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Traffic control optimization strategy based on license plate recognition data

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HIGHLIGHTS

- Implemented online optimization and feedback compensation in the control system.
- Applicable to traffic control system with license plate recognition data.
- Validated the framework with close-loop experiments in VISSIM and MATLAB.
- Demonstrated improvements in queue and delay reduction for coordinated intersections.

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ABSTRACT

Traffic signal control is essential to the efficiency of the road network's operation. In recent years, more and more detailed detection data provide potential data support for traffic signal control, such as license plate recognition (LPR) data. This study aims to develop a traffic signal control optimization method based on model predictive control (MPC) and LPR data. The proposed framework of a closed-loop control system is described in detail. First, the control objectives and queue prediction model for signalized intersection are determined. Then, online optimization and feedback compensation are discussed and implemented. Calculations of the arrival rate at the downstream are based on the LPR data detected at the upstream intersection, and dynamic optimization method of the offset is proposed for a coordinated control. The model is validated using the LPR data of two consecutive intersections with a traffic simulation platform. Results demonstrate that the model can restrain extreme long queuing, improve intersection capacity, and reduce intersection average delay. The developed model promotes the system operating efficiency and shows the general advantage of real-time optimization, feedback, and control. The proposed framework can be potentially applied by local traffic management centers to improve the quality of traffic signal control.

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1. Introduction

Urban traffic management requires a well-designed signal timing plan for signalized intersections to improve road network capacity utilization, safety, and operating efficiency. Many studies have focused on traffic signal control optimization (Papageorgiou et al., 2003) in the past decades. Studies on the traffic signal control strategy for urban signalized intersections mainly used road link traffic count data from a loop detector or a video monitoring system. This system provides aggregative traffic flow parameters, such as traffic flow volume, speed, and occupancy. A common optimization objective of intersection signal timing is the minimization of average delay or the combination of average delay and stop time of all vehicles through the intersection for an undersaturated condition. Measuring the actual delay of each vehicle using a traditional monitoring system is difficult. Therefore, the performance of signal timing plan at real-time and the feedback to the signal control system cannot be effectively monitored because of the limitation of the detected data.

The development of license plate recognition (LPR) data may provide an opportunity to create a control system with real-time feedback by directly measuring the delay of the high penetration rate of vehicles. The travel time and delay of each matched vehicle can be measured by matching plate numbers recognized for vehicles at the upstream and downstream intersections along a signalized arterial, and the queue length can be more accurately estimated. To date, the application of LPR has been limited to traffic signal control optimization because of the high costs of implementing large-scale camera coverage. In recent years, the support of rapidly developing high-definition techniques in China has resulted in the installation of red light enforcement cameras in many signalized intersections. Although the main aim of these cameras is red light running enforcement, they can recognize every passing vehicle through the stop line of intersections. Therefore, measuring the travel time of each vehicle based on LPR data is possible, although the recognition accuracy rate is not 100%. In practice, the accuracy of license plate number recognition is approximately 80%–95% based on the analysis of the LPR data collected by the authors from the traffic management bureau of four cities in China. The recognition rate depends on certain factors, such as the weather, light conditions, and various recognition methodologies of different companies. For example, the characters on the license plate, such as number zero and letter O, can influence the LPR accuracy.

At present, the inductive loop vehicle detector is not welcomed in cities in China because of its weaknesses. Installing the loop detector requires pavement cuts and blocking of traffic flow, and the detectors have high damage rates because of various reasons. Therefore, the development of LPR data may provide a new data resource for an advanced closed-loop adaptive traffic signal control system with feedback, such as arrival pattern prediction, delay calculation, and queue estimation.

Our study aims to develop a preliminary framework for coordinated signal control using LPR data. The main contribution of this study is a new framework with an optimization model for a closed-loop adaptive control system based on LPR data. This study considers the control objectives that involve average delay and residual queue for different traffic conditions. Real-time update of the traffic system state at the end of each signal cycle is used as feedback. The methodology evenly distributes traffic pressure between approaches. Therefore, this control strategy can be adaptable to intersections under coordinated control.

2. Literature review

Several countries have developed various types of large-scale, real-time traffic signal control systems. These systems can be divided into two categories: offline and online controls. A well-known offline control system is TRANSYT (traffic network and isolated intersection study tool) (Binning et al., 2005). Traditional online control systems include the SCATS (Sydney Coordinated Adaptive Traffic System) (Lowrie et al., 1982) and the SCOOT (split cycle offset optimizing technique) (Hunt et al., 1982), which are based on heuristic optimization algorithms. A series of model-based control strategies is available, such as OPAC (optimization policies for adaptive control) (Gartner, 1983), PRODYN (dynamic programming) (Henry et al., 1984), RHODES (real-time, hierarchical, optimized, distributed, and effective system) (Sen and Head, 1997), and CRONOS (ContROl of networks by optimization of switchovers) (Boillot, 1992). These adaptive control strategies calculate optimal switching times by predicting future traffic conditions based on historical data obtained from detectors instead of explicitly optimizing splits, offset, or cycles. Real-time dynamic optimization problems are solved online with a sample time of 2–5 s. Discrete variables are used to describe the effects of green or red phases on traffic flow (Papageorgiou et al., 2003). In the methodology, studies on traffic signal control have applied various types of optimization methods, including mixed integer programming, quadratic programming, linear programming, and dynamic programming (Chen and Sun, 2016; Papageorgiou et al., 2003).

