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Deep Learning-Based Predictive Traffic Signal Optimization for Smart Cities: A Comparative Analysis of Centralized and Edge-AI Urban Transportation Architectures

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ABSTRACT

Rapid urbanization, increasing vehicle ownership, and growing mobility demand have intensified congestion, energy inefficiency, and environmental degradation within urban transportation systems. Conventional traffic signal control infrastructures frequently rely on static timing mechanisms or centralized adaptive control architectures that struggle to respond effectively to real-time traffic variability and heterogeneous mobility conditions. This article comparatively evaluates two intelligent transportation architectures for predictive traffic signal optimization: centralized cloud-based traffic intelligence and decentralized edge-AI traffic management systems. Using computational transportation simulation, deep reinforcement learning, urban traffic-flow analytics, and Internet of Things (IoT)-enabled sensing environments, the study investigates how distributed transportation intelligence influences congestion mitigation, travel-time efficiency, energy consumption, and environmental sustainability. Comparative analysis demonstrates that edge-AI traffic optimization significantly improves adaptive signal responsiveness, reduces average vehicle delay, enhances intersection throughput, and lowers transportation-related emissions under highly dynamic urban traffic conditions. The findings further reveal that decentralized transportation intelligence strengthens scalability and resilience within smart-city infrastructures by minimizing communication latency and enabling localized decision autonomy. This article contributes to transportation engineering scholarship by integrating intelligent transportation systems theory, deep reinforcement learning, edge computing, and sustainable urban mobility analysis into a unified systems-engineering framework. The study also provides operational implications for future smart-city governance, intelligent infrastructure deployment, and sustainable urban transportation transformation.

Keywords
Intelligent transportation systems; smart cities; traffic signal optimization; deep reinforcement learning; edge computing; urban mobility; sustainable transportation; IoT infrastructure; transportation engineering; adaptive traffic control

INTRODUCTION

Urban transportation systems are undergoing profound transformation due to rapid urbanization, expanding mobility demand, technological digitalization, and increasing sustainability pressures. According to the United Nations, nearly 68% of the global population is expected to reside in urban environments by 2050, substantially intensifying pressure on transportation infrastructures, traffic management systems, and urban mobility governance (United Nations, 2022). Simultaneously, vehicle ownership growth, freight logistics expansion, and increasing commuter density have generated escalating congestion costs, energy inefficiency, environmental pollution, and public health risks across metropolitan regions worldwide.

Transportation congestion constitutes not only an operational inefficiency but also a multidimensional engineering and sustainability challenge. The International Transport Forum estimates that urban traffic congestion contributes significantly to fuel waste, greenhouse gas emissions, commuter productivity losses, and transportation system unreliability (ITF, 2023). Conventional traffic management systems frequently rely upon static signal timing plans that cannot dynamically adapt to fluctuating traffic conditions, emergency events, multimodal transportation variability, or real-time urban mobility patterns. Even adaptive traffic systems based on centralized control architectures often experience delayed responsiveness due to communication bottlenecks, centralized computational dependency, and limited scalability across highly complex urban transportation networks.

The emergence of smart-city technologies has intensified interest in intelligent transportation systems (ITS) integrating artificial intelligence, IoT sensing environments, edge computing, and predictive traffic analytics. Contemporary ITS infrastructures increasingly incorporate computer vision systems, connected vehicle communication, wireless sensor networks, adaptive signal control, and machine learning-driven transportation optimization mechanisms (Zhang et al., 2021). These technologies enable transportation systems to operate as interconnected cyber-physical mobility ecosystems capable of autonomous adaptation and real-time traffic management.

Among contemporary AI methodologies, deep reinforcement learning (DRL) has emerged as one of the most influential computational approaches for adaptive traffic optimization. Reinforcement learning allows transportation agents to learn dynamic traffic-control policies through iterative interaction with urban traffic environments. Previous studies demonstrate that DRL-based signal optimization can improve traffic throughput, reduce queue lengths, and enhance adaptive coordination across intersections (Wei et al., 2019). However, many existing implementations remain dependent upon centralized cloud-based computational infrastructures that struggle under highly dynamic and latency-sensitive urban mobility conditions.

Edge computing has therefore gained increasing significance within intelligent transportation engineering because it enables localized processing and decentralized decision-making directly near transportation infrastructures. Edge-AI architectures reduce communication latency, improve responsiveness, minimize bandwidth dependence, and strengthen system resilience within distributed urban mobility environments (Shi et al., 2020). Nevertheless, comparative engineering scholarship evaluating centralized versus edge-based traffic intelligence architectures remains limited.

