A Review of Urban Real-time Traffic Signal Control

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Abstract. Urban traffic congestion was a challenging problem. In recent years, researchers in the fields of transportation and computer science devoted considerable attention to studying real-time traffic signal control (RTSC) to alleviate urban traffic congestion. This paper reviewed various methods for RTSC, categorizing them based on the algorithms. Additionally, simulators were summarized to validate algorithm performances, and the analysis further explored the interrelationships between different traffic entities, optimization objectives, and network types. Finally, potential avenues for future research in traffic signal control (TSC) were discussed, with the aim of providing valuable references to researchers working on intelligent transportation systems (ITS) for practical implementations.

Keywords: Urban traffic congestion; real-time traffic signal control (RTSC) ; intelligent transportation systems (ITS) .

1. Introduction

The economy continues to grow rapidly, and the number of cars on the roads is increasing significantly, leading to a rise in urban traffic congestion. This congestion, in turn, results in losses of $121 billion and heightens emissions of pollutants, further exacerbating environmental pollution [1]. Moreover, urban traffic congestion has adverse effects on both health and well-being [2]. Currently, there are already 19 cities in our country with over 3 million cars. While limiting car travel could alleviate traffic congestion, such measures are not in line with the intelligent transportation development direction of our country [3,4].

Traffic congestion was a complex issue that arose from various factors, including the inadequate arrangement of traffic infrastructure, driver's psychology, and insufficient TSC. The effective solution to alleviate traffic congestion lay in TSC [5]. Optimizing TSC reduced vehicle total travel time by 34% and CO2 emissions by 18.25% [6,7]. Due to its advantages, researchers are increasingly interested in studying TSC. Currently, many cities still rely on fixed-time control for TSC, which are manually determined based on historical traffic flow data. However, traffic flow is influenced by factors such as weather, accidents, and sudden changes in demand, making it challenging for preset signal control to adapt to actual traffic conditions. Therefore, enhancing the efficiency of the TSC requires the investigation of RTSC.

Webster and Miller introduced the vehicle minimum delay formula, and Robertson developed a simulator [8-10]. Building upon these advancements, subsequent researchers proposed a variety of RTSC algorithms.

Based on the aforementioned context, the objectives of this paper were as follows: 1) To review significant works in the field of TSC, providing a comprehensive understanding of its development in the realm of RTSC, and further summarized the encountered problems and challenges. 2) To extract and analyze the pertinent traffic entities, optimization objectives, and traffic network types that necessitated consideration in RTSC from a practical standpoint. 3)To identify the simulators most utilized by researchers and summarized their applicability and distinct advantages. 4) To categorize the existing methods, models, and prevailing trends in this field based on algorithms and discussed the mainstream approaches. 5)To summarize the findings areas for further research.

2. Real-time traffic signal control

In the early 20th century, modern traffic lights were introduced in the United States. Later, Webster published traffic signals settings in 1958, which established the theoretical basis for contemporary TSC [8].

Fig. 1 illustrates that the control strategy serves as the core of the TSC system. The control strategy is updated based on the future predicted value of traffic flow and the current measured value to minimize the time overhead of traffic flow. If this task is controlled manually, the control strategy requires manual updates. If controlled automatically, the strategy is updated by the control system. The control strategy determines the efficiency of the entire control system to a large extent, so it is necessary to design a control strategy and apply an automatic control method [11].

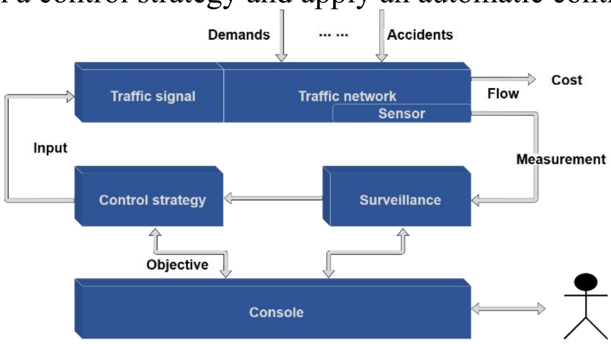

Fig. 1 Traffic signal control system

The development of TSC can be categorized into two stages: fixed-time control and real-time control [5]. The fixed-time control adjusts traffic flow by using historical traffic flow data from different periods to artificially set vehicle passing times. It performs well when traffic flow is constant. However, the traffic network is dynamic, and any preset traffic signal fails to adapt well to actual traffic conditions, prompting the emergence of real-time control strategies. Real-time control included actuated control and adaptive control strategies [12,13].

