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RESEARCH ARTICLE

A V2I communication-based pipeline model for adaptive urban traffic light scheduling

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Abstract Adaptive traffic light scheduling based on real-time traffic information processing has proven effective for urban traffic congestion management. However, fine-grained information regarding individual vehicles is difficult to acquire through traditional data collection techniques and its accuracy cannot be guaranteed because of congestion and harsh environments. In this study, we first build a pipeline model based on vehicle-to-infrastructure communication, which is a salient technique in vehicular adhoc networks. This model enables the acquisition of fine-grained and accurate traffic information in real time via message exchange between vehicles and roadside units. We then propose an intelligent traffic light scheduling method (ITLM) based on a "demand assignment" principle by considering the types and turning intentions of vehicles. In the context of this principle, a signal phase with more vehicles will be assigned a longer green time. Furthermore, a green-way traffic light scheduling method (GTLM) is investigated for special vehicles (e.g., ambulances and fire engines) in emergency scenarios. Signal states will be adjusted or maintained by the traffic light control system to keep special vehicles moving along smoothly. Comparative experiments demonstrate that the ITLM reduces average wait time by 34%–78% and average stop frequency by 12%–34% in the context of traffic management. The GTLM reduces travel time by 22%–44% and 30%–55% under two types of traffic conditions and achieves optimal performance in congested scenarios.

Keywords traffic light scheduling, vehicular ad hoc networks, pipeline model, vehicle-to-infrastructure communication, intersection

1 Introduction

In urban environments, the explosive growth in the number of vehicles and limited capacity of road networks have led to frequent occurrences of traffic congestion, particularly at major intersections. These issues have increased travel costs and negatively impacted road safety. Adaptive traffic light scheduling methods have been proved to be the most economical and important means to alleviate traffic congestion [1], thereby significantly improving traffic efficiency and safety.

One of the key challenges in designing efficient adaptive traffic light scheduling methods is how to precisely collect real-time traffic information. Currently, traffic information is mainly collected by video cameras [2–6], sensor networks [7–11], and vehicular adhoc networks (VANETs) [12–18]. Video cameras and sensor networks have been widely adopted over the past few decades. However, unfavorable

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conditions (e.g., rainy or foggy days) and vehicle occlusion negatively affect the accuracy of vehicle statistics when utilizing video cameras. Furthermore, because of the intrinsic limitations of sensors, only a restricted amount of information can be acquired. For example, loop detectors can only detect the quantity of vehicles without considering vehicle types and magnetic sensors are incapable of sensing immobile vehicles [7]. In contrast to video cameras and sensor networks, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications are comparatively less sensitive to harsh surroundings and fine-grained information on vehicles, such as lane position, speed, priority, among others, can be easily collected via message exchange. Such information can be utilized to design more reasonable and flexible traffic light scheduling methods. For example, the authors in [15] estimated the real-time queue length of vehicles based on the individual positions and speeds of vehicles and implemented a queue-based adaptive signal control method.

Compared to video cameras and sensor networks, V2V/V2I communications are more reliable and efficient for collecting real-time traffic information. However, several important, fine-grained information elements regarding vehicles, such as their types and turning intentions, are typically ignored in existing V2V/V2I communication-based methods. Collecting this information is extremely important for efficient traffic light control. For example, because of its length or size, a heavy vehicle occupies more space and spends more time passing through an intersection compared to a light vehicle. Therefore, the types of vehicles should be considered to distinguish their effects on traffic conditions. Furthermore, because right-turning vehicles do not interfere with traffic flow in other directions, they can pass through intersections at any time if and only if the impacts of non-motorized vehicles (e.g., bicycles) and pedestrians are not considered. In such cases, the right-turning vehicle decides whether it should obey current traffic control or pass through an intersection immediately.

In this work, we first construct a V2I communication-based pipeline model. Specifically, two road side units (RSUs) located near an intersection constitute a *virtual pipe* for collecting information regarding vehicles that move toward the intersection in a specific area. Through message exchange between vehicles and RSUs, a vehicle's fine-grained information (identifier, traveling lane, type, and priority) is recorded once the vehicle enters the pipeline. All the recorded fine-grained information regarding vehicles will be processed and delivered to the traffic signal control system as the basis for traffic light scheduling. Based on the pipeline model, we then propose an intelligent traffic light scheduling method (ITLM) by considering vehicle types and turning intentions. According to the "demand assignment" principle, a signal phase with a large number of vehicles will be assigned a longer green time, which will ensure that average vehicle wait time and stop frequency are significantly reduced. Furthermore, a green-way traffic light scheduling method (GTLM) is investigated for special vehicles (e.g., ambulances and fire engines) to improve rescue times in emergency scenarios. Once a special vehicle is noticed by checking its priority information, the traffic light control system adjusts the current signal states to allow special vehicles to pass through the intersection preferentially.

Our main contributions are summarized as follows:

1) A V2I communication-based pipeline model is constructed with the aid of RSUs. The model provides the ability to collect fine-grained and accurate real-time traffic information for traffic light scheduling. Unlike existing V2V/V2I communication-based methods, several important, fine-grained elements of vehicles are considered in our model, such as vehicle types and turning intentions.

2) We propose an ITLM based on the pipeline model. The ITLM focuses on improving driving quality at intersections, meaning average vehicle wait time and stop frequency are significantly reduced. Additionally, a GTLM is investigated to improve the rescue times of special vehicles.

3) A number of comparative experiments are performed to demonstrate the effectiveness of the proposed pipeline model and traffic light scheduling methods.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 details the models, assumptions, and definitions utilized in this study. This is also where the V2I communication-based pipeline model is described. Sections 4 and 5 provide detailed explanations of the ITLM and GTLM, respectively. In Section 6, we discuss the simulation results. Finally, we conclude this paper in Section 7.

2 Related work

We will now review existing traffic information collection techniques by categorizing them into three classes: 1) image and video processing techniques, 2) sensor network techniques, and 3) V2V/V2I communication techniques.

2.1 Image and video processing techniques

With recent progress in computer vision technology, video cameras have become a feasible and efficient method for traffic flow monitoring. Image and video processing techniques focus on detection, tracking, and recognition of lanes, vehicles, incidents, and behaviors, which are important for handling traffic-related problems.

Various image and video processing techniques for detecting and recognizing vehicles were introduced in [2–4]. Specifically, Li et al. [4] proposed an effective vehicle detection approach based on the combination of an and-or graph (AOG) and hybrid image templates (HITs) to circumvent the problem of vehicle occlusion. Their approach included three steps. First, the AOG for vehicle representation was constructed and the HITs were utilized to mathematically characterize the AOG nodes. Then, training images were collected to learn the parameters for the AOG. Finally, a bottom-up inference model was utilized to detect vehicles in test images. However, the proposed method cannot be applied in nighttime traffic conditions. The researchers in [5, 6] presented methods to utilize live video feeds from cameras at intersections for real-time traffic density estimation. Traffic light scheduling algorithms were proposed according based on the traffic density of the road. Similar to other image- and video-based methods, the negative effects introduced by harsh environments were unavoidable and not thoroughly discussed.

2.2 Sensor network techniques

As a relatively new mode of information acquisition and processing, sensor networks have received significant attention for traffic detection and avoiding traffic congestion [7].