Previous studies have investigated several dimensions of intelligent transportation optimization. Li et al. (2020) examined adaptive traffic control using reinforcement learning and reported measurable reductions in average vehicle delay. Similarly, Zheng et al. (2022) explored IoT-enabled smart intersections and demonstrated improvements in traffic-flow prediction accuracy. Other researchers have emphasized the role of edge computing in improving responsiveness within autonomous transportation infrastructures (Tang et al., 2021). However, existing technological scholarship remains fragmented regarding how decentralized transportation intelligence affects broader operational efficiency, sustainability performance, scalability, and urban mobility resilience.

Current literature reveals several major research gaps. First, many transportation studies evaluate AI algorithms independently without integrating systems-engineering analysis of infrastructure architecture. Second, comparative evaluation between centralized cloud intelligence and decentralized edge-AI traffic management remains underdeveloped. Third, existing transportation optimization studies frequently prioritize congestion metrics while neglecting energy consumption and environmental sustainability implications. Fourth, benchmarking frameworks capable of simultaneously evaluating latency, adaptability, throughput, emissions reduction, and scalability remain insufficiently integrated.

This study addresses these limitations through a comparative computational analysis of two smart-city traffic optimization architectures: centralized cloud-based transportation intelligence and decentralized edge-AI transportation intelligence. The article evaluates how distributed AI-enabled traffic optimization mechanisms influence urban mobility efficiency, congestion mitigation, environmental sustainability, and transportation-system resilience.

The novelty of this research emerges from several integrated contributions. First, the article develops a comparative transportation-engineering framework linking deep reinforcement learning, edge computing, and sustainable urban mobility systems. Second, the study integrates transportation simulation, IoT sensing analysis, adaptive signal optimization, and environmental-performance evaluation into a unified interdisciplinary methodology. Third, the article operationalizes transportation sustainability through measurable engineering variables including vehicle delay, queue dynamics, travel-time efficiency, energy consumption, communication latency, and emissions reduction. Finally, the research contributes theoretically by conceptualizing intelligent transportation systems as decentralized adaptive mobility ecosystems rather than merely centralized traffic-control infrastructures.

The analytical framework guiding this study follows the relationship:

Urban sensing infrastructure → Deep reinforcement learning optimization → Adaptive traffic control → Congestion mitigation and energy efficiency → Sustainable urban mobility resilience.

Accordingly, the primary objective of this article is to comparatively evaluate how decentralized edge-AI traffic optimization architectures influence transportation efficiency, sustainability, and urban mobility resilience relative to centralized cloud-based intelligent transportation systems.

METHODOLOGY

This study employed a comparative computational transportation-engineering research design integrating urban traffic simulation, deep reinforcement learning optimization, IoT-enabled transportation sensing, and systems-level sustainability analysis. Two intelligent transportation architectures were comparatively evaluated: a centralized cloud-based traffic optimization framework and a decentralized edge-AI traffic management architecture operating across distributed smart intersections. The analytical framework aligned transportation systems engineering theory with reinforcement learning adaptation and smart-city mobility analysis to investigate how computational architecture influences traffic responsiveness, congestion mitigation, and sustainability performance. Urban traffic environments were modeled using SUMO (Simulation of Urban Mobility) integrated with TensorFlow-based deep reinforcement learning agents and edge-computing simulation environments. The comparative design was selected because centralized and decentralized transportation intelligence systems represent fundamentally different operational paradigms characterized by distinct communication structures, computational responsiveness, and adaptive coordination mechanisms. Primary analytical variables included average vehicle delay, queue length, traffic throughput, intersection waiting time, communication latency, fuel consumption, transportation-related carbon emissions, and adaptive signal responsiveness under variable traffic-density conditions.

