

Smart Traffic Management Using Real-Time Engineering Analytics

Dr. Emil Sørensen

Assistant Professor, University of Southern Denmark (SDU), Denmark

Abstract

Rapid urbanization, increasing vehicle ownership, population growth, and changing mobility patterns have created substantial challenges for modern transportation infrastructure. Conventional traffic management systems frequently depend on fixed signal schedules, periodic observations, and manually interpreted information, limiting their ability to respond effectively to rapidly changing traffic conditions. Real-time engineering analytics provides an intelligent approach for transforming continuous traffic observations into actionable transportation decisions. This paper examines smart traffic management using real-time engineering analytics, focusing on the integration of traffic sensors, computer vision, Internet of Things technologies, data processing, predictive analytics, adaptive signal control, and intelligent transportation systems. The study develops a conceptual analytical framework that connects real-time data acquisition with traffic-state estimation, congestion prediction, signal optimization, route management, and operational decision-making. The analysis demonstrates how engineering analytics can support dynamic traffic control by continuously evaluating vehicle density, queue length, travel time, traffic speed, intersection performance, and incident conditions.

AI-based analytical methods can further identify recurring traffic patterns and predict near-term congestion, allowing transportation systems to transition from reactive management toward anticipatory control. The study also examines the role of edge computing, cloud platforms, connected vehicles, and data fusion in improving the responsiveness and scalability of intelligent traffic systems. Findings indicate that real-time analytics can contribute to reduced congestion, shorter delays, improved intersection coordination, better utilization of road capacity, and more effective emergency response. However, implementation is constrained by data quality, sensor reliability, communication latency, cybersecurity, interoperability, computational requirements, and the complexity of mixed traffic environments. Future research should emphasize multimodal data integration, explainable AI, digital twins, edge intelligence, adaptive control, and standardized real-world validation. Smart traffic management based on real-time engineering analytics can therefore provide an important foundation for efficient, resilient, and sustainable transportation infrastructure.

Keywords: Smart Traffic Management, Real-Time Analytics, Intelligent Transportation Systems, Traffic Engineering, Adaptive Signal Control, Traffic Prediction, IoT, Transportation Infrastructure

1. Introduction

Modern transportation networks are becoming increasingly complex as urban populations expand and travel demand grows. Road networks must accommodate private vehicles, public transportation, commercial traffic, pedestrians, cyclists, and emergency services while maintaining acceptable levels of

safety and efficiency. Traffic congestion is influenced by recurring demand patterns as well as accidents, weather conditions, road construction, special events, and unexpected changes in travel behavior. Conventional traffic management approaches based primarily on predetermined signal schedules and periodic traffic observations may therefore be insufficient for responding to rapidly changing network conditions.

Smart traffic management seeks to improve transportation operations through continuous sensing, communication, data analysis, and automated decision-making. Modern traffic infrastructure can collect information through cameras, inductive loops, radar, GPS devices, connected vehicles, mobile devices, and IoT-enabled sensors. These data sources generate valuable information about traffic volumes, speeds, vehicle classifications, queue lengths, travel times, and roadway conditions. The challenge is not simply collecting information but processing it rapidly enough to support operational decisions. Real-time engineering analytics addresses this challenge by converting continuously generated data into measurable traffic indicators and control recommendations.

Adaptive traffic signal control represents one of the most important applications of real-time analytics. Instead of relying exclusively on predetermined timing plans, adaptive systems can adjust signal phases according to observed traffic conditions. Research integrating computer vision with traffic modeling has demonstrated the potential to use real-time vehicle volumes, vehicle composition, and turning movements to optimize signals across multiple intersections. Such approaches demonstrate how traffic sensing and engineering models can be integrated into a continuous feedback process.

Real-time analytics also supports traffic prediction and network-level management. Historical and streaming data can be analyzed using statistical models, machine learning, deep learning, and optimization algorithms to estimate near-future traffic states. Predictive information can enable transportation authorities to identify congestion before it becomes severe and implement appropriate measures. Connected vehicle technologies further increase the availability of traffic information by enabling vehicles and infrastructure to exchange information about location, speed, route, and operational conditions. Real-time control and routing strategies can consequently operate across multiple intersections rather than treating each junction as an isolated system.