2.1 Actuated control

Actuated control, as introduced by Dunne and Potts in 1964 [14], utilized a pre-set control logic that involved variations in green time, phase sequence, and other factors. This approach utilized road sensors to detect vehicle arrivals, resulting in an extension of the green time. However, it solely detected vehicle presence without considering the volume of arrivals or effectively responding to the traffic demands of each phase. Consequently, it fell short in minimizing overall vehicle delay (VD) and was most suitable for road networks composed of major and minor roads [15,16].

2.2 Adaptive control

Adaptive control were similar to actuated control. Unlike the actuated control, the adaptive control utilized a flow prediction model to periodically predict future vehicle arrivals at the target intersection based on the phase sequence and duration of the green light during the formulation of the optimal control strategy. Then, based on the predicted future vehicle arrivals, the phase sequence and green light duration were updated, creating a dynamic recursive optimization process. Several RTSC systems were developed based on adaptive control, such as SCATS, SCOOT, and UTOPIA [17-19].

3. Comprehensive analysis based on traffic entities and optimization objectives

Real-world traffic includes various entities, such as personal vehicles, transit vehicles, pedestrians, and emergency vehicles. In cases where the traffic consists solely of personal vehicles, the optimization objectives of the algorithms revolve around mobility metrics such as VD, vehicle queue lengths (VQL) , and throughput [20-23]. However, when multiple types of traffic entities are involved, researchers face the challenge of establishing multiple optimization objectives for the algorithms and assigning priorities among the traffic entities. Due to the complexity of considering all types of traffic entities, studies often simplify the problem by focusing on a limited set of traffic entities. In fact, a significant majority (more than 80%) of the references cited in this paper exclusively considered personal vehicles [24].

3.1 Only personal vehicles are considered

In the context of isolated intersections, Murat et al. proposed a multi-phase signal control model based on fuzzy logic [16]. This study utilized a weighted average to calculate the average VD, considering the varying traffic volumes in each direction of the intersection. Subsequently, the green time and phase sequence were adjusted based on the traffic flow to mitigate VD. To ensure a balanced distribution of vehicles in each direction, the optimization objective of minimizing VQL was considered. Maadi et al. demonstrated that minimizing the VQL can effectively reduce VD [24,25]. Excessive VQL could lead to prolonged waiting times for vehicles at the intersection, as frequent starts and stops hindered traffic flow, directly impacting driver satisfaction. Therefore, it was crucial to consider both VQL and stops [26,27]. Furthermore, some researchers integrated the optimization of throughput maximization with VQL and stops to achieve reductions in VD [28-30].

In a general network, there existed multiple paths for vehicles to travel from the origin to the destination. However, if all vehicles took shortcuts to the destination, it led to an increase in vehicles total travel time. Wong et al. utilized an iterative approach of signal optimization and path assignment to achieve a balanced traffic flow in the region, resulting in a significant 15% reduction in vehicle travel time [31].

In an arterial, vehicles could smoothly traverse multiple sections controlled by traffic lights at a consistent speed, known as the 'Green wave'. This technique considered both the average speed of vehicles on the arterial road and the average waiting time of vehicles in other phases [32-34]. Over the years, extensive research had been conducted on the 'Green wave' technology, leading to its widespread implementation in major cities such as Beijing and Shanghai in China.

In recent years, the issue of global warming heightened the importance of ecological preservation. Consequently, researchers shifted their attention to studying the ecological impact of traffic congestion [7,35]. Aslani et al. contributed to this area by developing a model that examined three types of vehicle emissions (carbon monoxide, hydrocarbons, and nitrogen oxides) associated with air pollution. Their objective was to minimize exhaust emissions and promote the sustainability of ecological development [36].

3.2 Both personal vehicles and others are considered

In areas characterized by high pedestrian flows, such as cultural and economic centers and ferry crossings, the ratio of pedestrians to vehicles could reach as high as 2:1 or even greater. However, the green times allocated at intersections typically prioritized vehicles, neglecting the needs of pedestrians. Consequently, pedestrians often encountered difficulties crossing the intersection during the red light for vehicles [37]. Therefore, it was important to incorporate pedestrian flow into traffic signal optimization. Akyol et al. proposed a method in which the feasible space for pedestrians and vehicles was divided into narrow stripes, and movement was governed by orderly rules. This approach yielded a 7% reduction in pedestrian delays and a 9% reduction in VD [38]. Additionally, Yazdani et al. recently introduced an intelligent vehicle-pedestrian traffic signal model [39]. The model calculated the minimum delay for both pedestrians and vehicles and assigned the optimal green time accordingly. In cases where a pedestrian running a red light was detected, the signal interrupted the flow of vehicles to ensure safety.

