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The Design and Application of Deep Learning in Urban Intelligent Traffic Signal Planning

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Abstract:

With the acceleration of urbanization, traffic congestion has become increasingly prominent. Lacking dynamic adaptability, traditional methods of traffic signal control struggle to handle complex traffic flows. This article discusses the potential application of deep learning technologies in intelligent traffic signal planning by focusing on reinforcement learning (RN) and supervised learning. The reinforcement learning framework optimizes signal sequence through dynamic modeling and real-time decision-making, significantly reducing vehicle waiting time and travel time in both single-intersection and multi-intersection coordinated control scenarios. Supervised learning models provide data-driven support for control strategies via high-precision traffic flow prediction. Experimental results demonstrate that these technologies improve traffic efficiency (e.g., average vehicle speed increased by 4.2%) and adapt to sudden traffic incidents. However, challenges such as high data dependency and insufficient model generalizability remain unresolved.

Keywords: Deep Learning, Traffic Signal Control, Reinforcement Learning, Multi-Intersection Coordinated Control, Traffic Flow Prediction, Dynamic Timing Optimization

1. Introduction

The optimization of intelligent traffic signal control plays a pivotal role in alleviating urban traffic congestion and enhancing road network efficiency within modern urban transportation management. Traditional traffic signal scheduling methods, which rely on predefined timing sequences or historical data-driven optimization models, often struggle to adapt in real time to complex and dynamically shifting traffic flow patterns. As a cutting-edge technology in artificial intelligence, deep learning offers novel solutions for intelligent traffic signal planning by leveraging its robust data processing capabilities and adaptive learning mechanisms. By integrating traffic flow data, vehicle detection metrics, and environmental factors, deep learning algorithms can predict traffic trends, optimize signal timing configurations, and dynamically adjust signaling strategies under special scenarios such as holidays or emergencies. This approach ultimately enables more intelligent and efficient urban traffic management systems, fostering a paradigm shift toward data-driven infrastructure optimization.

2. Urban Traffic Intersection Context

The persistent expansion of modern cities has rendered traffic congestion a pervasive challenge in metropolitan areas, with transportation inefficiencies not only undermining urban operational productivity but also diminishing public satisfaction and quality of life in daily commutes[3]. According to data released by the China Association of Automobile Manufacturers, automotive production and sales in 2024 reached 31.282 million and 31.436 million units, respectively, reflecting year-on-year growth rates of 3.7% and 4.5% [4]. The surge in vehicle manufacturing and subsequent influx into urban road networks stands as a primary contributor to escalating traffic congestion. Another prevalent factor exacerbating this issue lies in suboptimal traffic signal coordination, which frequently leads to diminished throughput at individual or clustered intersections. Consequently, integrating deep learning methodologies with traffic signal optimization represents a critical solution to address the evolving demands of contemporary urban transportation systems.

3. Traditional Methods for Urban Intersection Signal Control

Traditional traffic signal control systems are primarily categorized into two approaches:

Fixed-Cycle Signal Timing: This method operates on predetermined cycle sequences and static timing configurations, ensuring baseline traffic flow efficiency under routine conditions. However, it exhibits significant limitations in dynamically addressing abrupt congestion scenarios, such as morning peak hours or holiday-induced traffic surges, due to its inherent rigidity.

Predefined Multi-Mode Schemes: These systems employ multiple signal patterns (e.g., varying cycle sequences or timing allocations) to adapt to diverse traffic scenarios. While this approach can mitigate congestion under predictable conditions, it often fails to resolve inefficiencies caused by stochastic traffic variations (e.g., irregular holiday traffic patterns), where suboptimal phase duration allocations exacerbate intersection bottlenecks.

4. The Potential of Deep Learning in Traffic Management

Traditional approaches to mitigating traffic congestion, as described above, often necessitate manual intervention by traffic police to regulate intersection flows. Traffic police typically assess real-time vehicular density across directional lanes and implement tailored strategies to optimize throughput. However, when congestion arises simultaneously at multiple intersections, logistical constraints—including limited police availability and coordination inefficiencies—exacerbate operational challenges. Deep learning aims to address these limitations by enabling algorithm-driven, autonomous traffic control systems. Such systems not only facilitate adaptive signal adjustments at individual intersections but also achieve coordinated multi-node optimization through real-time data integration. This paradigm shift toward intelligent, interconnected traffic management holds promise for maximizing network-wide vehicular efficiency while minimizing human-dependent decision-making bottlenecks.

