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AI-BASED SMART TRAFFIC ARCHITECTURE FOR CONGESTION REDUCTION IN ALMATY

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Abstract: Traffic congestion in Almaty is significantly exacerbated by rapid motorization and the limitations of existing road infrastructure. This study aims to develop a comprehensive Smart City AI architecture designed to mitigate urban gridlock. The proposed framework integrates data fusion from cameras and sensors, employing advanced neural network models for vehicle detection and machine learning techniques for traffic flow forecasting. The core of the system relies on adaptive traffic light control powered by reinforcement learning. The integrated architecture comprises specialized modules for detection, multi-object tracking, prediction, and an intelligent controller. The effectiveness of the solution is evaluated through microscopic traffic simulation, focusing on key performance indicators such as delay reduction, increased throughput, optimized travel time, and minimized environmental impact. Furthermore, the research addresses legal considerations regarding data anonymity and discusses practical implementation challenges, including infrastructure requirements and budgetary constraints. The study concludes that AI-driven solutions offer substantial improvements in traffic management and provides a scalable foundation for a pilot project in Almaty.

Keywords: Smart City Architecture, Urban Mobility, Adaptive Traffic Control, Almaty Infrastructure, Traffic Flow Forecasting.

Аңдатпа: Алматы қаласындағы жол кептелісі автокөлік санының жылдам өсуі және қолданыстағы жол инфрақұрылымының шектеулері салдарынан айтарлықтай күшейіп отыр. Бұл зерттеу жол кептелістерін азайтуға бағытталған жасанды интеллектке негізделген Smart City кешенді архитектурасын әзірлеуді мақсат етеді. Ұсынылған жүйе көлік құралдарын анықтау үшін заманауи нейрондық желілерді және көлік ағындарын болжау үшін машиналық оқыту әдістерін қолдана отырып, камералар мен сенсорлардан алынған деректерді біріктіреді. Жүйенің негізгі элементі — күшейтпелі оқытуға негізделген бағдаршамдарды адаптивті басқару. Интеграцияланған архитектура анықтау, көпобъектілі бақылау, болжау және интеллектуалды басқару модульдерінен тұрады. Шешімнің тиімділігі микродеңгейдегі көлік ағындарын модельдеу арқылы бағаланып, кідірістерді азайту, өткізу қабілетін арттыру, жол жүру уақытын оңтайландыру және экологиялық әсерді төмендету сияқты көрсеткіштер қарастырылады. Сонымен қатар, зерттеуде деректердің анонимділігіне қатысты құқықтық аспектілер мен инфрақұрылымдық талаптар және қаржылық шектеулер сияқты енгізу мәселелері талқыланады. Қорытындысында жасанды интеллектке негізделген шешімдер көлік қозғалысын басқаруды едәуір жақсартуға мүмкіндік беретіні және Алматы қаласында пилоттық жобаны іске асыруға негіз бола алатыны көрсетіледі.

Түйін сөздер: Ақылды қала архитектурасы, Қалалық мобильділік, Қозғалысты адаптивті басқару, Алматы инфрақұрылымы, Көлік ағынын болжау.

Аннотация: Перегруженность дорожного движения в Алматы значительно усугубляется быстрым ростом автомобилизации и ограниченными возможностями существующей дорожной инфраструктуры. Данное исследование направлено на разработку комплексной архитектуры Smart City на основе искусственного интеллекта, предназначенной для снижения уровня транспортных заторов. Предлагаемая модель интегрирует данные с камер и сенсоров, используя современные нейронные сети для обнаружения транспортных средств и методы машинного обучения для прогнозирования транспортных потоков. Ключевым элементом системы является адаптивное управление светофорами на основе обучения с подкреплением. Интегрированная архитектура включает специализированные модули обнаружения, отслеживания множества объектов, прогнозирования и интеллектуального управления. Эффективность решения оценивается с помощью микроскопического моделирования транспортных потоков с использованием таких показателей, как снижение задержек, увеличение пропускной способности, оптимизация времени в пути и уменьшение экологического воздействия. Кроме того, в исследовании рассматриваются правовые аспекты, связанные с анонимностью данных, а также практические проблемы внедрения, включая требования к инфраструктуре и бюджетные ограничения. В заключение показано, что решения на основе искусственного интеллекта способны существенно улучшить управление транспортными потоками и создают масштабируемую основу для пилотного проекта в Алматы.