Collotta et al. [8] proposed a dynamic traffic light control system that combined a wireless sensor network (WSN) for real-time traffic monitoring with multiple fuzzy logic controllers. The WSN was responsible for detecting queued vehicles during each signal phase and the number of queued vehicles was utilized to determine the phase execution order. Next, the fuzzy logic controllers calculated an appropriate green time duration for each signal phase. One drawback of this approach is that a large number of sensors must be deployed because the queue length of vehicles may be several hundred meters long and the types of vehicles are not distinguished by sensors. Yang et al. [9] constructed a system to detect and classify vehicles based on three-axis anisotropic magneto resistive sensors. Specifically, signal variance was utilized by a fixed-threshold state machine algorithm to detect vehicles within a single lane. The detected vehicles could be classified into several types based on extracted signal features and a hierarchical tree methodology. However, multi-lane scenarios were not considered and the detection method was effective only when the speed of vehicles fell within a limited range.

2.3 V2V/V2I communication techniques

With the rapid development of intelligent transportation systems (ITS), VANETs have become a research hotspot in recent years. VANETs are widely utilized in many fields based on V2V/V2I communication techniques [19], such as cooperative downloading [20, 21] and safety message broadcasting [22, 23]. Furthermore, VANETs also provide a promising means for collecting fine-grained traffic information and designing adaptive traffic light control systems.

Sanguesa et al. [13] presented a V2X (i.e., V2V and V2I combined) architecture, which was an upgraded version of the solution proposed in [14], to estimate real-time traffic density in urban environments according to the number of received beacons. To make accurate estimations, both the number of beacons received per RSU and per vehicle were considered, as well as the characteristics of road map topology. However, the beacons periodically emitted by vehicles are prone to collide with each other. This phenomenon occurs frequently in congested traffic conditions. Feng et al. [17] designed an adaptive signal phase allocation algorithm based on V2I communication techniques. Broadcasted safety messages that contain the locations and speeds of vehicles were collected by RSUs for optimizing phase sequence and duration, but the individual differences between vehicles were ignored. Lee et al. [18] concluded that V2V/V2I communication techniques not only improve ride quality, but also have positive effects in terms of energy saving and emission reduction.

Among the sensing and communication techniques described above, V2V/V2I communication techniques are the best method for acquiring real-time, fine-grained traffic information, and are the least sensitive to harsh environments. However, the turning intentions and types of vehicles, which can enhance the effectiveness of traffic light scheduling methods, are ignored in existing V2V/V2I communication-based methods. In the method proposed in this paper, these important elements of vehicles are considered.

3 Models, assumptions, and definitions

This section describes three models with specific assumptions: the 1) intersection model, 2) signal phase distribution model, and 3) V2I communication-based pipeline model.

The intersection model and signal phase distribution model are presented to represent basic research scenarios. The V2I communication-based pipeline model is then described in detail.

3.1 Intersection model

Cross-shaped intersections are simple, ubiquitous, and occupy an important position in urban traffic environments. Therefore, optimizing an isolated intersection can improve the performance of an entire traffic network [24]. In this paper, we consider a typical cross-shaped intersection model is considered with the following assumptions:

1) The shape of the intersection is a standard "cross" and the traffic light control system is located in the center.

2) It is a three-lane road and the intersection allows vehicles to go straight, turn left, and turn right. U-turns are forbidden.

3) The vehicles strictly follow the traffic signals and there are no accidents.

4) The effects of non-motorized vehicles (e.g., bicycles) and pedestrians on traffic flow are not considered.

Our proposed traffic light scheduling methods have no direct relationship with the shape of the intersection. We only assume a standard "cross" intersection here to simplify the related descriptions.

3.2 Signal phase distribution model

To avoid interference between traffic flows, we assign four signal phases to the intersection, as found on most roads. As shown in Fig. 1, right-turning vehicles can pass through intersection at any time because they do not interfere with other traffic flows.

3.3 Pipeline model

To implement an adaptive traffic light control system, it is necessary to collect information regarding vehicles approaching intersections. As mentioned in Sections 1 and 2, video cameras, sensors, and V2V/V2I communication-based methods can provide the ability to estimate traffic density. In contrast to video cameras and sensor networks, V2V/V2I communications are less sensitive to harsh environments and fine-grained information regarding vehicles can be easily collected via message exchange. Therefore, V2V/V2I communications are considered to be the most promising means of solving traffic control problems.

However, several important, fine-grained elements of vehicles, such as vehicle types and turning intentions, are ignored in existing V2V/V2I communication-based methods. To remedy this issue, we first construct a V2I communication-based pipeline model for detecting real-time, fine-grained information regarding vehicles and consider the types and turning intentions of vehicles.

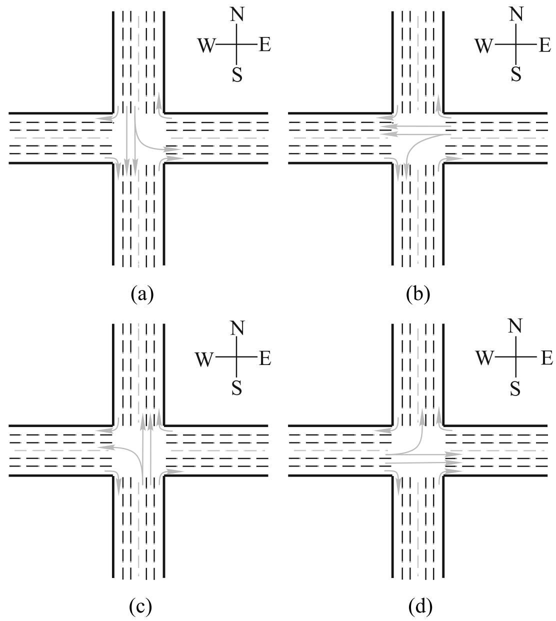

Fig. 1 Distribution of signal phases. (a) 1st phase; (b) 2nd phase; (c) 3rd phase; (d) 4th phase

3.3.1 Realization of pipeline model

The essence of the pipeline model is to collect and process fine-grained information regarding vehicles in the pipeline via RSUs. Such information includes vehicle identifiers, traveling lanes, types, and priorities. The traffic light control system will utilize the aforementioned information to allocate appropriate green time for each signal phase.

Figure 2 presents a scenario of the pipeline model in which the traffic flows are crossing the intersection from west to east. The length of the pipeline is D and the length of road is L. RSU_1 and RSU_2 are essential parts of the pipeline model that are located on both sides of the pipeline for collecting information regarding vehicles when they enter or leave the pipeline. The central data server processes the vehicle information that is forwarded by the RSUs and the traffic light control system allocates reasonable green time for each phase based on the processed information.

When a vehicle enters the pipeline, the vehicle sends an arrival message (AM) to RSU_1 that includes the vehicle identifier, traveling lane, type, and priority. When a vehicle leaves the pipeline, the vehicle sends a departure message (DM) to RSU_2, which only includes the vehicle identifier. Upon receiving an AM, RSU_1 stores relevant information regarding the vehicle in the central data server. Upon receiving a DM, RSU_2 deletes relevant information regarding the vehicle from the server. Both RSU_1 and RSU_2 maintain real-time information regarding vehicles inside the pipeline. The processed information is delivered to the traffic light control system for allocating the green time for each phase.