MPC modelling, an advanced and powerful method of process control (Morari and Lee, 1999), can compensate for prediction errors with a closed-loop strategy. MPC has been widely studied and applied in the traffic signal control in urban networks, anda series of effective traffic control strategies has been proposed in the past 20 years (Ye et al., 2019). Makys and Kozak (2011) developed the signal control model of intersections as a hybrid system with some important assumptions, including the constant arrival and departure of cars from intersections. Based on the simplified estimation of queue length, the control system aims to minimize the number of vehicles that face red lights. Kooistra (2012) developed a dynamic signal control strategy by solving the binary nonlinear optimization problem with the control objective of minimizing the total waiting time of vehicles in the system. The order of lights and the different cycle lengths are also discussed to study their influence on the effect of traffic signal control. Lin et al. (2011) developed a fast MPC strategy by solving a mixed-integer linear programming problem to increase real-time feasibility. Le et al. (2013) unified traffic light control and route guidance in a model-predictive control framework. Yuan et al. (2014) developed a coordinated signal timing optimization model based on the ant colony algorithm with the identification of traffic bottlenecks. Chow et al. (2020) analyzed the performance of the centralized and decentralized MPC-based optimization approaches. Yao et al. (2019) proposed a rolling horizon optimization algorithm with a dynamic vehicle arriving prediction. Zhang and Su (2021) established a coordination control optimization model for a heterogeneous network of signalized and non-signalized intersections, where the information of real-time speed and turning rate of the links are exploited.

Some traffic control models based on MPC use store-and-forward modeling (SFM) (Gazis and Potts, 1963) as the traffic flow model, which considers continuous traffic outflow and assumes sufficient traffic demand. Several studies (Diakakiet al., 2000, 2002) have applied the SFM technique and a multivariable feedback regulator approach to develop a traffic-responsive urban control strategy. Some researchers have improved optimization methods (Aboudolaset al., 2010, 2009). Although these new models can more accurately describe the system, real-time computational feasibility is another problem. Further studies (Tettamanti et al., 2008, 2010) have extended the model by dividing the whole system into several subsystems and developing a distributed control strategy to improve real-time feasibility. These models, which are based on the SFM technique and MPC, effectively balance traffic pressure among different links but mainly focus on the long-term converged states of links. Therefore, such models are suitable for large-scale networks under an over-saturated condition. The optimization of cycle time and offset is not directly considered in the models. van de Weg et al. (2020) established an MPC optimization model for network signal control to minimize the total travel time of the network, which consider the queue length of the intersection and the upstream shockwave progress.

Previous studies on signal control strategies based on MPC mainly consider the system state (i.e., weighted square sum of the number of queued vehicles in each link) at the end of the control time horizon (i.e., length of the signal cycle). Although the prediction model is consistent with the traditional principles of MPC, different approaches of the intersection may not be equally treated. For example, in the under-saturated condition, the queue length at the end of a cycle is the largest for the first signal phase but the smallest for the last signal phase. Furthermore, most previous strategies disregard the influences of changing cycle times and the non-zero offset, which pose a challenge to the calculation of the downstream arrival rate and timing plan implementation. For instance, simultaneously optimizing splits for a group of signal controllers is no longer possible because the starting times of the next cycle for these controllers are different.

LPR is an emerging detection technology and may provide an opportunity to enhance accurate and wide-penetrated individual trip detection. The LPR system has been extensively used in various applications in transportation systems nowadays, including traffic law enforcement, congestion pricing, and toll collection (Chang et al., 2004). The travel information (e.g., travel time, delay, and movement) of the matched vehicles and the network state (e.g., average speed) can be directly assessed by matching plate numbers recognized for vehicles at different intersections along a signalized arterial. According to Du et al. (2013), most studies on LPR can achieve an overall accuracy rate higher than 90%, and the processing speed is fast enough for practical application. The LPR data can record the time of individual vehicles passing stop lines at the upstream and downstream intersections compared with control strategies, such as SCATS and SCOOT, which use loop detectors to obtain traffic flow data. The real travel time between two intersections can be calculated as the time difference of the same vehicle. If the free flow travel time is given, then the real delay value can be obtained, and feedback can be provided to the traffic signal control, thus developing a closed-loop control system. The LPR data-based traffic state estimation has been attracting considerable research interests.