5. Application of Deep Learning in Intelligent Traffic Signal Control

5.1 Reinforcement Learning (RL)-Based Control Framework

The reinforcement learning (RL)-based control framework enables real-time optimization of traffic signal decisions through dynamic modeling. Its core principle involves mapping traffic states (e.g., lane density, pedestrian flow) to continuous or discrete actions (e.g., phase switching, green signal ratio adjustments) and iteratively refining control policies via reward functions that balance efficiency, equity, and safety. This framework leverages deep learning architectures, such as YOLO for object detection and LSTM for temporal pattern extraction, to derive high-fidelity state representations. Algorithms like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) facilitate rapid policy updates under dynamic conditions. In practice, RL-driven systems, exemplified by Shenzhen's *TrafficGo* platform[5], dynamically adapt signal cycles and green ratios based on real-time traffic flow, achieving significant reductions in average vehicle delay at individual intersections. Nonetheless, challenges persist, including high data dependency, inference latency, and susceptibility to local optima, necessitating further advancements in lightweight model design and multi-agent collaboration for scalable urban deployment.

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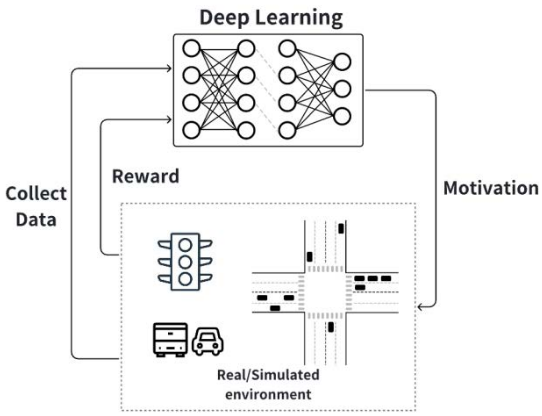

Figure 1 Deep Learning-Traffic Signal Control Framework

5.1.1 Single-Intersection Control (State-Action-Reward Modeling)

Pan T. proposed a dual-phase framework integrating offline pretraining and online learning for single-intersection signal control, emphasizing structurally refined state-action-reward (SAR) modeling. The methodology employs a phase-gate (phase-specific gating) neural network architecture to differentiate decision logic across signal phases, enhancing traffic flow adaptability. A memory palace mechanism is introduced to mitigate sample imbalance issues, such as policy degradation due to memory dominance by high-frequency actions [5]. Experimental results demonstrate that, compared to traditional fixed-signal control, the RL-based approach significantly reduces vehicle waiting time (57.1%), queue length (40.9%), and total travel time (16.8%) across balanced, imbalanced, and abrupt traffic scenarios. However, scalability to multi-intersection coordination remains challenging, and robustness under extreme traffic events requires further investigation.

Qin Qiao et al. developed an enhanced Advantage Actor-Critic (A2C) algorithm for critical intersections near large-scale event venues [6]. By reconstructing the reward function to disaggregate vehicle queuing time based on travel modes and introducing passenger-load parameters to amplify public transit delay impacts, the model prioritizes event participant demands during phase transitions. The state space (22×14-dimensional) captures lane-specific flow rates, queuing grids, and bus counts, while the action space dynamically adjusts green durations across four phases. A dynamic ε-greedy strategy balances exploration and exploitation. Simulation on the Beijing Capital Gymnasium intersection via SUMO platform reveals a total delay reduction of 65.7% compared to conventional fixed-time control, a 21.4% improvement over DQN, and a 38.6% decrease in bus waiting time, validating efficacy in transit priority and system-wide efficiency. Limitations include isolated control assumption and reliance on empirical parameter tuning for simulations.

Sharma M. et al. implemented a YOLOv3-based object detection system integrated with SORT (Simple Online and Realtime Tracking) for vehicle trajectory association, enabling real-time traffic volume estimation via virtual detection lines. The system dynamically allocates green time to high-density traffic directions and incorporates emergency vehicle priority protocols. Experimental results [7] demonstrate a 40% reduction in vehicle waiting time and 25% decrease in travel delay under complex Indian road conditions, with hardware costs reduced by more than 90% compared to inductive loop solutions. Key strengths include adaptability to unstructured traffic environments, end-to-end visual perception for precise flow analysis, and historical pattern learning for cycle optimization. However, detection accuracy declines by **approximately 15%** under high vehicle density, and performance is compromised by nighttime light interference and low-visibility conditions. While peak-hour efficiency improvements are notable, coordinated control capabilities in extreme congestion scenarios remain unverified.

5.1.2 Multi-Intersection Coordinated Control (Multi-Agent RL)

Liu Yi et al. [8] applied reinforcement learning to urban traffic signal control through a case study of eight adjacent intersections in Shenzhen’s Bantian district. Their framework utilizes a Deep Q-Network (DQN) architecture, which processes traffic image sequences as inputs and outputs Q-values for signal phase selection. To enhance training stability, the authors integrated experience replay and target network mechanisms. The reward system employs a hierarchical structure balancing traffic efficiency, safety, and equity, while incorporating traffic state recognition (e.g., free-flow, congestion, gridlock). Post-implementation data indicate a 4.2% increase in network-wide average vehicle speed. A critical limitation is the dependency on specialized hardware for data acquisition, which constrains adaptability to heterogeneous traffic environments.