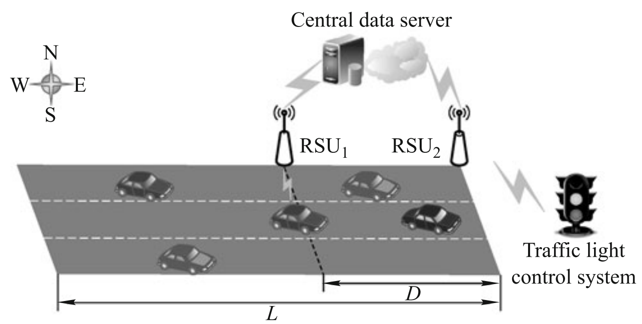

Fig. 2 Scenario of the pipeline model

3.3.2 Driving rules within the pipeline

A three-lane road is considered in our work. It consists of a left lane, straight lane, and right lane. According to the distribution of signal phases, vehicles in the pipeline should observe the following rules:

1) Left turn traffic flows drive on the left lane.

2) Right turn traffic flows drive on the right lane.

3) Straight traffic flows drive on the straight lane and left lane simultaneously.

In general, straight traffic flows have more vehicles than other traffic flows. Therefore, the model can improve the smooth flow ability of traffic by permitting straight traffic flows to drive on the straight lane and left lane simultaneously. According to the distribution of signal phases, left turn traffic flows share the green time with straight traffic flows, meaning they are in the same signal phase.

3.3.3 Length of the pipeline

In this paper, the maximum green time $T_{\max G}$ is the basis for calculating the length of the pipeline, meaning all queued vehicles that see a green light in the pipeline can pass through the intersection during $T_{\max G}$. Suppose that the pipeline is full of queued vehicles and they begin to pass through the intersection one by one. The final queued vehicle should leave the pipeline before $T_{\max G}$ expires. As the vehicle travels through three stages (i.e., waiting start, accelerating forward, and uniform forward), the above relationship can be represented as

$$t_w + t_a + t_u \leqslant T_{\max G}. \tag{1}$$

Here, t_w, t_a, and t_u denote the waiting start time, accelerating forward time, and uniform forward time of the last queued vehicle in the pipeline.

To calculate the vehicle waiting start time, we must know how many vehicles can be queued in a single lane of the pipeline. The types of vehicles are classified as small, medium, and large in this paper. Correspondingly, the lengths of the vehicles are denoted by L_a, L_b, and L_c, and the quantities of the vehicles are denoted by N_a, N_b, and N_c, respectively, Additionally, the safety distance between two vehicles is denoted by L_{gap} and the average length of vehicles is denoted by L_{avg}. Theoretically, the maximum number of vehicles in a single lane of the pipeline can be calculated as

$$N_{\max} = \frac{D}{L_{avg} + L_{gap}}, \tag{2}$$

where L_{avg} is calculated as

$$L_{avg} = \frac{N_a \cdot L_a + N_b \cdot L_b + N_c \cdot L_c}{N_a + N_b + N_c}. \tag{3}$$

By analyzing the final queued vehicle's movement, we can conclude that t_w is equal to the overall reaction time of all queued vehicles in a single lane, t_a is equal to the ratio of the vehicle maximum speed and acceleration, and t_u is equal to the ratio of the remaining pipeline's length and acceleration. Let t_{rea} denote driver reaction time and the parameter a denote vehicle acceleration. From these values, we can get

$$t_w = t_{rea} \cdot N_{\max}, \tag{4}$$

$$t_a = \frac{v_{\max}}{a}, \tag{5}$$

$$t_u = \frac{D - \frac{1}{2} a \cdot {t_a}^2}{v_{\max}}. \tag{6}$$

By combining Eq. (1) through Eq. (6), we can calculate the length of the pipeline as

$$D \leqslant \frac{v_{\max} \cdot \left(L_{avg} + L_{gap}\right) \cdot \left(T_{\max G} - \frac{v_{\max}}{2a}\right)}{v_{\max} \cdot t_{rea} + L_{avg} + L_{gap}}. \tag{7}$$

3.3.4 Relative definitions

Definition 1 Traffic ability. The number of vehicles that can pass through the intersection within an hour under current traffic conditions.

Definition 2 Traffic volume. The number of vehicles that will appear within an hour under current traffic conditions.

Definition 3 Waiting time. The total time that a vehicle remains in a waiting state before passing through the intersection, denoted WT.

Definition 4 Stop frequency. The number of stops before a vehicle passes through the intersection, denoted SF.

Definition 5 Ride quality. Reflects vehicle driving performance at an intersection. Specifically, a good ride quality means that under the premise of ensuring traffic safety, there is a short average WT and small average SF for all vehicles.

Definition 6 Maximum green time. The longest green time allocated to one signal phase during normal traffic control, denoted $T_{\max G}$.

Definition 7 Minimum green time. The shortest green time allocated to one signal phase during normal traffic control, denoted $T_{\min G}$.

4 Intelligent traffic light scheduling method based on pipeline model

4.1 Basic concept of ITLM

An efficient traffic light scheduling method should reduce the average WT and average SF as much as possible under the premise of ensuring traffic safety. The pipeline model collects real-time, fine-grained information regarding vehicles as they enter or leave the pipeline, which provides the basis for allocating green time for each signal phase according to the "demand assignment" principle. In other words, a shorter green time should be assigned to reduce WT when the traffic volume is small. Otherwise, a longer green time should be assigned to reduce SF.

4.2 Specific steps of ITLM

Allocating green time for each signal phase is actually the process that determines the control of green time. When a particular phase gets control, it will allocate appropriate green time according to current traffic conditions. After the green time expires, the control of green time will be transferred to the next phase.

Because of individual vehicle differences, it is inappropriate to allocate green time based only on vehicle quantity or density. Because there are three types of vehicles considered in this paper, we can compute the total weight that influences the allocation of green time by accumulating each vehicle's weight in the pipeline.

In the design of the ITLM, we ignore the impact of right-turn traffic flows on green time allocation. We suppose that there are N vehicles that see a green light in the pipeline during the current signal phase. The weight of vehicle i is denoted W_i and the total weight is denoted W_{sum}. We can write the expression for W_{sum} as

$$W_{sum} = \sum_{i=1}^{N} flag \cdot W_i. \tag{8}$$

Here, the values of $flag$ and W_i are calculated as

$$flag = \begin{cases} 1, & straight\ or\ turn\ left, \\ 0, & turn\ right. \end{cases} \tag{9}$$

$$W_i = \begin{cases} W_a, & small\ vehicle, \\ W_b, & middle\ vehicle, \\ W_c, & large\ vehicle. \end{cases} \tag{10}$$

When in a particular signal phase, vehicles that belong to that phase begin to pass through the intersection one by one. As time passes, the frequency of passing vehicles decreases and eventually equals the frequency of arriving vehicles. Additionally, there is an increasing number of stopped vehicles that belong to other phases and wish to pass through the intersection. To improve the use efficiency of green time, we must allocate it to the next phase when the total weight W_{sum} of the current phase is reduced to a certain value. Suppose that the value, which is called the weight threshold in this paper, is W_t. Then, the specific steps for allocating green time are as follows:

Procedure 1

Step 1: When a vehicle i enters the pipeline, it sends AM_i to RSU_1, which includes the vehicle's identifier, traveling lane, type, and priority. When the vehicle exits the pipeline, DM_i is sent to RSU_2, which only includes the vehicle's identifier.