Zhan et al. (2015) proposed a lane-based and real-time queue length estimation model by using the LPR information. The LPR data from adjacent intersections are utilized in this study, and a car-following-based traffic flow model is applied to reconstruct the vehicle trajectories to ensure that the real-time queue length of the lane is estimated. Other traffic information that can be obtained by the LPR data includes speed profile (Mo et al., 2017), turning rate (Mahmoud et al., 2021), and origin-destination demand (Mo et al., 2020) in the literature. Given the low proportion of the LPR system installed in past, several types of data similar to the LPR data (e.g., radio frequency identification, a.k.a. RFID, and Bluetooth) have been more widely used in previous studies for traffic state estimation. Takaba et al. (1991) applied vehicle detectors and license plate readers in measuring vehicle travel time and conducted a field survey in several cities in Japan. Wu and Yang (2013) used RFID data, which include the plate number and the detection time for individual vehicles, in real-time queue length estimation. The queue delay of vehicles is collected to measure the queue length of the intersection. The LPR or LPR-like data are an emerging resource of traffic information and is increasingly being used in urban transportation management and traffic detection systems. Meanwhile, the LPR data-based traffic control optimization strategy has not received adequate research attention in recent years.

This study is aimed at developing an MPC-based coordinated traffic signal control framework, where the advantages of the LPR data are exploited. In comparison with previous studies, this research basically attempts to achieve the purpose in three aspects of improvement. 1) LPR data collection and processing technologies are integrated in the proposed framework, and a variety of traffic information (i.e., traffic volume, travel time, and queue length) can be used for decision; 2) Feedback of the prediction error are obtained to the control system through the proposed MPC-based optimization model, and a closed-loop control is realized; 3) Dynamic control objectives are designed in the traffic signal control strategy, which is adaptive to the variance and fluctuation of the traffic in real-world networks.

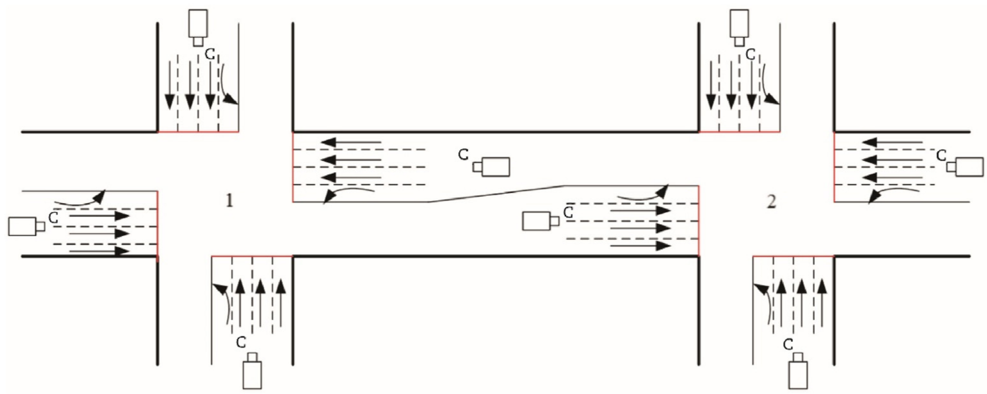

Fig. 1 – Two typical signalized intersections with red light running enforcement cameras.

Table 1 – Snapshot of the raw data of the automated number plate recognition system.

Unique ID	Year	Month	Day	Hour	Minute	Second	Intersection ID	Approach ID	Lane number
hbRKM372	2013	Nov	11	8	0	55	1310000004	2	2
bjGQS201	2013	Nov	11	8	1	6	1310000004	2	3
hbRLH182	2013	Nov	11	8	1	47	1310000047	3	2
hbRHU719	2013	Nov	11	8	1	42	1310000051	4	1

3. LPR data collection

Research shows that the driving behavior of violating the red signal is common at signalized intersections in cities (Retting et al., 2008). The use of automated red light enforcement cameras is major countermeasure to red light running in China. Fig. 1 presents two typical signalized intersections with red light running enforcement cameras located near the stop line. The right turn is not shown in Fig. 1 because right turns on red are permitted in China.

Recently, the red light running enforcement cameras are not only used for red light running enforcement but also for vehicle detection. Specifically, these cameras automatically photograph vehicles whose drivers violate red lights during the red light stage. Meanwhile, these cameras will automatically photograph every vehicle passing through the stop line during the green light stage. When a vehicle passes over the stop-line is photographed by an LPR system camera, the number plate of each vehicle is identified, and a record of this vehicle is stored in the database.

Each record of a vehicle in the database is a unique ID that includes vehicle plate number, vehicle passing time, intersection ID, approach ID, and lane number. Table 1 shows a snapshot of the data.

Some useful parameters for traffic signal control can be calculated or estimated based on the raw data.

