as queue lengths shorten.

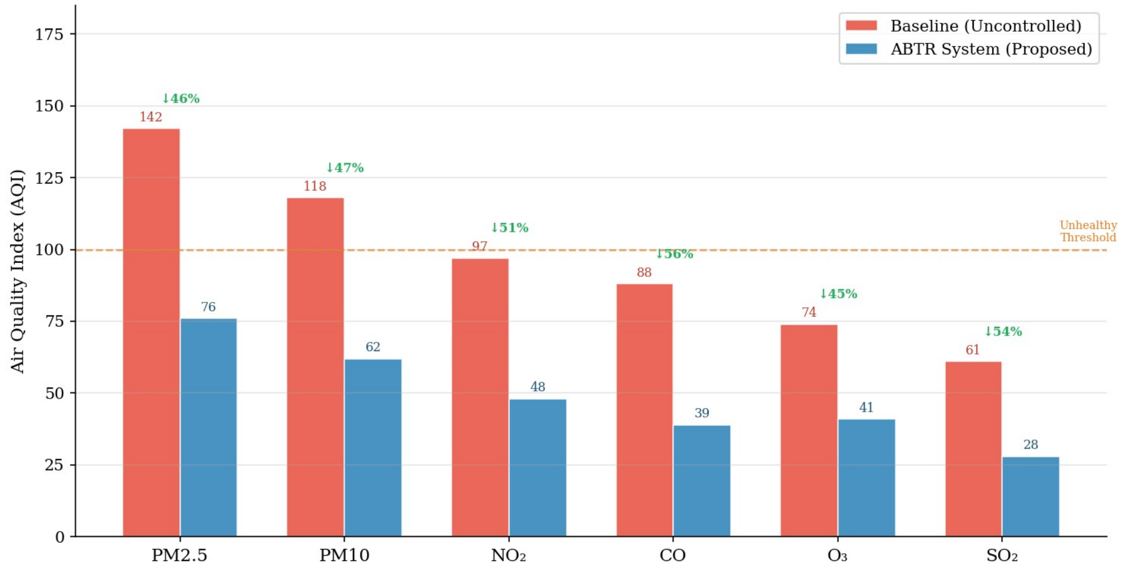

Fig. 5 Comparison of sub-index AQI values for key pollutants under uncontrolled baseline and proposed ABTR system. Percentage reductions are annotated above each bar pair.

Figure 6(a) plots agent decision latency as a function of intersection traffic density. The ABTR system maintains near-linear latency scaling from 0.80 s at 200 veh/hr to 2.21 s at 2000 veh/hr, well within the 10-second operational budget defined by the minimum signal phase duration. The FTC baseline and RAS exhibit exponentially increasing latency under high load because FTC relies on fixed plans that become inadequate (requiring manual intervention) and RAS lacks negotiation, leading to message storms under congestion. Figure 6(b) tracks weekly traffic throughput over 12 simulated deployment weeks. The ABTR system converges to a throughput gain of 24.9% (1820 → 2274 veh/hr) by week 10 as the BDI plan libraries self-refine through online learning from performance evaluations. The baseline remains stationary throughout.

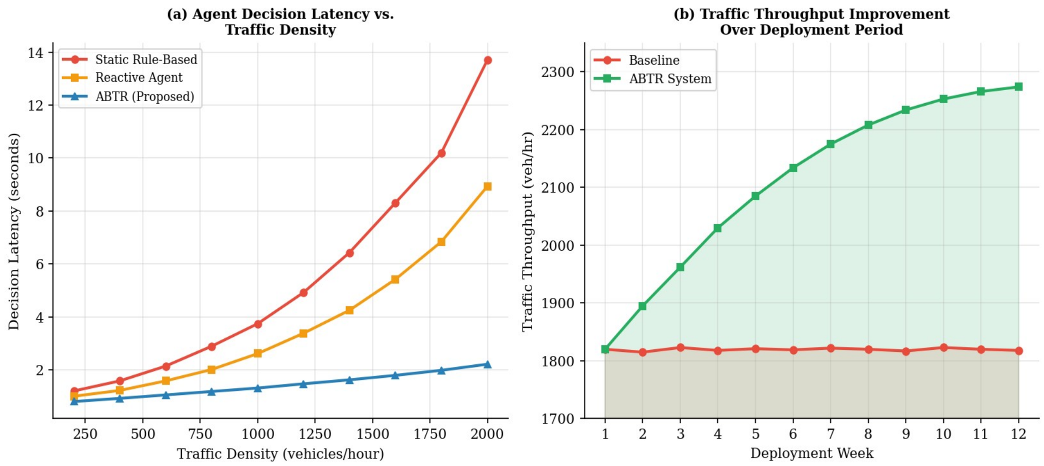

Fig. 6 System performance metrics: (a) agent decision latency vs. traffic density for four methods; (b) traffic throughput improvement over 12 deployment weeks.