Step 2: The central data server calculates the total weight W_{sum} according to the collected vehicle information and forwards W_{sum} to the traffic light control system.

Step 3: The traffic light control system checks whether or not the signal phase has control of the green time. If the signal phase has control, then the process proceeds to Step 4. Otherwise, the process returns to Step 1.

Step 4: The traffic light control system compares W_{sum} and W_t. If $W_{sum} > W_t$, this indicates that the road is relatively congested and execution proceeds to Step 5. Otherwise, execution skips to Step 8.

Step 5: The traffic light control system allocates green time for the current signal phase.

Step 6: The traffic light control system continues to compare W_{sum} and W_t. If $W_{sum} > W_t$, this indicates that the road is still relatively congested and execution proceeds to Step 7. Otherwise, execution skips to Step 8.

Step 7: The traffic light control system checks whether or not the length of persistently allocated green time T_G for the current signal phase is longer than $T_{\max G} - T_{\min G}$. If so, then the process proceeds to Step 8. Otherwise, the process returns to Step 5.

Step 8: The traffic light control system allocates an additional $T_{\min G}$ for the current signal phase.

Step 9: The traffic light control system transfers control of green time to the next phase and the procedure is completed.

The process of allocating green time is illustrated in Fig. 3. It is indicated in Fig. 3 that when traffic is sparse, the condition $W_{sum} > W_t$ is difficult to meet and the current signal phase will be allocated a short green time. Conversely, when traffic is dense, the condition $W_{sum} > W_t$ can be satisfied for a relatively longer duration and the current signal phase will be allocated a longer green time. In other words, the length of allocated green time is proportional to W_{sum}. Additionally, Steps 7 and 8 ensure that the length of allocated green time is between $T_{\min G}$ and $T_{\max G}$. Therefore, the ITLM allocates green time based on a "demand assignment" principle.

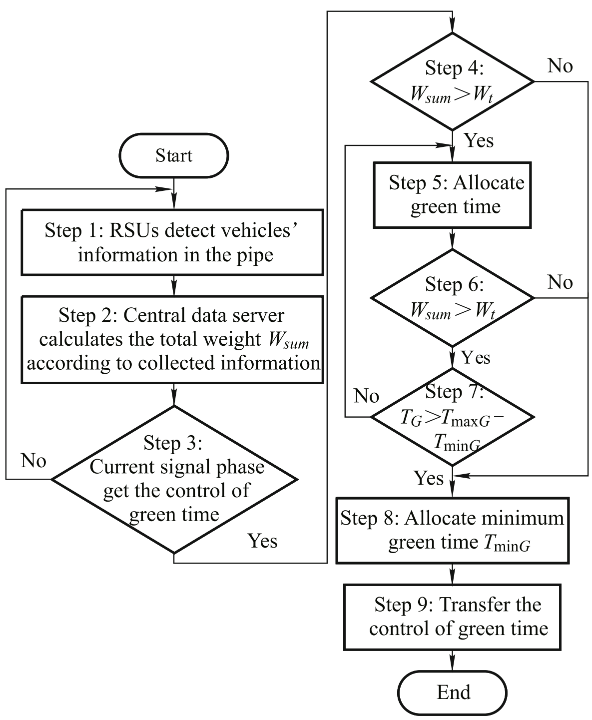

Fig. 3 The process of allocating green time

5 Green-way solution based on pipeline model

The term "special vehicles" typically refers to ambulances and fire engines. To reach an accident site as quickly as possible, special vehicles do not have to obey traffic control under the premise of ensuring road safety. However, they may be blocked because of stopped vehicles due to red lights and limited road capacity, which is exacerbated in congested traffic conditions.

To solve this problem and save rescue time, we borrow the basic concept from green-waved traffic control. Green-waved traffic control is commonly considered to be one of the most efficient strategies to regulate traffic signals on urban arteries. It allows traffic flows to successfully pass through multiple intersections [25]. However, only normal vehicles driving along main roads can optimally benefit from this type of traffic control because typical green-waved traffic control is unsuitable for special vehicles because of the uncertainly of their paths. In this paper, by considering the control of traffic lights along the paths of special vehicles, a variant of green-waved traffic control called the green-way traffic light scheduling method (i.e., GTLM) is presented based on the pipeline model.

5.1 Basic idea of GTLM

We assume that only special vehicles have the right to send an AM with high priority. When RSU_1 in the pipeline model receives a vehicle's AM, it can judge whether or not the vehicle is a special vehicle by checking the priority information in the AM. Once RSU_1 receives an AM with high priority, it notifies the traffic light control system immediately. The traffic light control system then adjusts the current signal states to keep the special vehicle moving smoothly through the pipeline. After the special vehicle leaves the pipeline, the traffic light control system returns to its normal state.

5.2 Specific steps of GTLM

When a special vehicle enters the pipeline, it continuously sends AMs with high priority to RSU_1 until the vehicle receives a response. Once RSU_1 receives these types of messages, it notifies the traffic light control system to make appropriate signal adjustments according to the current signal states. In other words, it transfers the control of green time to the traffic flow that contains the special vehicle. This allows the special vehicle and normal vehicles in front of it to pass through the intersection as quickly as possible.

It is worth noting that the aforementioned scenario may result in very short green times, especially if the signal suddenly switches states, which may lead to adverse effects on driving safety. Therefore, the system must ensure that the duration of the current green time is longer than $T_{\min G}$ before switching the signal states. Suppose that the duration of green time is T_l when the special vehicle enters the pipeline. The specific steps for signal adjustment are as follows.

Procedure 2

Step 1: When a special vehicle enters the pipeline, it repeatedly sends AMs with high priority information to RSU_1 until the vehicle receives a response. RSU_1 reports this emergency to the traffic light control system.

Step 2: The traffic light control system checks whether or not the special vehicle will encounter a green light, if so, then the process proceeds to Step 3. Otherwise, the process skips to Step 4.

Step 3: The traffic light control system keeps the signal states unchanged. Execution skips to Step 7.

Step 4: The traffic light control system checks whether or not the duration of green time T_l is longer than $T_{\min G}$. If so, execution proceeds to Step 5. Otherwise, execution skips to Step 6.

Step 5: The traffic light control system switches the light to green immediately for the special vehicle and execution skips to Step 7.

Step 6: The traffic light control system keeps the signal states unchanged within the period $T_{\min G} - T_l$ and then switches the light faced by the special vehicle to green. Execution proceeds to Step 7.