1) Traffic volume: the traffic volume of each direction and movement can be calculated because these red light cameras photograph every vehicle passing through the stop line, which is similar to a loop detector near the stop line. Although recognition accuracy is lower than 95%, the proportion of capture of all the vehicles passing through the stop line is approximately 100%. Therefore, the accuracy of the traffic volume is high at more than 98%.
2) Travel time (delay): a vehicle is photographed at the upstream and downstream intersections. The time difference between the upstream and the downstream intersections is the travel time of the vehicle. Delay of the vehicle can be calculated with the data as well. A character of the delay extracted from the LPR data is its high penetration rate of vehicles. This rate is higher than that of GPS-based detectors, which record a low penetration rate of vehicles.
3) Queue length: in comparison with the traditional section detector, such as the loop detector, an advantage of using the LPR data to estimate the queue length is that we know which vehicles passed through downstream intersection and which ones did not. The LPR data are useful for analyzing probable vehicle trajectory, which is beneficial for queue length estimation (Zhan et al., 2015).

These traffic flow parameters provide new data for traffic signal timing plan optimization and feedback.

4. Closed-loop control system framework

Fig. 2 demonstrates the framework of a closed-loop control strategy with real-time feedback based on the LPR data that can be used for an isolated intersection, signalized arterial, and road network. The “LPR system” module photographs passing vehicles, recognizes the plate number, produces the detailed LPR data record for every vehicle (Table 1), and stores these records in the “historic traffic flow database.” The “traffic state prediction” module uses the data stored in the “historic traffic flow database” to predict the traffic state in the next control horizon, which is one cycle in this study. In this framework, this module is responsible for predicting the arrival rate, queue length for each movement at each approach, and average delay for the intersection. The

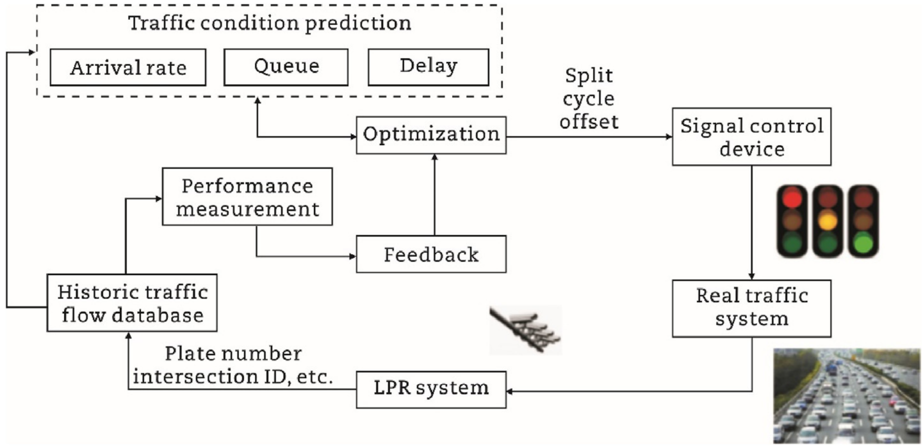

Fig. 2 – Framework of the closed-loop control system.

"optimization" module optimizes and exports the optimal splits, cycle length, and offset. The "performance measurement" module measures the performance of the timing plan of the previous cycle based on the calculation of the actual delay of the matched vehicles and the estimation of the queue length. The "feedback" module uses the control performance index to compensate for the prediction error and model mismatch, which ensure that the optimization for the next control horizon is based on the latest system state.

5. MPC-based model for the isolated intersection control

The isolated intersection signal control is the most fundamental element of an urban traffic signal control system. This part proposes the traffic signal control optimization method based on the MPC for the isolated intersection, which is used in the arterial coordinated control strategy.

The main concept of MPC is to solve an optimization problem over a finite future horizon. The problem is formulated to minimize the difference between the actual and the target outputs with model constraints. After the target outputs are first determined according to the specific problems, the prediction models are developed to compute the predicted outputs given the control inputs. The feedback mechanism is introduced in the MPC to compensate for the prediction errors and contribute to a more robust control strategy. In the MPC-based isolated intersection traffic control model, the target is the average delay or the residual queue depending on the different traffic conditions. The control objective, prediction model, model constraints, and feedback mechanism of the proposed MPC-based isolated intersection traffic control model based on LPR data are described as follows.

The notations used in the model development are presented in Table 2 to describe the evolution of the models.

5.1. *Control objectives*

In this study, the control objectives for the under-saturated condition and the over-saturated condition are different. The minimum intersection average delay is commonly used as the control objective for the under-saturated condition, which is also applied to this study. Under the over-saturated condition, the delay can no longer be used as a feasible control objective because of the accumulation of vehicle queue on some approaches (Denney et al., 2008), especially at close intersections. Residual queue is defined as the number of vehicles that have reached the intersection but failed to pass the stop line before the end of green time (Adam, 2012). Residual queue is an important sign for the over-saturated condition. Controlling the residual queue can help in avoiding severe traffic congestion and the spill back condition inside the road network. Accordingly, the control objective for saturation is to minimize and uniformize the residual queue for all movements. These two control objectives, minimum intersection average delay and minimum residual queue, may be directly assessed or calculated using LPR data and are adaptive to changing traffic conditions.