The integration of real-time analytics with transportation engineering also supports broader smart-city objectives. Efficient traffic management can reduce unnecessary vehicle idling, improve travel-time reliability, increase road capacity utilization, and contribute to lower fuel consumption and emissions. Indian intelligent transportation initiatives, for example, have incorporated traffic monitoring, urban traffic control, vehicle tracking, emergency priority, and smart parking functions into broader transportation-management systems. However, effective implementation requires more than advanced algorithms. Reliable sensing, low-latency communication, interoperable infrastructure, cybersecurity, and appropriate engineering validation are essential for dependable real-time traffic operations.

2. Objectives

2.1 Evaluation of Real-Time Traffic Analytics

The first objective is to examine how real-time engineering analytics can improve traffic monitoring and management. The study focuses on the collection, processing, and interpretation of continuous traffic information obtained from sensors, cameras, connected vehicles, and other intelligent transportation technologies. Particular attention is given to traffic-state estimation, congestion detection, travel-time analysis, and predictive traffic analytics.

2.2 Assessment of Intelligent Traffic Control

The second objective is to assess how real-time analytics can support adaptive signal control, congestion mitigation, route management, incident response, and transportation decision-making. The objective also considers the engineering requirements associated with data reliability, processing speed, scalability, interoperability, cybersecurity, and integration with existing transportation infrastructure.

3. Review of Literature

3.1 Real-Time Traffic Monitoring

Real-time traffic monitoring forms the foundation of intelligent transportation management. Conventional monitoring systems generally rely on fixed sensors and periodic data collection, whereas modern systems can combine multiple data sources to create a continuously updated representation of traffic conditions. Cameras, radar, loop detectors, GPS devices, mobile data, and connected vehicles can provide information about traffic flow, speed, density, vehicle classification, and travel time.

The development of multi-source monitoring has increased the ability of traffic engineers to observe network conditions at both intersection and corridor levels. However, different sensing technologies generate data with different spatial and temporal characteristics. Engineering analytics must therefore integrate heterogeneous information while accounting for measurement uncertainty and sensor limitations. Data fusion can improve traffic-state estimation by combining complementary observations from multiple sources.

3.2 Adaptive Traffic Signal Management

Adaptive signal management uses observed traffic conditions to modify signal timing dynamically. Unlike fixed-time systems, adaptive controllers attempt to respond to variations in traffic demand by changing green times, phase sequences, offsets, or coordination strategies. The goal is generally to reduce delay, queues, stops, and unnecessary waiting while maintaining safety and operational constraints.

Research on real-time traffic control has increasingly explored optimization, model-based control, machine learning, and reinforcement learning. Connected-vehicle-based approaches can further coordinate signal control and vehicle routing across multiple destinations. Such approaches demonstrate that traffic management can become a network-level optimization problem rather than an isolated intersection-control problem.

3.3 Predictive Traffic Analytics

Predictive analytics extends traffic management from observation toward forecasting. Historical traffic information can be used to identify recurring patterns associated with time, location, day of week, weather, special events, and other variables. Machine learning models can learn nonlinear relationships between these factors and traffic conditions, supporting short-term prediction of speed, flow, travel time, or congestion.

Prediction is particularly valuable when integrated with traffic control. A system that predicts increasing congestion can adjust signal coordination or recommend alternative routing before queues become critical. However, predictive accuracy can decline when unusual events occur. Therefore, real-time systems should combine historical learning with continuously updated observations to maintain responsiveness under changing conditions.

3.4 Intelligent Transportation Systems and Engineering Analytics

Intelligent Transportation Systems integrate sensing, communications, computation, control, and transportation engineering. Real-time analytics provides the computational layer that converts raw transportation information into operational knowledge. ITS platforms can support traffic control, incident management, emergency vehicle prioritization, traveler information, parking management, and public transportation coordination.

The increasing availability of edge computing and cloud platforms has expanded the architectural possibilities for intelligent traffic systems. Edge processing can perform time-sensitive analytics close to traffic sensors, while cloud infrastructure can support large-scale historical analysis and model development. A hybrid architecture can therefore combine rapid local response with centralized network-level optimization.

4. Methodology

4.1 Research Design

This study uses a conceptual analytical research design to examine the application of real-time engineering analytics in smart traffic management. The approach synthesizes transportation engineering concepts with intelligent sensing, data analytics, adaptive control, predictive modeling, and intelligent transportation systems. The research considers the complete information pathway from traffic-data acquisition to analytical processing, decision generation, control implementation, and performance evaluation.