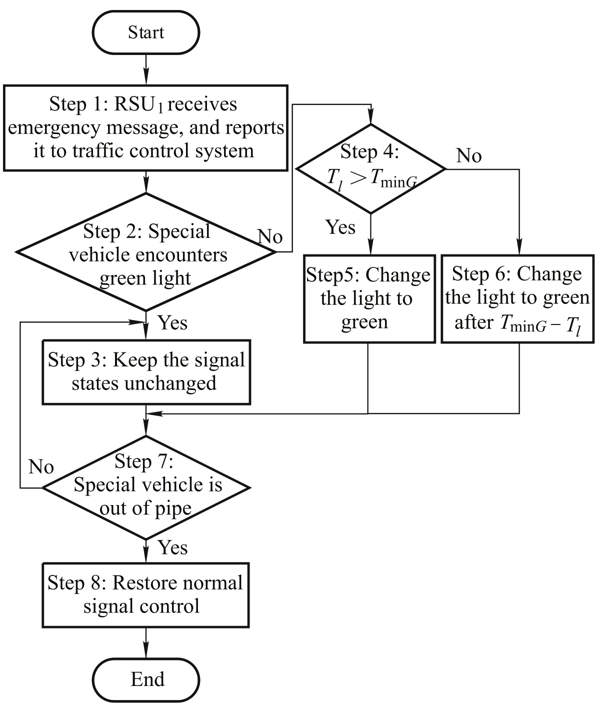

Fig. 4 The process for adjusting signal phases

Step 7: If the special vehicle exits the pipeline, then it continuously sends DMs with high priority to RSU_2 until the vehicle receives a response. RSU_2 reports this message to the traffic light control system and execution proceeds to Step 8. Otherwise, execution returns to Step 3.

Step 8: The traffic light control system restores the previous ITLM and the process ends.

The process for adjusting signal states is illustrated in Fig. 4.

To some extent, special vehicles affect normal signal allocation, meaning they affect driving quality at intersections. However, compared to the number of ordinary vehicles, there is typically a very small number of special vehicles. The GTLM allows the traffic flows to be controlled normally once special vehicles leave the pipeline. Therefore, this type of green-way solution is effective. The greatest advantage of the GTLM is that special vehicles are given the ability to choose appropriate paths when they are performing rescue tasks. The traffic light control system adjusts signal states according to special vehicle paths, which reduces the rescue time of special vehicles on the path.

6 Experiments and analysis

In this section, we first discuss our simulation environment and data. We then analyze the performance of the ITLM under three different traffic conditions. Specifically, we attempt to determine how $T_{\min G}$ and W_t influence ride quality. Finally, the performance of the GTLM is evaluated in an emergency scenario.

6.1 Simulation environment and data

"Vehicles in Network Simulation" (Veins) [26] is an open-source framework for performing vehicular network simulations. It is implemented based on the network simulator "objective modular network tested in C++" (OMNeT++) [27] and road traffic simulator "simulation of urban mobility" (SUMO) [28]. By utilizing OMNeT++ 4.6 and SUMO 0.21.0, we simulated a common urban traffic environment based on Veins 3.0. The main simulation parameters are listed in Table 1.

To evaluate the performance of the traffic light scheduling methods in different situations, three types of traffic conditions were defined and simulated in our study. Figure 5 describes simulated traffic data over a one-hour period, which reflects the highly dynamic nature of traffic flows.

1) Sparse traffic conditions. All vehicles will pass through the intersection directly or stop only once.

2) Moderate traffic conditions. A few vehicles may stop

more than once before passing through the intersection, but this will not lead to congestion.

Table 1 Simulation parameters

Parameters	Value	Parameters	Value
D	200m	$v_{\max}$	50km/h
L_a, L_b, L_c	4m,6m,10m	$v_{\max S}$	90km/h
N_a, N_b, N_c	7:2:1	L_{ab}	500m
a	2.6m/s^2	L_{bc}	800m
L_{gap}	2m	L_{cd}	800m
t_{rea}	1.5s	L_{de}	1000m
P_a, P_b, P_c	1:3:1	L_{ef}	600m
W_a, W_b, W_c	1:1.75:2.25	L_{fg}	300m
$T_{\max G}$	60s		

3) Dense traffic conditions. Many vehicles may stop more than once before passing through the intersection, which will result in congestion.

6.2 Simulation and analysis of the pipeline model

Figure 3 indicates that green time allocation is mainly affected by the minimum green time $T_{\min G}$, maximum green time $T_{\max G}$, and weight threshold W_t. To simplify the problem, $T_{\max G}$ was set to be constant in our study and we mainly focused on how $T_{\min G}$ and W_t influence traffic flow quality, average WT, and average SF.

6.2.1 Influence on traffic flow quality

Figure 6 reveals that traffic flow quality is relatively stable when traffic is sparse or moderate. However, in dense traffic conditions, when the value of W_t is small (less than 10), the traffic flow quality decreases with an increase in W_t. The theoretical traffic volume in Fig. 6 represents the expected traffic volume when all vehicles pass through the intersection in an hour without any limitations.

6.2.2 Influence on average *WT*

As shown in Fig. 7, when traffic is sparse, average WT is proportional to $T_{\min G}$. Additionally, average WT decreases with an increase in W_t and will become stable when W_t is sufficiently large (greater than 15). However, when traffic is moderate or dense, average WT initially decreases with an increase in W_t. It then it begins increasing when the value of W_t is sufficiently large (greater than 20). Overall, a small $T_{\min G}$ and appropriate W_t result in a small average WT under any traffic conditions.

6.2.3 Influence on average *SF*

Figure 8 demonstrates that when traffic is sparse, average SF is proportional to $T_{\min G}$. Additionally, average SF decreases with an increase in W_t and will become stable when W_t is sufficiently large (greater than 15). However, when traffic is moderate or dense, average SF initially decreases with an increase in W_t. It then begins to increase when the value of W_t is sufficiently large (greater than 15). Overall, a small $T_{\min G}$ and appropriate W_t result in a small average SF value under any traffic conditions.

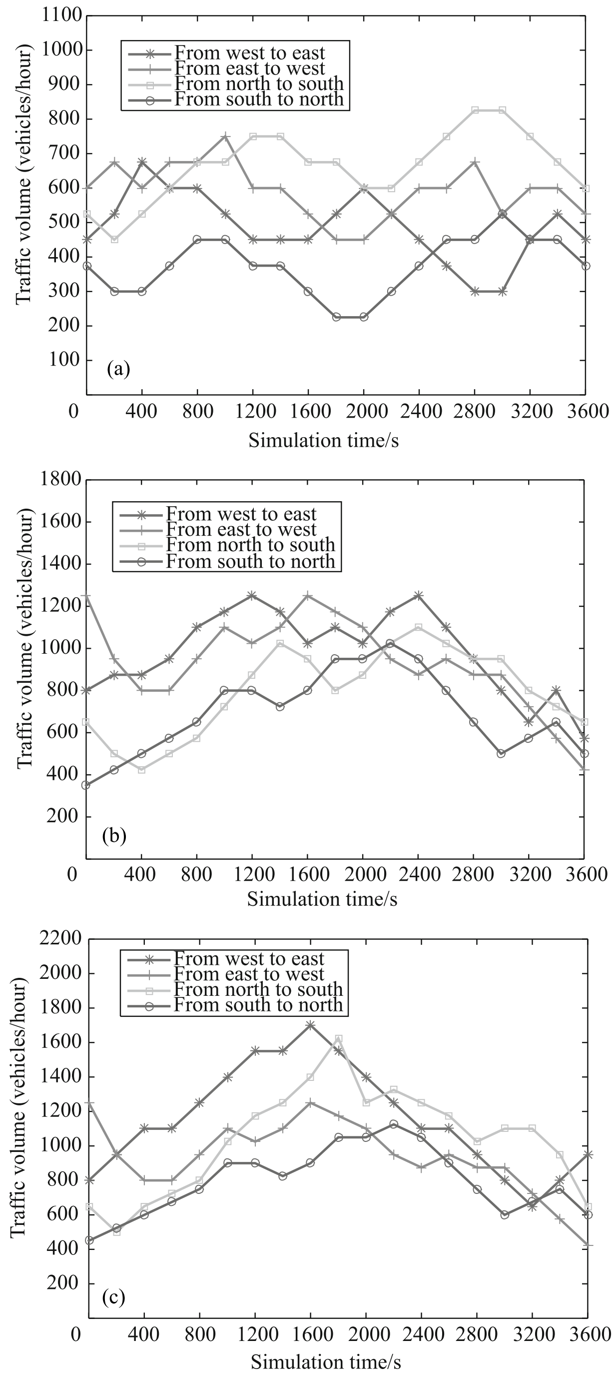

Fig. 5 Three types of traffic conditions. (a) Sparse traffic conditions; (b) moderate traffic conditions; (c) dense traffic conditions