The expressions of the two control objectives are shown as follows.

(1) Saturated and over-saturated traffic flow conditions

$$\min_{u^m(k+1)} J = \sum_{m=1}^{4} \sum_{(j,l)\in\prod^m} \left[q_{jl}^m(k+1)\big/q_{jl}^{\max}\right]^2 \tag{1}$$

(2) Under-saturated traffic flow condition

$$\min_{u^m(k+1)} d = \sum_{\{j,l\}} \mathrm{DL}_{jl}(k+1) \Big/ \sum_{\{j,l\}} \mathrm{Q}_{jl}(k+1) \tag{2}$$

where J is the control objective function of the residual queue, d is the average vehicle delay of the intersection, $\mathrm{DL}_{jl}(k+1)$ is the total delay for direction l of approach j of the intersection during the $(k+1)$th cycle, and $\mathrm{Q}_{jl}(k+1)$ is the accumulated number of arriving vehicles during the $(k+1)$th cycle.

The control objective is automatically selected on the basis of the detected data and estimated traffic flow condition. The

Table 2 – Notation.

Symbol	Definition
j	Index of the approach (1-eastbound, 2-southbound, 3-westbound, and 4-northbound)
l	Index of the movement direction of lanes (1-through, 2-left turning, and 3-right turning)
m	Index of the signal phase (1, 2, ⋯, M)
k	Index of the signal cycle (1, 2, ⋯, K)
$q_{jl}^m(k)$	Number of the queued vehicles at the end of the mth phase of the kth cycle on the l direction lanes of approach j
$A_{jl}^m(k)/D_{jl}^m(k)$	Number of arriving/leaving vehicles in the mth phase of the kth cycle on the l direction lanes of approach j
$V_j^m(k)$	Average arrival rate in the mth phase of the kth cycle for approach j
$g^m(k)$	Effective green time of the mth phase of the kth cycle
β_{jl}	Turning rate, which can be estimated based on the LPR data
I_{jl}^m	If the vehicles on the l direction lanes of approach j have the right of way in the mth phase, then $I_{jl}^m = 1$; otherwise, $m = 0$.
s_{jl}	Saturated flow rate of the l direction lanes of approach j
$C(k)$	Cycle length of the kth cycle
$\text{Loss}(k)$	Total lost time of the kth cycle
$g_{\min}/g_{\max}$	Minimum/maximum effective green time
$C_{\min}/C_{\max}$	Minimum/maximum cycle length
$q_{jl}^{\max}$	Queue limit for the l direction lanes of approach j
$p_{jl}^m(k)$	Real (estimated) number of the queued vehicles at end of the mth phase of the kth cycle on the l direction lanes of approach j
$\prod^m$	Set of lanes of the different approaches with the right of way in the mth phase

selection process includes two stages. In the first stage, the situation is tested by checking the value of objective function J whether the traffic condition is oversaturated or not. If the value of J is zero, then the residual queue $q_{jl}^m(k)$ is zero, implying that the traffic condition is under-saturated. In the second stage, if the status is over-saturated, then the optimized results in stage one remain. If the status is under-saturated, then control objective function d will be further optimized.

5.2. *Delay prediction model*

In this study, we focus on a typical intersection with four approaches and four signal phases (W&E through, W&E left turning, N&S through, and N&S left turning). Given that the right turn on red is allowed in China, right turn vehicles are mostly not controlled by the traffic signal light.

The calculation of delay for vehicles with the right of way during the first signal phase is illustrated in Fig. 3, where $Q(t)$ is the cumulative arrival curve, and $L(t)$ is the cumulative departure curve. In this figure, ①, ②, ③, and ④ represent the four phases of a cycle, and the flat part of the $L(t)$ corresponds to the phases of the red light for the given approach. The delay can be obtained by solving the definite integral computation problem.

$$\text{DL} = \int_{T}^{T+C} [Q(t) - L(t)]\text{d}t + \varepsilon \tag{3}$$

where ε is the adjustment factor used to update the DL calculation function based on the actual delay of every vehicle whose number plate is correctly recognized. In practice, ε is updated at each cycle on the basis of the estimation error of the DL of the past five cycles.

$Q_{jl}(k+1)$ is calculated as follows.

$$Q_{jl}(k+1) = \sum_{m=1}^{4} A_{jl}^m(k+1)g^m(k+1) \tag{4}$$

5.3. *Queue prediction model*

As previously discussed, prediction for the residual queue is dependent on the effective prediction of the queue length for each approach. The estimation of the queue length for each approach at the end of the signal phase is necessary for the calculation of the control objective. Therefore, developing the transition equation is important for the number of queued vehicles among the different signal phases.