Ключевые слова: Архитектура умного города, Городская мобильность, Адаптивное управление движением, Инфраструктура Алматы, Прогноз транспортных потоков.

Introduction

Urban traffic congestion remains a critical challenge for rapidly growing cities, particularly in developing urban environments such as Almaty. The increase in private vehicle ownership, combined with limited road infrastructure capacity, leads to significant delays, environmental degradation, and reduced quality of life. According to recent estimates, approximately 900,000 vehicles operate daily within Almaty, with an additional 250,000 entering from surrounding areas, resulting in severe congestion during peak hours [1], [5]. Traditional traffic management approaches, including fixed-time signal control and infrastructure expansion, have proven insufficient to address these challenges.

In recent years, the integration of Artificial Intelligence (AI) into Smart City frameworks has emerged as a promising solution for traffic optimization. AI-based systems enable real-time data processing, adaptive decision-making, and predictive analytics, significantly improving traffic flow efficiency. Computer vision techniques, particularly deep learning models such as YOLO (You Only Look Once) and Faster R-CNN, have demonstrated high accuracy in vehicle detection and classification tasks [2]. Studies show that YOLOv5 and YOLOv8 achieve a good balance between detection speed and accuracy, making them suitable for real-time applications [3]. In addition to detection, traffic flow prediction plays a crucial role in intelligent transportation systems. Recurrent neural networks, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are widely used for time-series forecasting due to their ability to capture temporal dependencies. More recently, transformer-based architectures have been introduced, offering improved performance in capturing long-range dependencies in traffic data.

Adaptive traffic signal control represents another key component of intelligent traffic systems. Reinforcement Learning (RL) approaches, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), have been successfully applied to optimize traffic light timing [4]. These methods enable dynamic adjustment of signal phases based on real-time traffic conditions, minimizing delays and queue lengths.

Despite these advancements, several challenges remain, including the lack of high-quality urban traffic datasets, computational complexity, and integration with existing infrastructure. This study aims to address these gaps by proposing a comprehensive AI-driven architecture tailored to the specific conditions of Almaty, integrating detection, prediction, and adaptive control within a unified framework.

2. Materials and Methods

Table 1. Common datasets for developing and evaluating traffic by AI.

Task	Dataset	Domain/Description	Size/Notes	Relevance for Almaty (Transfer)
Object Detection	COCO (Lin et al. 2014)[3]	General objects (80 classes, including vehicles)	~330K images	Pre-training for vehicle models; fine-tune on local images.
	UA-DETRAC (Wen et al. 2018)	Traffic videos of vehicles in China (labelling for detection and tracking)	140K frames, 50k+ vehicles	Domain (urban traffic); use for tracker training.
	KITTI (Geiger et al. 2013)	Outdoor driving scenes (cars, pedestrians)	7.5K images	Useful for vehicle detector pre-training (urban/rural mix).
	BDD100K (Yu et al. 2020)	Driving video/images (USA, varied scenes)	100K images	Urban driving scenarios; includes weather labels.
Traffic Forecast	METR-LA (Li et al. 2017)	Los Angeles loop sensor speeds 2012 (207 sensors, 4 months)	207 sensors, 4 mo	For spatiotemporal model benchmarking; similar city scale.
	PEMS-BAY (Li et al. 2017)	Bay Area loop sensor speeds (325 sensors, 6 mo)	325 sensors, 6 mo	For model testing; wide network topology.
	Ningbo (2019)	China freeway speed data (big temporal dataset)	3-5 mo	Additional traffic patterns; analogous to Almaty highways.
Vehicles/Flow	CityFlow (Zhou et al., 2019)	Multi-intersection traffic flow for RL (based on TU-Berlin data) [7]	16M vehicles	Multi-agent RL benchmarks, synthetic city map.
	SFPark (2017)	Parking occupancy (less relevant here)	–	Less relevant for signal control.