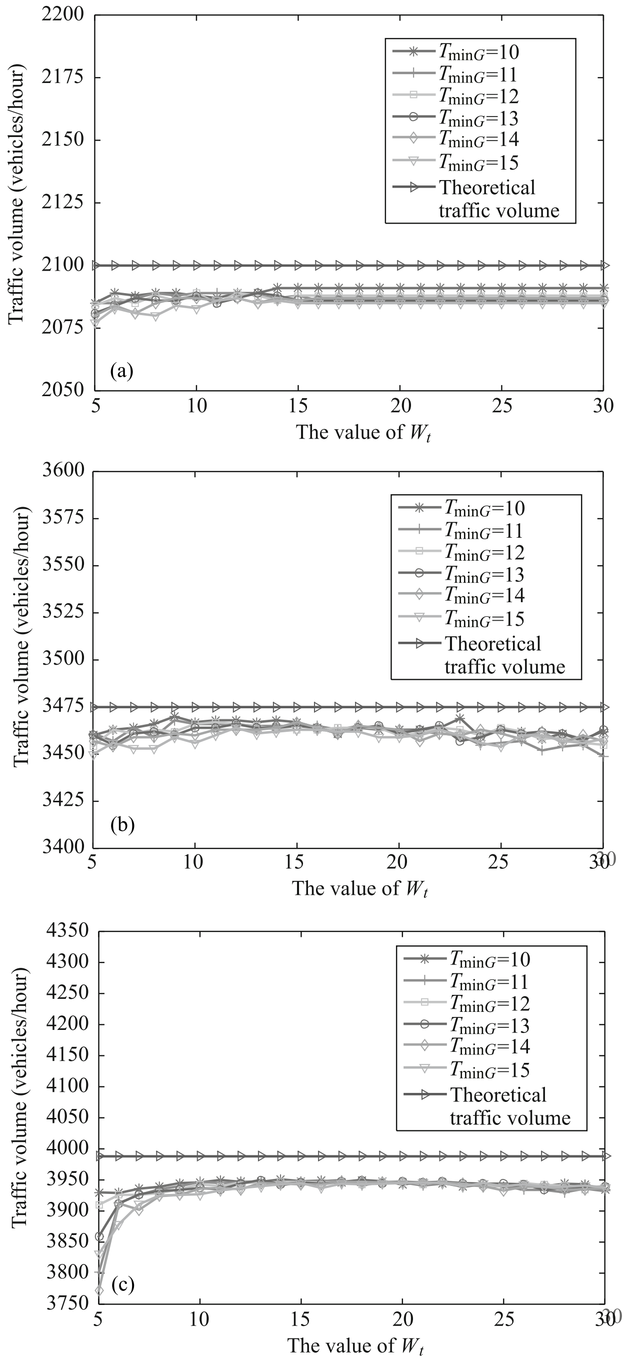

Fig. 6 Influence on traffic flow quality. (a) Sparse traffic conditions; (b) moderate traffic conditions; (c) dense traffic conditions

6.2.4 Conclusions of simulations

In the above simulations, we studied how $T_{\min G}$ and W_t influence overall ride quality, which includes traffic flow quality, average WT, and average SF. Our conclusions from these simulations are as follows:

1) In the overwhelming majority of cases, $T_{\min G}$ and W_t have little influence on actual traffic flow quality. However, under dense traffic conditions, real traffic flow quality will be reduced because of congestion.

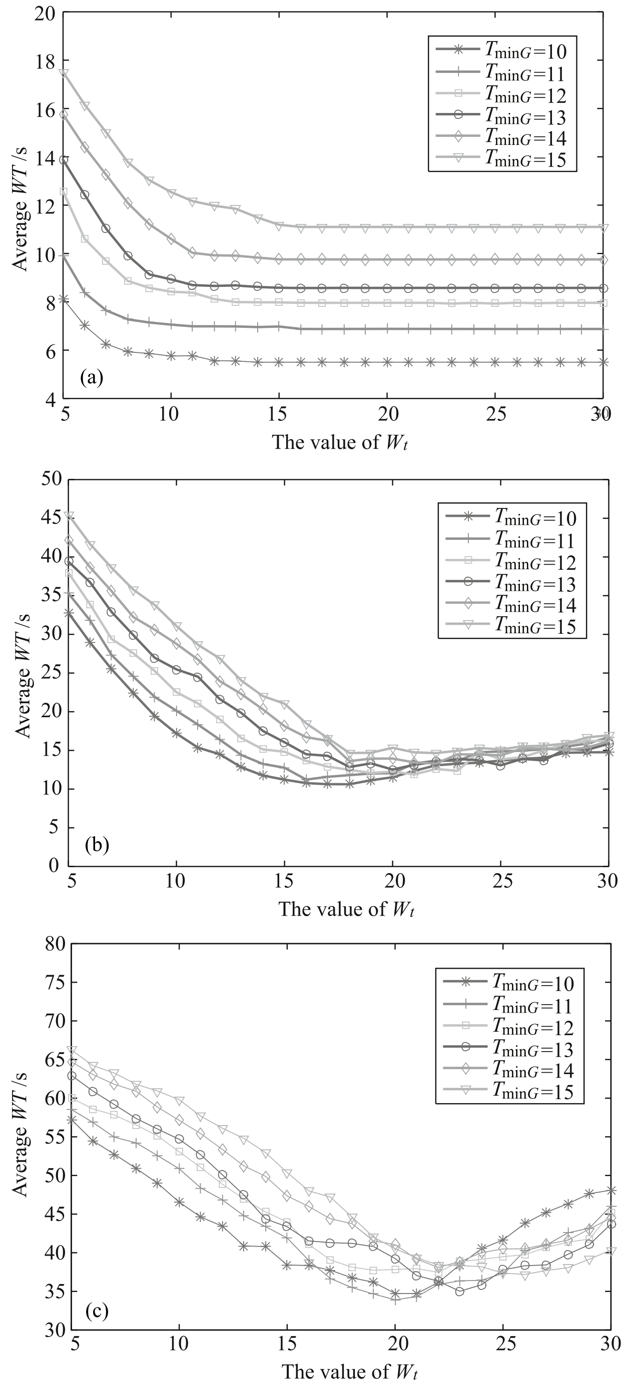

Fig. 7 Influence on average WT. (a) Sparse traffic conditions; (b) moderate traffic conditions; (c) dense traffic conditions

2) When traffic is sparse, the average WT and average SF are proportional to $T_{\min G}$.