The traffic flow state transition equation is as follows. This equation shows the relationship of the queued vehicles at the end of the mth phase with the $(m+1)$th phase.

$$q_{jl}^{m+1}(k) = q_{jl}^m(k) + A_{jl}^m(k) - D_{jl}^m(k) \tag{5}$$

The number of arriving vehicles in each signal phase can be calculated as follows.

$$A_{jl}^m(k) = V_j^m(k)\beta_{jl}g^m(k) \tag{6}$$

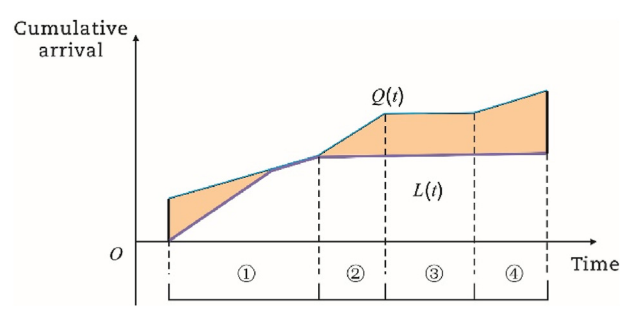

Fig. 3 – Illustration of the delay calculation.

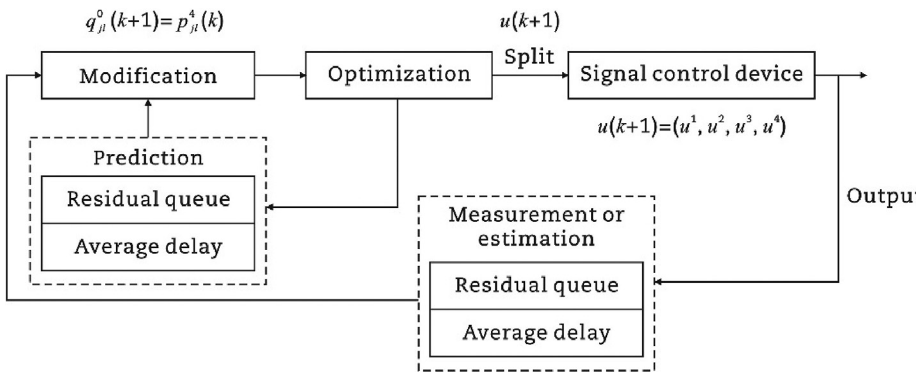

Fig. 4 – Mechanism of the rolling horizon optimization and feedback.

Fig. 3 shows that $V^m_j(k)$ can be predicted from the LPR data and the signal timing plan of the upstream intersection. β_{jl} can be estimated on the basis of the LPR data from the upstream and downstream intersections, and it is periodically updated.

The number of leaving vehicles in each signal phase is given by

$$D^m_{jl}(k) = \min\left\{I^m_{jl}s_{jl}g^m(k), q^{m-1}_{jl}(k) + A^m_{jl}(k)\right\} \tag{7}$$

Item $I^m_{jl}s_{jl}g^m(k)$ represents the number of vehicles leaving at a saturated traffic flow rate during the entire effective green time. This situation occurs during the saturated or over-saturated traffic condition. Based on the LPR data, s_{jl} can be estimated from the time difference of the vehicles continually passing through the stop line during green time with the saturation headway. Item $q^{m-1}_{jl}(k) + A^m_{jl}(k)$ represents the total number of queued vehicles at the end of the previous phase and arriving vehicles during this phase. The real number of leaving vehicles should be the minimum of these two items. The following equation shows the cohesive relation among consecutive signal cycles.

$$q^0_{jl}(k+1) = q^4_{jl}(k) \tag{8}$$

Eqs. (5)–(8) are based on the deterministic arrival type and not on the randomness of the vehicle arrival type.

5.4. *Model constraints*

The constraints of the isolated intersection traffic control model are expressed as follows.

(1) Cycle time constraint

$$\sum_{m=1}^{4} g^m(k) = C(k) - \text{Loss}(k) \tag{9}$$

(2) Green time constraint

$$g_{\min} \le g^m(k) \le g_{\max} \tag{10}$$

(3) Cycle length constraint

$$C_{\min} \le C(k) \le C_{\max} \tag{11}$$

(4) Queue length constraint

$$q^m_{jl}(k) \le q^{\max}_{jl} \qquad \forall m, j, l \tag{12}$$

6. Rolling horizon optimization and feedback

Fig. 4 shows the mechanism of the rolling horizon optimization and feedback system in this study. The residual queue and the average delay in the next cycle are functions of the current queued vehicles, predicted traffic demand, and signal timing parameters, which are the control variables adopted in the next cycle. The optimal control problem is solved by obtaining the detected (or estimated) traffic state at the end of cycle k and the predicted traffic demand during cycle k+1. At the end of cycle k+1, the optimal control problem is updated, and the control variable (signal timing parameters) is calculated for cycle k+2. The split vector $g(k+1)$ is the main control variable optimized at the end of each cycle for an isolated intersection. After implementing the optimized signal timing parameters, the queue length at the end of the cycle can be estimated, and the actual average delay for the previous cycle can be measured.