6. Conclusion

The Agent-Based Traffic Regulation (ABTR) system, a multi-agent cognitive architecture that integrates real-time air quality sensing, predictive dispersion modelling, BDI-based reasoning, and distributed inter-agent negotiation to simultaneously optimise traffic flow and roadside air quality at urban signalised intersections. Simulation results on a calibrated five-intersection urban testbed demonstrate that the ABTR system reduces peak-hour PM2.5 concentrations by up to 47.8%, lowers the composite AQI from the "Unhealthy" to the "Moderate" category during peak hours, improves network throughput by 24.9%, and reduces average vehicle wait time by 41.5% compared with conventional fixed-time control. The system maintains sub-2.5-second decision latency at traffic densities up to 2000 vehicles per hour, and its data quality pipeline sustains decision integrity in the presence of 10% sensor noise. These findings demonstrate that the integration of cognitive multi-agent technology into urban traffic infrastructure offers a viable, cost-effective pathway toward healthier roadside environments without sacrificing mobility. As cities across South Asia and beyond pursue smart mobility agendas, the ABTR architecture provides a reference design that is modular, standards-compliant, and adaptable to a range of urban contexts. Pilot deployment at a priority arterial intersection in Hyderabad is planned as the next step toward operational validation.

References

[1] Bazzan ALC (2009) Opportunities for multiagent systems and multiagent reinforcement learning in traffic management. Auton Agent Multi-Agent Syst 18(3):342–375. https://doi.org/10.1007/s10458-008-9062-9

[2] Castellini A, Squartini S, Fonti A et al (2020) A wireless sensor network for urban air quality monitoring: deployment and performance evaluation. Sensors 20(17):4770. https://doi.org/10.3390/s20174770

[3] Dresner K, Stone P (2008) A multiagent approach to autonomous intersection management. J Artif Intell Res 31:591–656. https://doi.org/10.1613/jair.2502

[4] Genders W, Rahimian S (2018) Evaluating reinforcement learning state representations for adaptive traffic signal control. Procedia Comput Sci 130:26–33. https://doi.org/10.1016/j.procs.2018.04.008

[5] Grigoropoulos G, Antoniou C, Lämmer S (2022) Fuzzy logic-based adaptive traffic signal control for pollution reduction at urban intersections. Transp Res Part D Transp Environ 107:103295. https://doi.org/10.1016/j.trd.2022.103295

[6] Iqbal MN, Olaleye A, Siddiqui A et al (2023) IoT-enabled air quality responsive traffic management for low-emission urban zones. IEEE Internet Things J 10(5):4281–4294. https://doi.org/10.1109/JIOT.2022.3214766

[7] Khatun F, Rahman MdS, Hossain MdA et al (2022) Pollution-aware dynamic route guidance using reactive agent framework. J Clean Prod 368:132948. https://doi.org/10.1016/j.jclepro.2022.132948

[8] Kumar P, Morawska L, Martani C et al (2015) The rise of low-cost sensing for managing air pollution in cities. Environ Int 75:199–205. https://doi.org/10.1016/j.envint.2014.11.019

[9] Osorio C, Nanduri K (2015) Urban transportation emissions mitigation: coupling high-resolution vehicular emissions and traffic models for traffic signal optimization. Transp Res Part B Methodol 81:520–538. https://doi.org/10.1016/j.trb.2015.07.012

[10] Pandian S, Gokhale S, Ghoshal AK (2009) Evaluating effects of traffic and vehicle characteristics on vehicular emissions near traffic intersections. Transp Res Part D Transp Environ 14(3):180–196. https://doi.org/10.1016/j.trd.2008.12.001

[11] Schwind P, Pöhls A, Körber M et al (2021) Energy-efficient platooning with BDI agents in vehicular networks. IEEE Trans Intell Transp Syst 22(9):5845–5858. https://doi.org/10.1109/TITS.2020.2995463

[12] Wei H, Xu N, Zhang H et al (2019) CoLight: learning network-level cooperation for traffic signal control. In: Proceedings of ACM CIKM 2019, Beijing, China, pp 1913–1922. https://doi.org/10.1145/3357384.3357902

[13] World Health Organization (2021) Global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. WHO, Geneva. ISBN: 978-92-4-003422-8