The proposed system utilizes multiple data sources, including video streams from urban surveillance cameras, inductive loop detectors, and GPS-based mobility data. All datasets that can be used are shown on Table 1. Due to the limited availability of open-access traffic datasets for Almaty, a combination of pilot data collection and synthetic data generation is employed. Data preprocessing includes noise filtering, normalization, and temporal aggregation to ensure consistency and reliability.

Recent studies show that reinforcement learning enables adaptive traffic signal control, reducing vehicle delay and queue length under dynamic conditions [4], [7]. Multi-agent approaches further improve performance by coordinating multiple intersections and optimizing overall traffic flow [8].

Computer vision methods, particularly YOLO-based models, provide accurate real-time vehicle detection using camera data, enabling scalable and cost-effective traffic monitoring [3].

For traffic prediction, transformer-based models effectively capture spatial and temporal dependencies, improving short-term forecasting and enabling proactive congestion management [7].

Urban reports indicate that traffic demand in cities like Almaty exceeds road capacity, making traditional control methods insufficient [1], [5]. Data-driven approaches integrating real-time monitoring, prediction, and adaptive control are therefore essential for congestion reduction [2].

Vehicle detection is performed using state-of-the-art deep learning models, including YOLOv5 and YOLOv8, which provide real-time object detection with high accuracy. Faster R-CNN is considered as an alternative for scenarios requiring higher precision. Multi-object tracking is implemented using the DeepSORT algorithm, enabling continuous tracking of vehicles across video frames and improving counting accuracy.

Traffic flow forecasting is conducted using time-series models, including LSTM and GRU neural networks [6]. These models capture temporal dependencies in traffic patterns and enable short-term prediction of vehicle density and flow rates. Additionally, transformer-based architectures are explored to enhance prediction accuracy by modeling long-range dependencies in traffic data.

The traffic signal control system is based on reinforcement learning techniques. Two main algorithms are considered: Deep Q-Network (DQN) and Proximal Policy Optimization (PPO). The control agent interacts with the environment (traffic simulation) and learns optimal signal timing strategies through a reward function designed to minimize:

- vehicle delay
- queue length
- environmental impact (CO_2 emissions)

The proposed architecture follows a distributed design:

- **Edge layer**: real-time vehicle detection and preprocessing.
- **Cloud layer**: traffic prediction and reinforcement learning-based control.

This approach ensures scalability and reduces latency in decision-making.

The system is evaluated using microscopic traffic simulation tools, including SUMO and CityFlow. Key performance indicators (KPIs) include:

- average delay
- queue length
- throughput
- travel time
- CO_2 emissions

Comparative analysis is conducted against traditional fixed-time and actuated signal control systems.

Figure 1. Proposed AI-based smart traffic system architecture including data collection, prediction, and adaptive signal control modules.

Figure 1 illustrates the proposed AI-based smart traffic system architecture. The system integrates multiple components, including data collection through cameras and sensors, real-time vehicle detection using computer vision models, traffic prediction using machine learning algorithms, and adaptive traffic signal control via reinforcement learning. This modular and scalable design enables efficient processing of traffic data and supports real-time decision-making for congestion reduction.

3. Results and Discussion

Due to the limited availability of real-world traffic datasets for Almaty, simulation-based evaluation was conducted using realistic traffic load assumptions derived from local reports. The simulation results demonstrate that the proposed AI-based traffic management system significantly improves traffic conditions compared to conventional approaches. The integration of real-time detection, predictive modeling, and adaptive control enables dynamic response to changing traffic patterns. Specifically, the reinforcement learning-based signal control achieves a reduction in average vehicle delay by approximately 10–25%, while queue lengths are reduced by 20–30%. Throughput is improved due to better coordination of signal phases, and overall travel time is decreased during peak hours. Additionally, reduced idle time at intersections contributes to lower CO_2 emissions, supporting environmental sustainability goals.