The feedback system aims to use the actual delay and the estimated queue length obtained from the LPR data to revise the delay and queue prediction model, which is the main function of the "modification" module. The modification for delay prediction is shown as Eq. (3), which is a simplified expression of the total delay prediction and is mainly used for the deterministic traffic condition. Adjustment factor ε is used for the consideration of the prediction error. However, if we want to obtain a more precise predicted delay, then future work should be conducted to realize the ideal precise feedback system. For example, the model should consider the microscopic traffic flow dispersion pattern to provide a more accurate predicted delay value. In terms of the modification of queue prediction, the estimation method for the residual queue based on the LPR data should be further developed to ensure that the system could return a more accurate estimation for the real residual queue. In this study, a preliminary implementation of feedback on the queue prediction is adopted. The estimated queue length, $p^4_{jl}(k)$ is assumed to be available for each approach at the end

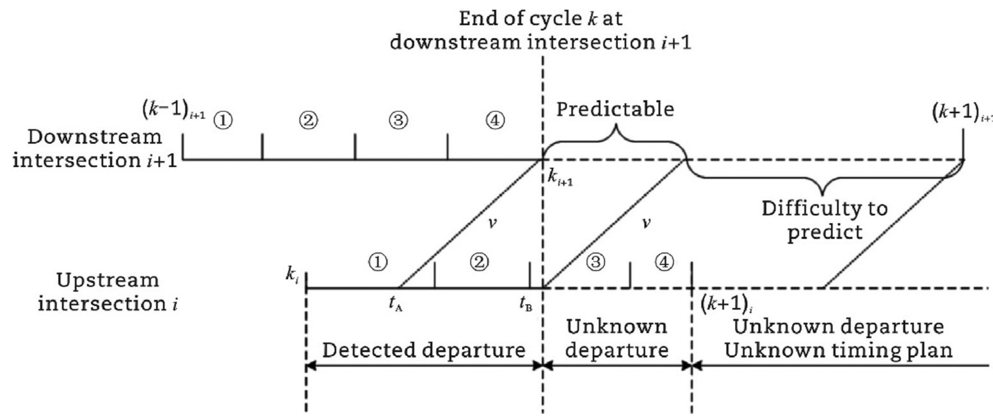

Fig. 5 – Prediction of the arrival rate at the downstream intersection.

of each cycle and used to replace the starting point of the queue prediction, $q_{jl}^{0}(k+1)$, for the next cycle. Therefore, the optimization for the next cycle is based on the "real" system state.

7. Coordinated control strategy

In urban road networks, some consecutive intersections with short distances, such as those not longer than 600 m, should be considered with coordinated signal control. Otherwise, independently controlling the close intersections may reduce the efficiency of a traffic system by breaking the platoon progression. Moreover, the poor design of offset between two intersections may lead to the inefficient use of green time or spillback. The estimation of the arrival rate and the optimization of the offset are fundamental to develop the coordinated control model based on the proposed isolated intersection traffic control model.

7.1. *Arrival rate at the downstream*

Some previous studies disregard the effect of the offset (Aboudolaset al., 2010; Diakaki et al., 2002) or assume the offset to be zero (Linet al., 2011) during the validation stage. In fact, a non-zero offset leads to difficulties in calculating the arrival rate at the downstream intersections and the implementation of the timing plan at each intersection.

This study assumes a constant arrival rate in each signal phase of a cycle, and all vehicles with the same direction turn on an approach have the same speed. Fig. 5 shows the process of predicting the arrival rate for the downstream intersection of the next cycle based on the detected traffic flow condition of the upstream intersection. Fig. 5 shows that the first part of the arriving vehicle rate at the downstream intersection in the $(k+1)$th cycle is predictable at the end of the kth cycle. This rate can be estimated by detecting the exact number of leaving vehicles from the upstream to the downstream intersection in the corresponding time period $t_A - t_B$. However, the arrival rate is difficult to predict for the remaining part of the $(k+1)$th cycle because the leaving vehicles at the upstream intersection and part of the signal timing plan in the corresponding time period of the upstream intersection are unknown. Therefore, the arriving traffic flow in the $(k+1)$th cycle is set as the estimated arriving traffic flow in the kth cycle plus an adjustment factor for the hard-to-predict part by assuming a similar traffic demand for continuous signal cycles, which can be updated every cycle, as shown in Eq. (13).

$$A_{jl}^{m}(k+1) = \left[\sum_{t\in E(m)} \mathrm{arr}(t)\right] \Big/ \left[u^{m}(k+1)+\xi\right] \tag{13}$$

where arr(t) is the estimated number of arriving vehicles in a one-second time instance in the kth cycle, $E(m)$ is the time period of the mth phase in the kth cycle, $u^{m}(k+1)$ is the effective green time to be optimized for the mth phase in the $(k+1)$th cycle, and ξ is an adjustment factor that is updated every cycle.