In many studies, transit vehicles and emergency vehicles received less attention as traffic entities due to concerns that prioritizing them would increase personal VD. However, in practical applications of TSC, the importance of transit vehicles and emergency vehicles could not be overlooked. Consequently, researchers focused on achieving a balance between personal vehicles, transit vehicles, and emergency vehicles, aiming to reduce personal VD while considering the priority of transit and emergency vehicles [40]. Ekeila et al. proposed a recursive algorithm for dynamic signals [41]. This algorithm prioritized transit vehicles while minimizing their impact on other vehicles on the road. Shamsi et al. introduced dynamic scheduling of red and green phases of traffic signals [42]. This method reducing 11% of individual vehicle waiting time and average delay from 27% to 40% of emergency vehicles , effectively resolving the conflicts between those vehicles.

4. Comprehensive analysis based on traffic network types

Traffic network types are categorized into isolated intersections, arterial, and general networks. Initially, studies focus solely on isolated intersections due to the significant increase in computational complexity as the number of lanes and intersection connections grows. However, with advancements in computer hardware and simulators, the computational capabilities improve, allowing for the expansion of the studied traffic network types (Fig. 2). Newly developed solution methods are typically validated using small traffic networks, thus research on TSC at isolated intersections remains active. Arterial, which are part of general networks, are less frequently studied independently. However, they are considered separately for performance verification purposes in 'Green wave' studies [43].

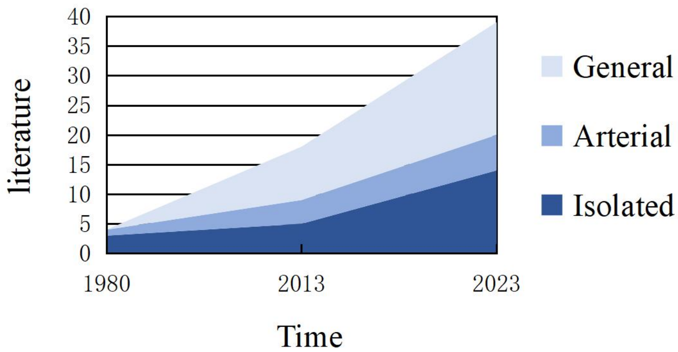

Fig. 2 Time variation of researchers' studies on traffic network types

5. Comprehensive analysis based on simulators

Researchers utilize simulators to model real-world traffic flows and analyze complex and dynamic changes in traffic flow. Based on the reviewed literature, approximately 90% of the studies employ traffic flow simulators or models. Among these researchers, over 60% prefer validation platforms like SUMO and VISSIM. Both SUMO and VISSIM support programming languages such as C++, Python, and JAVA, allowing users to interact with the environment and simulate various types of traffic entities, including vehicles and pedestrians, through a flow control interface library. Additionally, these simulators facilitate the importation of real road networks and the configuration of drive-in and drive-out modules at any network location.

While both SUMO and VISSIM offer similar functionalities, VISSIM has certain advantages in dealing with multiple traffic entities, arterial and general network types, and the study of Intelligent Transportation Systems (ITS). For example, VISSIM provides unique features for multi-area scheduling, intersection signal control, and prioritizing public transportation. Moreover, VISSIM encompasses a wide range of simulation capabilities for ITS, such as self-driving and connected vehicles, enabling researchers to better evaluate the impact of emerging technologies on traffic flow.

6. Comprehensive analysis based on algorithms

Reinforcement learning (RL) and heuristic algorithms constitute more than 70% of the literature reviewed, highlighting the effectiveness of these methods in TSC.

In the early TSC research, rule-based approaches were utilized to alleviate traffic congestion issues. This approach involves optimizing intersections by imposing restrictions on critical states, such as VQL or green time. When these limits are surpassed, the phase sequence can be altered, or the green time can be extended based on predefined rules. To approximate the definition of critical states, Murat et al. proposed the use of fuzzy rules [16]. Similarly, Lee et al. utilized fuzzy rules to adjust the phase sequence and compared it with actuated control under traffic stabilization conditions, resulting in performance enhancements ranging from 3.5% to 8.4% [7].