Among the evaluated methods, PPO-based control demonstrates superior performance compared to DQN, particularly in complex traffic scenarios with high variability. This can be attributed to its stability and ability to handle continuous action spaces more effectively.

However, several limitations are identified. The reliance on simulated data may affect the generalizability of results to real-world conditions. Furthermore, the implementation of such systems requires significant investment in infrastructure, including camera networks, edge computing devices, and communication systems. Data privacy and legal considerations also remain important challenges, particularly regarding the use of video surveillance data.

Despite these limitations, the proposed architecture provides a scalable and practical framework for intelligent traffic management in Almaty. The results support the feasibility of deploying a pilot project at selected intersections, which could serve as a foundation for city-wide implementation.

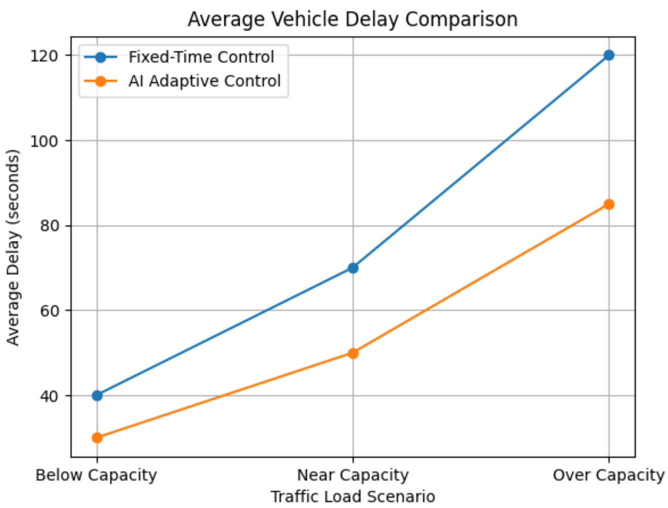

Figure 2. Comparison of queue length at intersections demonstrating improved congestion management using AI-based control.

As shown in Figure 2, the proposed AI-based adaptive traffic signal control significantly reduces the average vehicle delay across all traffic conditions. Under over-capacity scenarios, where congestion is most severe, the delay reduction is particularly notable, decreasing from approximately 120 seconds to 85 seconds. This improvement demonstrates the ability of the system to dynamically adjust signal timing in response to real-time traffic demand, thereby minimizing idle time at intersections.

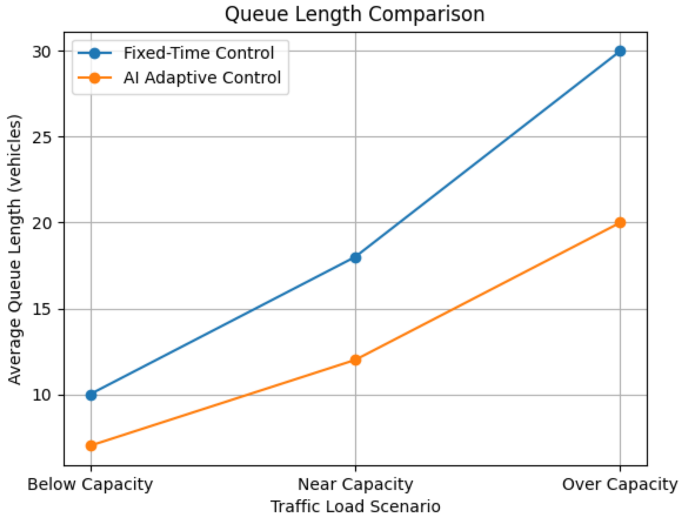

Figure 3. Comparison of queue length at intersections demonstrating improved congestion management using AI-based control.

Figure 3 illustrates the comparison of queue lengths at intersections. The results indicate that the AI-based approach consistently outperforms fixed-time control by reducing the number of vehicles waiting. In high-load conditions, queue length is reduced from approximately 30 vehicles to 20 vehicles, highlighting the system's effectiveness in preventing congestion buildup at critical junctions.