The computational analysis incorporated repeated traffic-flow simulations under heterogeneous urban mobility scenarios including rush-hour congestion, emergency-vehicle priority events, stochastic traffic fluctuations, and multimodal transportation variability involving buses, passenger vehicles, cyclists, and pedestrians. Deep Q-network reinforcement learning agents were trained through iterative environmental interaction to optimize traffic signal timing under dynamic conditions. Statistical evaluation integrated comparative throughput analysis, sensitivity testing, and multivariate transportation-performance benchmarking to assess differences between centralized and edge-AI architectures. Transportation datasets were derived from publicly available urban traffic benchmarks, smart-city mobility reports, and transportation-sensor simulation repositories frequently used within intelligent transportation systems research. Validation procedures included repeated simulation cycles under equivalent traffic-demand assumptions and cross-comparison with peer-reviewed adaptive traffic-control benchmarks. Ethical and technological considerations included transportation data anonymization, cybersecurity-aware communication modeling, and resilience analysis associated with distributed urban infrastructure operation. Although the study achieved strong computational reproducibility, limitations remain concerning the absence of full-scale metropolitan deployment and potential variability associated with real-world human driving behavior and heterogeneous infrastructure interoperability.

Findings and Discussion

1. Comparative Traffic Responsiveness and Congestion Mitigation

The comparative computational evaluation demonstrated substantial operational differences between centralized traffic intelligence and decentralized edge-AI transportation architectures. Centralized cloud-based systems exhibited relatively strong large-scale coordination capabilities but experienced significant responsiveness limitations during highly dynamic urban traffic conditions characterized by abrupt congestion variability and heterogeneous intersection behavior.

The centralized architecture depended heavily on continuous communication between distributed urban intersections and centralized processing servers. Consequently, adaptive traffic-control decisions frequently experienced synchronization delays under high-density traffic conditions. These delays generated temporary queue accumulation, reduced intersection responsiveness, and increased average vehicle waiting times. This reflects underlying system-level limitations within centralized transportation intelligence structures where traffic adaptation depends on communication-intensive coordination cycles.

By contrast, the edge-AI architecture significantly improved adaptive signal responsiveness because localized reinforcement learning agents processed traffic-flow information directly at intersection-level computational nodes. Comparative simulations demonstrated that edge-AI traffic optimization reduced average intersection delay by approximately 29% relative to the centralized system under equivalent congestion scenarios. Queue-length accumulation also declined substantially during peak-hour traffic periods.

The results suggest that decentralized traffic intelligence enables faster adaptation to localized traffic variability, thereby improving urban mobility continuity and reducing congestion propagation across interconnected transportation corridors. These findings align with previous transportation engineering scholarship emphasizing the importance of localized computational autonomy within smart-city infrastructures (Tang et al., 2021). However, the present study extends existing research by demonstrating that decentralized AI not only improves responsiveness but also strengthens overall transportation-network resilience.

From an operational perspective, these findings possess substantial implications for rapidly urbanizing metropolitan regions where transportation infrastructures increasingly struggle to accommodate fluctuating mobility demand. Intelligent decentralized traffic systems may therefore become essential components of future urban congestion-management strategies.

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2. Energy Consumption and Environmental Sustainability

Transportation congestion directly contributes to fuel waste, energy inefficiency, and greenhouse gas emissions due to prolonged idling, stop-and-go vehicle behavior, and inefficient acceleration cycles. Consequently, intelligent traffic optimization systems possess significant environmental implications beyond conventional transportation efficiency metrics.

The comparative evaluation demonstrated that edge-AI traffic management substantially improved transportation energy efficiency relative to centralized architectures. Because decentralized traffic optimization reduced queue accumulation and vehicle waiting time, fuel consumption and transportation-related emissions declined across all simulation environments. The computational analysis revealed an estimated reduction of approximately 17% in fuel-related emissions under high-density traffic conditions relative to centralized optimization.

The environmental improvements emerged through several interconnected mechanisms. First, adaptive signal coordination reduced unnecessary vehicle idling at intersections. Second, smoother traffic-flow continuity minimized acceleration-deceleration cycles associated with energy-intensive urban driving behavior. Third, localized traffic adaptation improved corridor-level traffic balancing, thereby reducing congestion spillover effects between adjacent intersections.

Importantly, the sustainability benefits extended beyond immediate fuel consumption reduction. Improved traffic-flow continuity may also reduce urban noise pollution, enhance public transportation reliability, and improve pedestrian mobility conditions within dense metropolitan environments. These findings therefore position intelligent transportation systems as important contributors to sustainable urban development and climate-mitigation strategies.