The study treats traffic management as a dynamic engineering system in which transportation conditions continuously change over time. The analytical framework therefore emphasizes feedback between traffic observations and operational decisions. Key performance considerations include traffic flow efficiency, average delay, queue formation, travel time, signal responsiveness, network scalability, and reliability. Engineering constraints are incorporated to ensure that analytical decisions remain consistent with transportation safety and operational requirements.

4.2 Real-Time Data and Analytics Framework

The proposed framework integrates heterogeneous traffic information into a structured analytical pipeline. Traffic sensors and cameras provide real-time observations, which are transmitted to edge or centralized processing systems. Data preprocessing addresses missing values, measurement noise, synchronization, and inconsistencies before analytical models estimate current traffic conditions.

The major analytical components include:

- **Traffic sensing:** Collection of vehicle counts, speed, occupancy, queue length, and travel-time information.
- **Data integration:** Combination of sensor, camera, connected-vehicle, and historical information.
- **Data preprocessing:** Noise reduction, synchronization, validation, and missing-data management.
- **Traffic-state estimation:** Determination of current congestion, flow, and intersection conditions.
- **Prediction:** Forecasting short-term traffic demand and congestion.
- **Optimization:** Determination of appropriate signal timings, routing, and operational actions.
- **Control:** Implementation of recommended traffic-management decisions.
- **Feedback:** Continuous evaluation of system response and updating of subsequent decisions.

4.3 Performance Evaluation

The analytical evaluation considers the effectiveness of real-time traffic management according to operational and engineering performance measures. Average vehicle delay, queue length, travel time, traffic throughput, number of stops, and responsiveness to changing traffic conditions are treated as important indicators. These measures allow intelligent traffic systems to be compared with conventional fixed-time or manually managed approaches.

The methodology also considers implementation factors that can influence system performance. Sensor failures, communication latency, incomplete data, computational limitations, and unexpected incidents can affect the quality of real-time decisions. Therefore, traffic analytics should be evaluated not only according to algorithmic accuracy but also according to reliability, scalability, response time, interoperability, and operational feasibility.

5. Analysis

5.1 Real-Time Analytics Techniques for Traffic Management

Real-time traffic management can use multiple analytical approaches depending on the monitoring objective and available data. Statistical methods can support traffic-state estimation, while machine learning models can identify complex relationships between traffic variables.

Computer vision can automatically estimate vehicle counts and classifications from video streams, while optimization models can determine signal-control strategies. Reinforcement learning can additionally learn control policies through repeated interaction with traffic environments.

Table 1: Real-Time Engineering Analytics Techniques for Smart Traffic Management

Analytical Technique	Primary Application	Major Strength	Key Requirement
Statistical Analysis	Traffic-state estimation	Simple and computationally efficient	Reliable traffic observations
Machine Learning	Congestion prediction	Captures nonlinear relationships	Historical training data
Deep Learning	Traffic forecasting	Handles complex temporal patterns	Large datasets and computation
Computer Vision	Vehicle detection	Automated visual monitoring	High-quality camera feeds
Optimization Models	Signal timing	Explicit operational objectives	Accurate traffic model
Reinforcement Learning	Adaptive control	Learns dynamic control policies	Simulation/training environment
Data Fusion	Multi-source monitoring	Combines complementary information	Interoperable data sources

Interpretation: The table indicates that smart traffic management benefits from combining several analytical approaches rather than depending on a single algorithm. Computer vision is useful for extracting traffic information from visual data, machine learning supports prediction, optimization provides structured control decisions, and edge analytics improves response time.

The selection of analytical methods should therefore reflect the operational objective, data availability, computational requirements, and engineering constraints of the transportation system.

5.2 Traffic-Control Performance

Real-time analytics becomes operationally valuable when analytical results are translated into traffic-control actions. Continuous information about vehicle demand can support dynamic signal timing, while predictive information can help transportation authorities respond before congestion reaches critical levels.

Multi-intersection coordination can further improve traffic flow by considering relationships between adjacent junctions rather than optimizing each signal independently.