3) When traffic is moderate or dense, the average WT and average SF initially decrease with an increase in W_t. They then begin to increase when the value of W_t is sufficiently large.

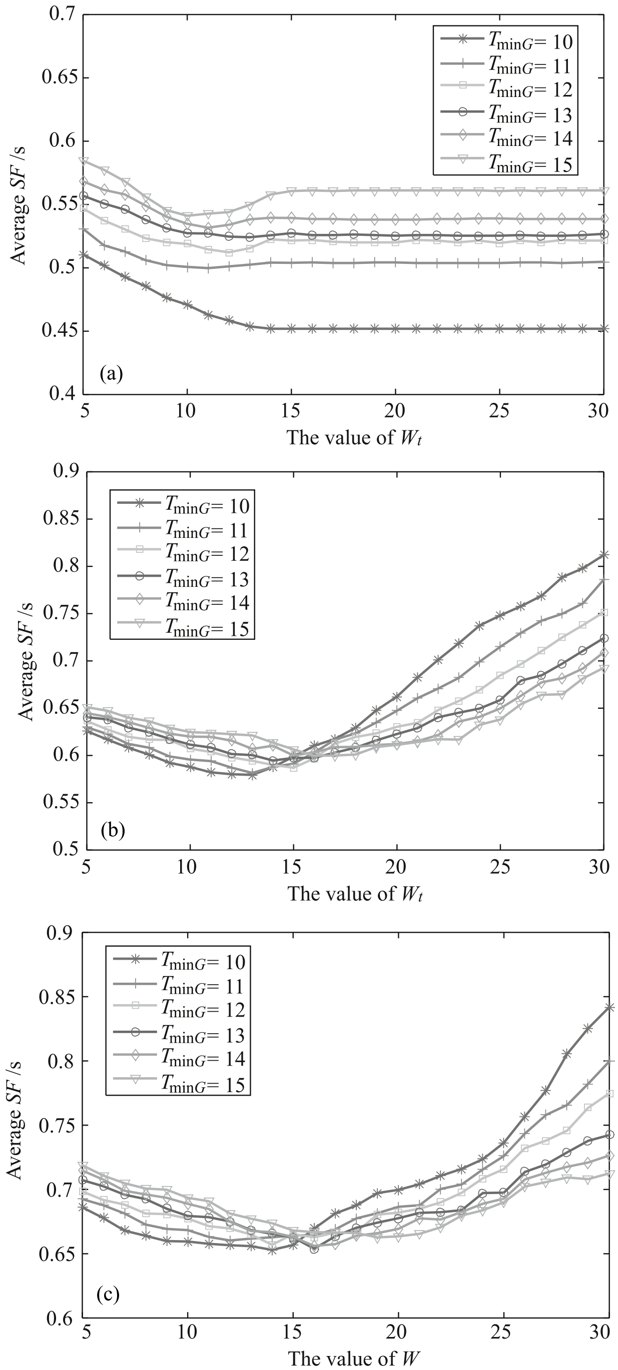

Fig. 8 Influence on average SF. (a) Sparse traffic conditions; (b) moderate traffic conditions; (c) dense traffic conditions

4) A small $T_{\min G}$ and appropriate W_t result in a short average WT and short average SF under any traffic conditions.

Therefore, to obtain better performance, one should utilize a small $T_{\min G}$ and appropriate W_t (approximately 15) in our traffic light scheduling method.

6.2.5 Comparative experiments and results

The ITLM was compared to the fixed-timing method in our comparative experiments. The length of one signal phase is 30 seconds and the values of $T_{\min G}$ and W_t are 10 and 15, respectively. Comparative experiments were conducted under three different traffic conditions. As one can see from Table 2, under the premise of ensuring traffic flow quality, the ITLM reduces average WT by 34%–78% and average SF by 12%–34%, which significantly improves overall ride quality at intersections.

6.3 Simulation and analysis of the GTLM

To evaluate the performance of the GTLM, a fire engine in an emergency scenario was simulated. Its travel path is illustrated in Fig. 9. Location A is the starting point, G is the accident site, and the other points (i.e., B, C, D, E, and F) are intersections along the path. The lengths of the road sections are denoted by L_{ab}, L_{bc}, L_{cd}, L_{de}, L_{ef}, and L_{fg}. The maximum speed of an ordinary vehicle is $v_{\max}$ and that of the fire engine is $v_{\max S}$.

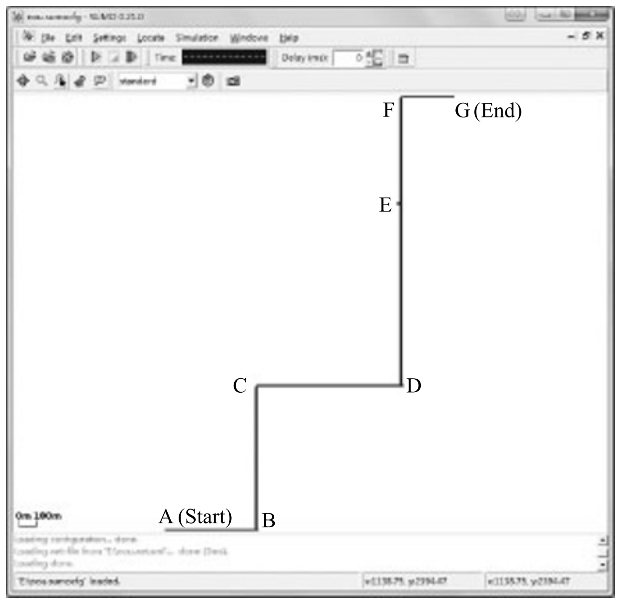

Fig. 9 Travel path of the fire engine

The GTLM was compared to the fixed-timing method in this simulation. It is clear that traffic volume has an impact on driving speed and that special vehicles may encounter different signal states due to different departure times. Therefore, traffic volume and departure time are two important factors that affect rescue time. Furthermore, the length of signal phases is another additional factor that should be considered.

First, in the case of a constant traffic volume (800 vehicles per hour), we analyze how the departure time and length of signal phases influences rescue time when utilizing the fixed-timing method. We select ten different lengths of signal

Table 2 Comparative results between the ITLM and fixed timing

Traffic conditions	Traffic ability(vehicles/hour)			Average WT (seconds)		Average SF (times)	
	Fixed timing	ITLM	Theoretically	Fixed timing	ITLM	Fixed timing	ITLM
Sparse	2077	2091	2100	24.5	5.5	0.60	0.45
Moderate	3446	3467	3475	32.3	11.2	0.68	0.60
Dense	3787	3948	3998	58.6	38.4	1.00	0.66

phases ranging from 15 to 60 seconds at intervals of five seconds. For each length, 10 trips with different departure times were simulated. Specifically, the departure time of the fire engine in the i-th experiment was

$$T_{start} = 100 + 0.1 \times i \times T. \tag{11}$$

Here, T denotes the signal cycle of the fixed-timing method. The rescue time T_{cost} is calculated as

$$T_{cost} = T_{end} - T_{start}. \tag{12}$$

Here, T_{end} denotes the arrival time of the fire engine.