Xia Gege et al. developed a multi-agent DQN framework for coordinated control of large-scale traffic networks. Each intersection operates as an independent agent with a multidimensional state space capturing vehicle positions, speeds, and signal phase statuses. The action space implements a binary decision protocol (“phase retention” or “phase switching”). The reward function integrates average queue length and delay time across the network, with spatial traffic flow features extracted by convolutional neural networks (CNNs). Coordinated optimization is enabled through synchronized experience replay and target network updates. Experiments in a 2×2 intersection model [9] demonstrate convergence after 200 training episodes, achieving stable average queue lengths of 3 vehicles per intersection and 15-second delays. Compared to fixed-time control, the method reduces overall delay by 35.37% and queue length by 38.51%, with optimal convergence parameters identified as learning rate = 0.001 and discount factor = 0.75. Strengths include dynamic adaptation to traffic fluctuations via multi-agent interactions; limitations encompass high computational complexity, prolonged training cycles, and unresolved challenges in communication latency and generalization across heterogeneous intersection configurations.

5.2 Supervised Learning-Based Traffic Flow Prediction and Optimization (LSTM, Transformer)

Alfonso Navarro-Espinoza et al. highlight that deep learning-based traffic flow prediction serves as a foundational component for reinforcement learning control frameworks. Long Short-Term Memory (LSTM) networks, which utilize gated recurrent units to model long-range temporal dependencies, demonstrate superior performance in short-term traffic flow forecasting. The authors propose a bidirectional LSTM architecture that integrates historical traffic data and meteorological variables, achieving an 18.6% reduction in root mean square error (RMSE) over 5-minute prediction horizons compared to traditional ARIMA models. To enhance temporal correlation modeling, the framework incorporates multi-head attention mechanisms, resulting in a 12.3% accuracy improvement over standalone LSTM models during weekday morning peak hours in Beijing [10]. The model exhibits robust adaptability to abrupt traffic disturbances (e.g., accidents), with validation in Shenzhen's Futian Central District showing 21.4% lower RMSE in 15-minute prediction tasks relative to single-model approaches. To address Transformer architectures' inherent computational complexity, the authors introduce a lightweight Transformer variant with sparse attention mechanisms, enabling deployment on embedded devices for real-time signal control. Despite balancing prediction accuracy and computational efficiency, LSTM-based methods still face limited generalizability to extreme traffic scenarios, which remains an open research challenge.

Xu M. proposed the Spatial-Temporal Transformer Network (STTN), which advances short-term traffic prediction through dynamic spatiotemporal dependency modeling. The framework comprises two innovative modules. Spatial Transformer: Employs self-attention mechanisms to capture directed spatial dependencies between traffic network nodes, synthesizing influences from similarity, connectivity, and covariance via multi-head attention. Temporal Transformer: Utilizes bidirectional self-attention to model long-range temporal dependencies, bypassing the sequence length limitations of RNNs and enabling multi-step parallel prediction to reduce error propagation. Experiments on PeMS-BAY and PeMSD7(M) datasets [11] demonstrate STTN's superiority in long-term predictions (≥30 minutes), achieving 15.4% lower mean absolute error (MAE) for 45-minute forecasts compared to ST-GCN and DCRNN benchmarks, alongside 10–40% higher training efficiency than Graph WaveNet. Key advantages include dynamic adaptation to traffic patterns via graph neural networks; efficient long-range dependency modeling via Transformer architectures. And the limitations include spatial attention complexity scales quadratically with node count, hindering scalability in large-scale road networks; no explicit integration of external factors (e.g., weather events) that disrupt traffic patterns.

6. Conclusion

Deep learning-driven intelligent traffic signal control technologies have provided transformative solutions for urban traffic management. Reinforcement learning (RL) enables adaptive decision-making across single-intersection to multi-intersection systems through dynamic environment modeling and online optimization mechanisms, significantly enhancing control flexibility in complex scenarios. Supervised learning techniques, integrating temporal modeling and cross-modal data fusion, have improved both the accuracy and robustness of traffic flow prediction.

While current research has achieved significant progress in state representation optimization, multi-objective reward design, and lightweight model deployment, three critical challenges remain:

First, the inherent conflict between data quality and real-time requirements: Sensor noise and occlusion artifacts frequently degrade model reliability. Second, the trade-off between local optimization and global coordination: Locally optimal decisions may propagate secondary congestion at the network level. Third, limited generalization capabilities in extreme scenarios: Existing models struggle to adapt to dynamic disruptions such as accidents or sudden traffic surges.

Future efforts should prioritize developing multi-agent collaborative architectures, edge-computing-accelerated strategies, cross-modal data fusion mechanisms, and fairness guarantees under ethical constraints. These advancements will bridge the gap between experimental validation and large-scale deployment of intelligent traffic signal systems, offering foundational technological support for

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building smart urban transportation networks.

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