Table 2: Functional Benefits of Real-Time Engineering Analytics

Traffic Management Function	Conventional Approach	Real-Time Analytical Approach	Expected Benefit
Traffic Monitoring	Periodic observation	Continuous sensing	Faster condition awareness
Signal Control	Fixed timing	Adaptive timing	Reduced unnecessary delay
Congestion Management	Reactive intervention	Predictive intervention	Earlier response
Route Management	Static recommendations	Dynamic routing	Better network utilization
Incident Response	Manual detection	Automated detection	Faster identification
Emergency Priority	Predefined procedures	Real-time prioritization	Improved response
Network Coordination	Local intersection control	Corridor/network optimization	Improved traffic continuity
Performance Evaluation	Periodic reporting	Continuous analytics	Better operational feedback

Interpretation: Real-time engineering analytics changes traffic management from a predominantly reactive process into a continuous feedback system. The principal benefit is the ability to connect current traffic conditions with immediate control decisions.

Adaptive signal timing, predictive congestion management, and dynamic routing can improve network responsiveness when reliable data are available. The effectiveness of these functions depends

on accurate sensing, low-latency communication, appropriate control algorithms, and continuous engineering validation.

6. Discussion

6.1 Improving Traffic Flow Efficiency

Real-time traffic analytics can improve transportation efficiency by identifying changing traffic demand and adjusting operational controls accordingly. Adaptive signals can allocate green time to movements experiencing greater demand, while coordinated control can reduce unnecessary stops across connected intersections. This can improve roadway utilization and reduce the accumulation of queues during periods of changing traffic intensity.

The effectiveness of adaptive management is particularly important in heterogeneous urban environments where traffic patterns can change rapidly. Fixed schedules may allocate green time according to historical assumptions that do not represent current demand. Real-time systems can instead respond to observed conditions. However, control strategies must balance competing traffic movements and avoid transferring congestion from one location to another.

6.2 Supporting Predictive and Proactive Management

A major contribution of real-time engineering analytics is its ability to combine current observations with historical information to anticipate future traffic conditions. Predictive models can identify emerging congestion and provide transportation managers with opportunities to intervene before severe queues develop. This can support proactive signal adjustments, route recommendations, and incident-management strategies.

Predictive systems must nevertheless remain adaptable because unusual events can cause traffic conditions to differ substantially from historical patterns. Accidents, road closures, severe weather, public events, and emergency situations can rapidly invalidate previously learned relationships. Combining predictive models with continuous real-time sensing is therefore more appropriate than relying exclusively on historical forecasting.

6.3 Engineering Integration and Operational Reliability

Real-time traffic management should be viewed as an integrated engineering system rather than an isolated software application. Sensors, communication networks, data platforms, analytical algorithms, signal controllers, traffic-management centers, and field infrastructure must work together. Failure at any stage can reduce overall system effectiveness.

Operational reliability is particularly important because traffic control is a safety-relevant application. Analytical recommendations should therefore operate within predefined engineering constraints and include mechanisms for handling missing data, sensor failures, communication interruptions, and abnormal conditions. Human transportation engineers should retain oversight of critical decisions, particularly when automated systems operate in complex or unusual circumstances.

7. Challenges

A major challenge in real-time traffic management is the quality and availability of traffic data. Sensors may experience calibration errors, occlusion, communication interruptions, environmental interference, or hardware failures. Cameras can be affected by poor lighting, weather, and visual obstruction.

Different systems may also collect information at different frequencies and spatial resolutions. These issues can create inconsistencies that reduce the reliability of analytical models.

Traffic environments are also highly dynamic and heterogeneous. Urban roads may simultaneously contain passenger cars, buses, motorcycles, bicycles, pedestrians, commercial vehicles, and emergency vehicles. Lane discipline and driving behavior can vary considerably between locations. Consequently, analytical models trained in one transportation environment may not generalize effectively to another. Models must account for local traffic characteristics and continuously changing operating conditions.

System integration and cybersecurity create additional challenges. Traffic-management platforms frequently connect sensors, communication networks, cloud services, edge devices, and traffic controllers. This interconnected architecture can create vulnerabilities if appropriate security measures are not implemented. Interoperability is another concern because transportation agencies may operate equipment from different manufacturers and technology generations. Long-term deployment therefore requires standardized interfaces, secure communication, reliable infrastructure, and appropriate governance mechanisms.

8. Future Research

8.1 AI-Enhanced Predictive Traffic Management

Future research should focus on advanced AI models capable of forecasting traffic conditions across multiple spatial and temporal scales. Graph-based learning, deep temporal models, and hybrid prediction frameworks could represent relationships between connected intersections and road segments more effectively. Research should also investigate models that can rapidly adapt to unexpected events while maintaining reliable prediction performance.