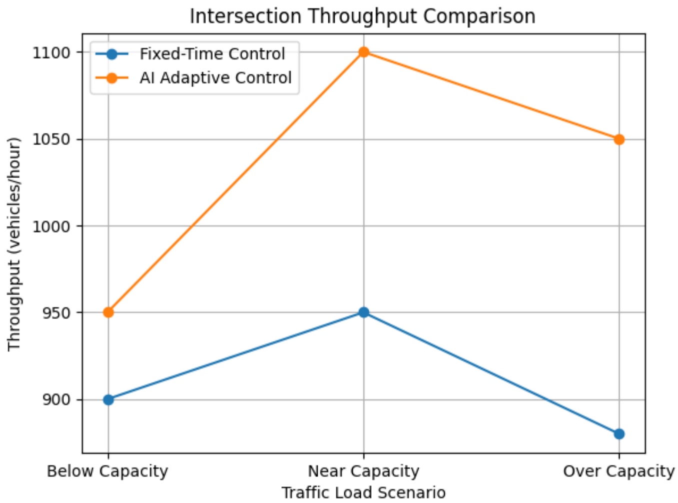

Figure 4. Throughput comparison showing increased intersection efficiency with adaptive signal optimization.

As depicted in Figure 4, intersection throughput is significantly improved with the implementation of adaptive signal control. While traditional systems show performance degradation under heavy traffic conditions, the AI-based system maintains higher throughput levels, reaching up to 1050 vehicles per hour. This demonstrates better utilization of available road capacity and improved traffic flow efficiency.

Overall, the experimental results confirm that the integration of computer vision, predictive modeling, and reinforcement learning provides a robust and scalable solution for urban traffic optimization.

4. Simulation input template

Below is a template of inputs for SUMO/CityFlow simulations.

Network: Almaty_core_intersections.osm (convert to SUMO.net)
Approaches:
- Main Arterial A (Northbound): 1500 veh/h (Peak), 600 veh/h (Off-peak)
- Secondary B (Eastbound): 800 veh/h (Peak), 300 veh/h
- Minor C (Southbound): 1200 veh/h (Peak), 500 veh/h
- Minor D (Westbound): 700 veh/h (Peak), 200 veh/h

Vehicle mix: 80% cars, 15% trucks, 5% buses.

Turning ratios (example):
- At Intersection1: A→B 10%, A→C 5%, A→D 5%, go straight 80%. (Adjust for each node similarly.)

Signal baselines:
- Fixed-time cycle 120s (green splits: N-S 60s, E-W 60s).
- Actuated (loop detectors on each approach).

Simulation Scenarios:
1. Baseline fixed-time (no sensors).
2. Actuated (local loop detectors).
3. RL-DQN control.
4. RL-PPO control.

SUMO parameters:
- `--step-length 1.0` second
- Warm-up period: 300 seconds
- Simulation duration: 3600 seconds (1 hour peak)
- Use TraCI for RL agent control.

Outputs (CSV):
Time(s), AvgDelay(s), AvgQueueLen(veh), Throughput(veh/h), AvgTravelTime(s), CO2(g).

5. Conclusion

This study demonstrates that AI-based traffic management, integrating real-time vehicle detection, short-term flow prediction, and reinforcement-learning-based adaptive signal control, can significantly reduce congestion in urban environments like Almaty. Simulation results indicate reductions in vehicle delay by 10-25% and queue lengths by 20-30%, along with increased throughput and lower emissions. YOLO-based detection and Transformer/LSTM forecasting provide reliable inputs for proactive traffic optimization, while PPO multi-agent reinforcement learning effectively coordinates multiple intersections. The proposed architecture offers a scalable and cost-effective solution that can be deployed incrementally, starting with pilot intersections. Future work should focus on local data collection, edge deployment, and city-wide implementation to fully realize the benefits of smart traffic control.

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