Table 1. Comparative Matrix of Engineering Variables, System Mechanisms, and Technical Outcomes

Variable	Case/System 1: Centralized Cloud Traffic Intelligence	Case/System 2: Edge-AI Transportation Intelligence	Empirical/Computational Evidence	Analytical Interpretation
Traffic responsiveness	Dependent on centralized	Localized adaptive decision-making	Edge-AI reduced average delay by ~29%	Decentralized intelligence

	synchronization			improves real-time traffic adaptation
Queue-length control	Vulnerable to congestion accumulation	Dynamic localized optimization	Lower queue accumulation in edge simulations	Faster adaptation mitigates congestion propagation
Communication latency	Higher network dependence	Reduced transmission dependency	Faster signal responsiveness observed	Edge processing improves computational efficiency
Fuel consumption	Higher due to prolonged idling	Lower through smoother traffic flow	Estimated ~17% emission reduction	Intelligent adaptation improves sustainability
Infrastructure scalability	Centralized computational bottlenecks	Modular distributed scalability	Stronger performance in large-network simulations	Distributed systems support smart-city expansion
System resilience	Vulnerable to centralized disruption	Decentralized operational continuity	Local intersections maintained adaptive control	Distributed intelligence enhances resilience
Cybersecurity exposure	Centralized attack surface	Distributed data processing	Lower centralized vulnerability	Edge systems strengthen infrastructure security
Urban sustainability impact	Limited adaptive environmental optimization	Integrated congestion-emission reduction	Improved transportation continuity	AI-enabled mobility supports sustainable urban systems

The comparative matrix demonstrates that intelligent transportation performance emerges through interconnected relationships between computational architecture, traffic-flow adaptation, communication structures, and urban sustainability outcomes. Decentralized edge-AI systems influence transportation efficiency not merely through faster computation but through systemic transformation of adaptive mobility coordination itself.

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3. Scalability, Resilience, and Smart-City Infrastructure Integration

One of the most significant findings concerns infrastructure scalability and operational resilience within large-scale urban transportation systems. Centralized traffic intelligence systems frequently encounter computational bottlenecks as the number of intersections, connected vehicles, and sensor environments increases. Large-scale urban coordination requires continuous communication between distributed mobility infrastructures and centralized analytical servers, thereby increasing vulnerability to network congestion and processing overload.

The edge-AI architecture demonstrated substantially greater scalability because computational responsibilities were distributed across localized intersection nodes. Each intelligent intersection optimized local traffic conditions while simultaneously participating in limited distributed coordination processes. Consequently, system expansion did not proportionally increase centralized computational dependency.

The decentralized structure also improved resilience during partial infrastructure disruption scenarios. Simulated communication failures affecting individual intersections generated significantly lower network-wide disruption within edge-AI environments because localized traffic optimization continued operating independently. By contrast, centralized architectures experienced broader operational degradation during communication interruption events.

These findings possess important implications for future smart-city engineering. Urban transportation systems increasingly operate within interconnected infrastructures involving autonomous vehicles, public transportation coordination, emergency-response systems, and multimodal mobility networks. Scalable and resilient transportation intelligence therefore becomes essential for maintaining urban functionality under rapidly evolving mobility conditions.

Furthermore, the results suggest that distributed transportation intelligence may improve disaster-response capability within metropolitan regions. Adaptive localized mobility coordination could facilitate emergency evacuation routing, public-safety vehicle prioritization, and infrastructure resilience during extreme urban disruption events.

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4. AI Governance, Cybersecurity, and Human-Centered Urban Mobility

Although intelligent transportation systems provide substantial operational advantages, the findings also reveal important governance and cybersecurity implications associated with AI-driven urban infrastructure. Centralized transportation architectures create large-scale transportation data repositories vulnerable to cyberattacks, unauthorized surveillance, and infrastructure manipulation. Such vulnerabilities may threaten not only transportation efficiency but also broader urban security and public trust.

Edge-AI transportation systems reduce centralized data dependency because localized traffic processing occurs directly within intersection-level computational environments. This decreases the volume of continuously transmitted transportation data and reduces centralized attack surfaces. Consequently, decentralized transportation intelligence strengthens cybersecurity resilience within smart-city infrastructures.

However, the study also identified several engineering challenges associated with edge-AI systems. Distributed transportation intelligence requires sophisticated synchronization mechanisms to maintain network-wide traffic coordination while preserving localized autonomy. Inconsistent edge-device performance, infrastructure heterogeneity, and communication instability may generate coordination inefficiencies under highly volatile urban conditions.

The broader societal implications are equally important. Intelligent transportation systems influence accessibility, urban equity, pedestrian safety, and public mobility behavior. Therefore, future transportation engineering must balance technological optimization with human-centered urban design principles. Transportation AI should not solely prioritize vehicular throughput but also support multimodal accessibility, environmental sustainability, and equitable urban mobility outcomes.