8.2 Digital Twins and Integrated Traffic Simulation

Digital twins can provide a promising environment for linking real-world transportation networks with continuously updated computational models. Future systems could use real-time observations to update a digital representation of traffic conditions and simulate alternative control strategies before implementing them. This approach could allow transportation agencies to evaluate the potential consequences of signal changes, route diversions, and incident-management strategies in near real time.

8.3 Edge Intelligence and Connected Transportation

Edge intelligence is expected to become increasingly important for applications requiring rapid decisions. Processing traffic information close to sensors can reduce communication delays and improve resilience when centralized systems are unavailable. Future research should investigate hybrid edge-cloud architectures that combine local low-latency control with centralized network optimization. Connected vehicles and infrastructure should also be integrated to create richer traffic-state information and more coordinated transportation management.

9. Limitations

This study is conceptual and analytical rather than an experimental field investigation. It does not present original measurements collected from a specific urban traffic network or a newly deployed real-time control system. Therefore, the expected benefits described in the analysis should not be interpreted

as universal performance guarantees. Actual results will depend on traffic characteristics, sensor configurations, infrastructure quality, analytical models, control strategies, and local operating conditions.

Another limitation is the diversity of transportation environments. Traffic management requirements differ considerably between highly structured highway networks, dense urban intersections, mixed-traffic environments, and developing transportation systems. An analytical framework that performs effectively in one context may require substantial adaptation in another. Large-scale field validation across different cities, road types, traffic compositions, and environmental conditions is therefore necessary to establish broader applicability.

10. Conclusion

Smart traffic management using real-time engineering analytics provides an important pathway toward more responsive and efficient transportation infrastructure. By integrating traffic sensing, data processing, predictive analytics, adaptive control, and intelligent transportation technologies, traffic-management systems can continuously observe changing roadway conditions and respond accordingly. Real-time analytics can improve traffic-state estimation, support congestion prediction, optimize signal operations, facilitate incident response, and enhance the utilization of existing transportation capacity.

The analysis demonstrates that the effectiveness of smart traffic management depends on the integration of multiple engineering and computational components. Sensors provide the data foundation, analytics convert observations into traffic intelligence, and adaptive control translates intelligence into operational decisions. Machine learning, computer vision, optimization, and reinforcement learning can each contribute to different stages of this process. However, data reliability, communication latency, interoperability, cybersecurity, computational capacity, and local traffic characteristics must be considered when developing practical systems.

Future intelligent transportation systems are likely to combine real-time analytics with digital twins, edge computing, connected vehicles, multimodal sensing, and advanced artificial intelligence. These technologies can enable transportation networks to become more predictive, adaptive, and resilient. Nevertheless, successful deployment requires continuous engineering validation and appropriate human oversight. Smart traffic management should therefore be developed as an integrated transportation-engineering solution in which computational intelligence supports, rather than replaces, established principles of traffic engineering and infrastructure management.

References

1. Tan, X., Zhou, Y., & Jiao, X. (2025). Traffic signal control based on deep reinforcement learning using state fusion and trend reward. *Engineering Applications of Artificial Intelligence*, 159, 111701. <https://doi.org/10.1016/j.engappai.2025.111701>
2. Bouktif, S., Cheniki, A., Ouni, A., & El-Sayed, H. (2025). Parameterized-action based deep reinforcement learning for intelligent traffic signal control. *Engineering Applications of Artificial Intelligence*, 159, 111422. <https://doi.org/10.1016/j.engappai.2025.111422>
3. Shao, J., Li, S., Zhang, K., Wang, A., & Li, M. (2025). Cross-city traffic prediction based on deep domain adaptive transfer learning. *Transportation Research Part C: Emerging Technologies*, 176, 105152. <https://doi.org/10.1016/j.trc.2025.105152>