Evolutionary computation and swarm intelligence are heuristic algorithms inspired by nature. Evolutionary computation encompasses genetic algorithm (GA), genetic programming, and evolutionary programming, which emulate the natural evolutionary principle of meritocracy. Swarm intelligence, on the other hand, draws its origins from the collective behavior observed in biological species such as birds, ants, and bees. Yu et al. utilized GA to optimize traffic signals [44]. The algorithm assigned varying weighting coefficients based on different optimization objectives, considering the traffic flow ratio. By assigning these weights, the multi-objective optimization was transformed into a single-objective optimization, simplifying the calculation of throughput and VQL. Through simulations, it has been demonstrated that GA yield high-quality optimization solutions, and researchers have even developed simulation software based on GA to expand their capabilities [12,40]. Wu et al. constructed a traffic network model using particle swarm optimization for traffic signal control. Each particle in the swarm contained the signal plan for all nodes and was applied to a traffic network in the city of Changsha [45]. This algorithm exhibited faster convergence and lower delay compared to the GA.

Researchers have drawn inspiration from adaptive traffic control systems like SCOOT, SCATS, and UTOPIA and have subsequently developed Dynamic Programming (DP) [6]. These algorithms demonstrate versatility in handling multiple optimization objectives and various traffic flow scenarios. However, as the size of the traffic network increases, the recursive computation required by DP becomes computationally intensive. To address this challenge, researchers have explored the application of RL techniques to approximate the state space and tackle the aforementioned issue [46].

RL is a powerful approach for discovering improved actions through online interaction with the environment [47]. It typically involves three key elements: state, action, and reward. In this paradigm, an agent operates based on different states, and the environment provides feedback in the form of rewards to guide strategy improvement. The agent framework has gained traction in the development of large-scale distributed systems, with various intelligent methodologies being applied to transportation systems. These include the integration of game theory, vehicular networking, and RL. For instance, Kamal et al. introduced a cyber-physical multi-agent system that combines autonomous driving and vehicular networking to optimize TSC [48]. Their algorithm segments the current arterial into multiple well-spaced red and green intervals using a multi-intelligent agent system. When a vehicle approaches a red interval, the intelligent agent notifies the vehicle about an upcoming red light at the intersection. The vehicle can then choose to accelerate and enter the green interval to avoid being blocked. Comparative analysis reveals that autonomous vehicles outperform SCOOT, especially at full penetration, achieving near wait-free TSC at intersections. In another study, Wu et al. proposed a Nash equilibrium algorithm combined with RL [49]. Each traffic signal at an intersection is treated as an agent, and their action strategies are mutually considered and rewarded based on the VQL. Once the actions of each agent stabilize, the algorithm seeks to optimize their strategies, ultimately achieving Nash equilibrium. By employing real topology and traffic data from a Chinese city, the algorithm demonstrates a remarkable 22.1% reduction in congestion time and a 9.7% reduction in network delay. This comprehensive approach fully accounts for the game and interactions among different agents, enabling large-scale optimization of TSC.

7. Conclusion

This paper provides an analysis of traffic entities, optimization objectives, simulators, and algorithms involved in RTSC. Drawing from a comprehensive review of relevant literature, this study presents the following key insights and trends in RTSC:

1) The scope of TSC research expands beyond optimizing personal VD to encompass broader concerns such as emissions, fuel consumption, and others VD. Consequently, TSC becomes increasingly complex, addressing societal needs on a larger scale. With the involvement of diverse traffic entities, optimization objectives and larger traffic network, efficiently processing the substantial volume of real-time data poses a significant challenge.
2) The consideration of traffic entities and traffic network types in TSC primarily focuses on personal vehicles and isolated intersections, deviating from the real-world scenario. Generalizing findings from the small scale to the larger scale remains a challenging task.
3) Although numerous algorithms and methods are developed for RTSC, their validation often relies on simulated data rather than real-world data. This lack of real data poses a challenge in verifying the accuracy of experimental results. Furthermore, translating scientific research into practical applications remains a substantial obstacle that hampers the integration of scientific studies into real-world context.
4) The number of studies on autonomous driving and connected vehicles steadily increases. Researchers demonstrate that VD can be attributed to drivers' slow responses to traffic signals, and the implementation of autonomous driving and connected vehicle technologies can alleviate road congestion by reducing human involvement. However, the practical benefits of these technologies in improving daily lives are not fully realized, which calls for effective enhancement of the autonomous driving experience and increased public confidence in autonomous vehicles. Challenges related to high latency communication and limited communication bandwidth for real traffic infrastructure also need to be addressed.
5) The application of heuristic algorithms, RL, and multi-intelligent agent systems in various traffic network types significantly enhances the capabilities of ITS in recent years. The combination of genetic optimization, particle swarm optimization, and RL shows promise as a potential direction for future development.

Overall, this review sheds light on the current state and future directions of RTSC, highlighting both challenges and opportunities in this dynamic field.

Acknowledgments

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