The findings therefore reinforce the importance of interdisciplinary transportation engineering integrating computational intelligence, urban planning, cybersecurity governance, environmental sustainability, and public-policy coordination into coherent smart-city development strategies.

Conceptual Framework

Adaptive Urban Mobility Intelligence Framework

This study proposes the following conceptual framework:

Urban IoT Sensing Infrastructure → Deep Reinforcement Learning Traffic Optimization → Adaptive Signal Coordination → Congestion Mitigation and Energy Efficiency → Sustainable and Resilient Smart-City Mobility

The framework conceptualizes intelligent transportation systems as distributed adaptive mobility ecosystems operating through continuous interaction between urban sensing infrastructures, AI-enabled computational adaptation, transportation-network coordination, and sustainability-oriented urban governance.

The first stage involves IoT-enabled transportation sensing systems collecting real-time mobility information through connected intersections, vehicle-detection systems, computer-vision infrastructures, and multimodal transportation analytics. These sensing environments generate the informational foundation for adaptive transportation intelligence.

The second stage concerns deep reinforcement learning optimization mechanisms that continuously adapt traffic-control policies according to dynamic urban mobility conditions. Reinforcement learning agents iteratively improve traffic-flow management through interaction with transportation environments characterized by congestion variability and heterogeneous mobility patterns.

The third stage involves adaptive signal coordination, where decentralized AI systems optimize traffic timing, queue balancing, emergency prioritization, and intersection responsiveness. This stage reflects the operational interaction between computational intelligence and urban mobility adaptation.

The fourth stage links adaptive transportation optimization to sustainability outcomes through congestion reduction, fuel-efficiency improvement, and emissions mitigation. Intelligent mobility coordination therefore contributes directly to environmentally sustainable urban development.

Finally, the framework proposes that distributed transportation intelligence enhances long-term smart-city resilience through scalable infrastructure coordination, cybersecurity-aware operation, and adaptive urban mobility governance.

CONCLUSION

This study comparatively evaluated centralized cloud-based traffic intelligence and decentralized edge-AI transportation architectures within smart-city traffic optimization environments. The findings directly address the research objective by demonstrating that decentralized edge-AI systems substantially improve traffic responsiveness, congestion mitigation, transportation energy efficiency, scalability, and urban mobility resilience relative to centralized intelligent transportation architectures.

The comparative analysis revealed that edge-AI transportation systems significantly reduce vehicle delay, improve intersection throughput, minimize queue accumulation, and lower transportation-related emissions under highly dynamic urban traffic conditions. These operational improvements emerged primarily because decentralized computational intelligence enabled faster localized adaptation and reduced communication latency within urban mobility infrastructures.

The study contributes theoretically by reconceptualizing intelligent transportation systems as distributed adaptive mobility ecosystems rather than centralized traffic-control infrastructures. This systems-oriented perspective integrates transportation engineering, deep reinforcement learning, IoT infrastructure analysis, sustainability studies, and smart-city governance into a unified analytical framework.

Empirically and computationally, the findings demonstrate that decentralized transportation intelligence simultaneously improves operational efficiency and environmental sustainability. Intelligent urban mobility systems therefore possess substantial potential to support climate-mitigation strategies, reduce transportation energy waste, and strengthen urban resilience.

The industrial and policy implications are significant. Municipal governments, transportation authorities, and smart-city planners may benefit from implementing edge-AI transportation systems capable of adaptive decentralized coordination. Such systems may improve urban mobility continuity while supporting scalable future transportation infrastructures involving autonomous vehicles, multimodal mobility platforms, and connected transportation ecosystems.

Nevertheless, several limitations remain. The study relied primarily upon computational simulation rather than full-scale metropolitan deployment. Real-world traffic behavior, human decision variability, infrastructure heterogeneity, and regulatory constraints may influence implementation outcomes. Future research should therefore integrate live urban pilot projects, connected autonomous vehicle coordination, digital twin transportation modeling, explainable AI governance mechanisms, and multimodal sustainability assessment into next-generation intelligent transportation engineering research.

Ultimately, this article demonstrates that decentralized edge-AI transportation intelligence represents not merely a computational innovation but a transformative engineering paradigm capable of reshaping sustainable urban mobility systems within future smart cities.

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