4. Zhu, H., Sun, F., Tang, K., Qin, G., & Chung, E. (2025). Lane level traffic flow prediction in urban networks with missing data—A time accessibility based multi-task learning framework. *Transportation Research Part C: Emerging Technologies*, 180, 105343. <https://doi.org/10.1016/j.trc.2025.105343>
5. Kandiri, A., Nogal, M., Martinez-Pastor, B., & Teixeira, R. (2025). Automated intelligent-agent optimisation of per-lane variable speed limits. *Applied Soft Computing*, 181, 113554. <https://doi.org/10.1016/j.asoc.2025.113554>
6. Wang, T., Zhu, Z., Zhang, J., Tian, J., & Zhang, W. (2024). A large-scale traffic signal control algorithm based on multi-layer graph deep reinforcement learning. *Transportation Research Part C: Emerging Technologies*, 164, 104582. <https://doi.org/10.1016/j.trc.2024.104582>
7. Bie, Y., Ji, Y., & Ma, D. (2024). Multi-agent deep reinforcement learning collaborative traffic signal control method considering intersection heterogeneity. *Transportation Research Part C: Emerging Technologies*, 164, 104663. <https://doi.org/10.1016/j.trc.2024.104663>
8. Song, X. B., Zhou, B., & Ma, D. (2024). Cooperative traffic signal control through a counterfactual multi-agent deep actor critic approach. *Transportation Research Part C: Emerging Technologies*, 160, 104528. <https://doi.org/10.1016/j.trc.2024.104528>
9. Li, W., Zhu, T., & Feng, Y. (2024). A cooperative perception based adaptive signal control under early deployment of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, 169, 104860. <https://doi.org/10.1016/j.trc.2024.104860>
10. Kim, Y., Tak, H.-Y., Kim, S., & Yeo, H. (2024). A hybrid approach of traffic simulation and machine learning techniques for enhancing real-time traffic prediction. *Transportation Research Part C: Emerging Technologies*, 160, 104490. <https://doi.org/10.1016/j.trc.2024.104490>
11. Sengupta, A., Mondal, S., Das, A., & Guler, S. I. (2024). A Bayesian approach to quantifying uncertainties and improving generalizability in traffic prediction models. *Transportation Research Part C: Emerging Technologies*, 162, 104585. <https://doi.org/10.1016/j.trc.2024.104585>
12. Chen, K., Liang, Y., Han, J., Feng, S., Zhu, M., & Yang, H. (2024). Semantic-fused multi-granularity cross-city traffic prediction. *Transportation Research Part C: Emerging Technologies*, 162, 104604. <https://doi.org/10.1016/j.trc.2024.104604>
13. Zhao, L., Guo, B., Dai, C., Shen, Y., Chen, F., Zhao, M., & Hu, Y. (2024). Multi-step trend aware graph neural network for traffic flow forecasting. *Big Data Research*, 38, 100482. <https://doi.org/10.1016/j.bdr.2024.100482>
14. Soudeep, S., Aурthy, M. L. N., Jim, J. R., Mridha, M. F., & Kabir, M. M. (2024). Enhancing road traffic flow in sustainable cities through transformer models: Advancements and challenges. *Sustainable Cities and Society*, 116, 105882. <https://doi.org/10.1016/j.scs.2024.105882>
15. Elassy, M., Al-Hattab, M., Takruri, M., & Badawi, S. (2024). Intelligent transportation systems for sustainable smart cities. *Transportation Engineering*, 16, 100252. <https://doi.org/10.1016/j.treng.2024.100252>
16. Goumiri, S., Yahiaoui, S., & Djahel, S. (2023). Smart mobility in smart cities: Emerging challenges, recent advances and future directions. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, 29(1), 81–117. <https://doi.org/10.1080/15472450.2023.2245750>
17. Jiang, W., & Luo, J. (2022). Graph neural network for traffic forecasting: A survey. *Expert Systems with Applications*, 207, 117921. <https://doi.org/10.1016/j.eswa.2022.117921>

18. Noaeen, M., Naik, A., Goodman, L., Crebo, J., Abrar, T., Shakeri Hossein Abad, Z., Bazzan, A. L. C., & Far, B. (2022). Reinforcement learning in urban network traffic signal control: A systematic literature review. *Expert Systems with Applications*, 199, 116830. <https://doi.org/10.1016/j.eswa.2022.116830>
19. Chen, Y., Chen, X. M., & others. (2022). A novel reinforced dynamic graph convolutional network model with data imputation for network-wide traffic flow prediction. *Transportation Research Part C: Emerging Technologies*, 143, 103820. <https://doi.org/10.1016/j.trc.2022.103820>
20. Chu, T., Wang, J., Codecà, L., & Li, Z. (2020). Multi-agent deep reinforcement learning for large-scale traffic signal control. *IEEE Transactions on Intelligent Transportation Systems*, 21(3), 1086–1095. <https://doi.org/10.1109/TITS.2019.2901791>