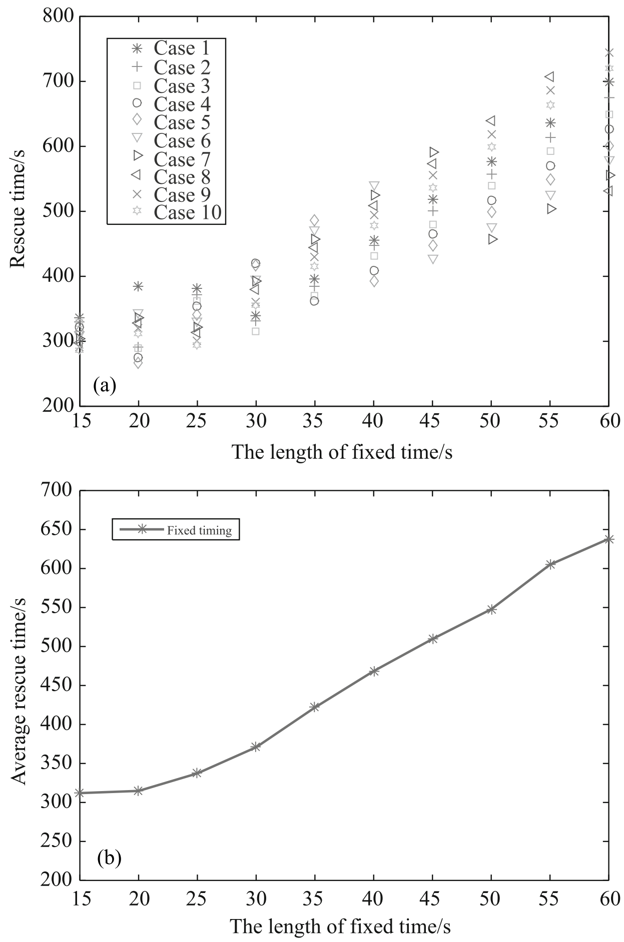

Fig. 10 Rescue times with different departure times. (a) Rescue times of fixed-timing method; (b) average rescue time of fixed-timing method

The rescue times for the fixed-timing method with different departure times are presented in Fig. 10(a) and the average results are presented in Fig. 10(b). It can be observed that the rescue time is clearly influenced by the departure time and that a longer fixed time leads to a longer rescue time.

Next, in the case of a constant traffic volume (800 vehicles per hour), the two methods were compared with different departure times. The length of one signal phase was 30 seconds. Ten trips with different departure times at intervals of 12 seconds were simulated and the comparative results are presented in Fig. 11. The results indicate that the rescue time is stable when utilizing the GTLM and that the GTLM achieves better overall performance compared to the fixed-timing method.

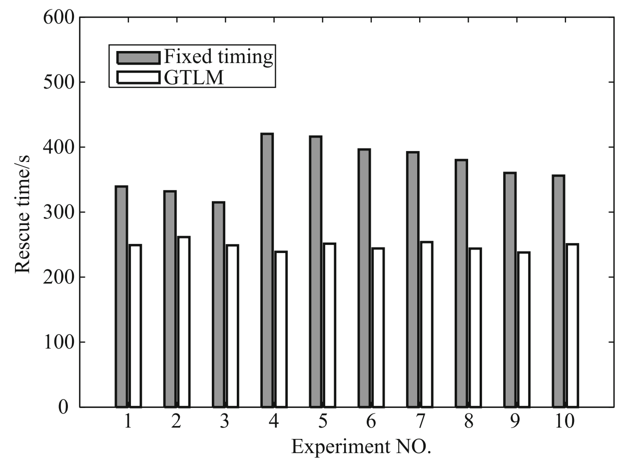

Fig. 11 Comparison of rescue times

Finally, the two methods were compared under different traffic conditions. The comparative results are presented in Fig. 12.

Figure 12 reveals that the GTLM reduces rescue time by 30%–55% compared to the fixed-timing method and works better under congested traffic conditions. Additionally, the special vehicle is allowed to choose a more appropriate route when performing rescues, meaning the traffic light control system will adjust signal states according to the special vehicle's path. This mechanism is extremely beneficial for handling emergencies.

7 Conclusions and future work

Adaptive traffic light scheduling methods are recognized as

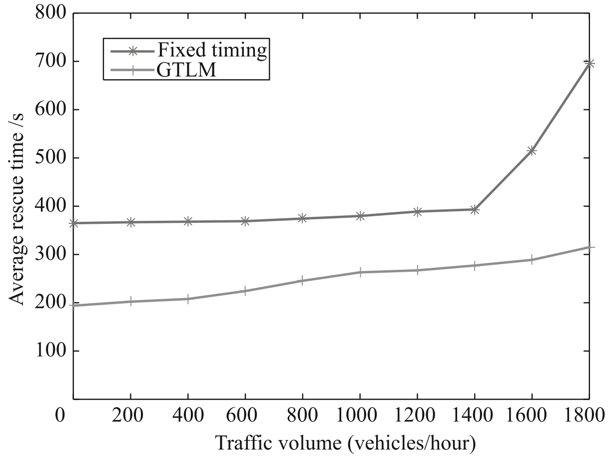

Fig. 12 Rescue times under different traffic conditions

the most economical and effective means of alleviating congestion in urban transport. It is vital to collect real-time traffic information when implementing these methods. However, fine-grained information regarding individual vehicles can be difficult to acquire because of the limitations of traditional collection techniques, whose accuracy is easily affected by congestion or severe environments. However, V2V/V2I communication techniques provide the ability to handle these problems.

This paper presented a V2I communication-based pipeline model that is capable of detecting fine-grained, accurate, and real-time traffic information via message exchange between vehicles and RSUs. In contrast to existing V2V/V2I communication-based methods, the types and turning intentions of vehicles are considered in our work. Based on the analysis of collected information, two types of traffic light scheduling methods were proposed. Specifically, the ITLM dynamically allocates appropriate green time for each signal phase according to the "demand assignment" principle, which can improve ride quality at intersections. The GTLM was proposed for special vehicles in emergency scenarios. It gives special vehicles priority to pass through intersections, which reduces rescue times.

The experimental results revealed that the ITLM achieves better performance than the fixed-timing method under various traffic conditions. It reduces average waiting time by 34%–78% and average stop frequency by 12%–34% under the premise of ensuring traffic safety. Furthermore, rescue time can be reduced by 30%–55% by the GTLM in emergency scenarios. Based on our results and analysis, we can conclude that the V2I communication-based pipeline model presented in this paper is a promising methodology for designing efficient traffic light scheduling methods for urban transport. For future work, we plan to improve our proposed pipeline model and the corresponding scheduling methods to adapt to extremely overcrowded traffic conditions.

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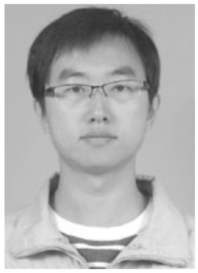

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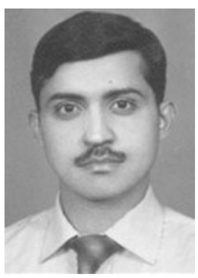

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