7.2. *Cycle and offset*

This study uses the traditional Webster equation to optimize the cycle length (Webster, 1958). The common cycle length for consecutive intersections is optimized every 10 min.

Coordinated control can be categorized into one-way and two-way coordination. Girianna and Benekohal (2003) developed a one-way coordinated control strategy for a two-way arterial under an over-saturated condition. Their study proved that releasing queues in a primary direction would not lead to the accumulation of queues in the opposing direction, and vice versa. In this study, a heavier traffic flow direction is assumed to be the primary direction, and the one-way coordinated control strategy is adopted.

Typical control strategies, such as Maxband (Little, 1966), do not efficiently work under an over-saturated condition (Liu et al., 2013). The objective of Maxband is to achieve bandwidth maximization and obtain the corresponding optimal offset. However, the calculated bandwidth may not be able to reach a non-negative value in this study, considering the long queue dissipation time. The objective of offset optimization in this study is to make leaving vehicles from the upstream intersection reach the end of the queue at the downstream intersection just as the queue dissipation wave reaches the end of the queue. This task may avoid unnecessary waiting for arriving vehicles from the upstream intersection and prevent spillback or inefficient use of green time.

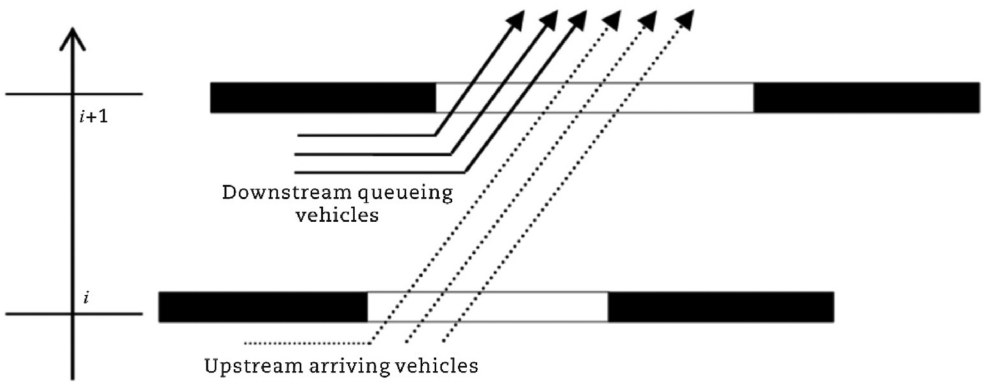

Fig. 6 – Ideal offset for one-way coordination.

Fig. 6 shows the ideal offset where leaving vehicles from the upstream intersection can pass the downstream intersection without waiting for the downstream queue to dissipate.

The offset, which is also optimized every 10min, can be enhanced using the following equation. The change in offset is realized by three continuous transition cycles to avoid dramatic changes in cycle length.

$$\varphi_{i,i+1}(k) = \frac{L - q_{i,i+1}(k)}{v} - \frac{q_{i,i+1}(k)}{\omega} \tag{14}$$

where L is the length of the link between the upstream intersection i and the downstream intersection $i+1$, v is the average speed of the leaving vehicles from the upstream intersection $i+1$, $q_{i,i+1}(k)$ is the estimated queue length at the beginning of green time for the coordinated direction at the downstream intersection, and ω is the propagation velocity of the queue dissipation wave.

8. Case study

The proposed control strategy was tested in a real traffic arterial with two continuous signalized intersections based on a simulation platform to show the efficiency of the MPC-based traffic control model based on the LPR data. The LPR data were collected for 1 d from two continuous signalized intersections located in a typical urban arterial in a city, as shown in Fig. 1. This arterial is located at the urban fringe, where the east-west through traffic flow is the dominating traffic. The eastbound and westbound approaches of these two intersections have three through lanes, one exclusive left-turn lane, and one exclusive right-turn lane. This study used traffic flow data from 7:30 am to 8:30 am to show the trend from the under-saturated to the over-saturated conditions.

Numerical computing software MATLAB (2012) and Excel were used for the simulation traffic simulator VISSIM (2007). VISSIM, which is a useful tool for analyzing traffic operation (Sun et al., 2013), provides performance indicators for evaluation based on the microscopic traffic simulation model. MATLAB can be used to perform the proposed complex optimization using the functions in the optimization toolbox (MATLAB, 2014). Codes were run in Excel VBA to control the simulation and optimization processes, and Excel spreadsheet was used to store the intermediate results to obtain the exchange of data between VISSIM and MATLAB. Thus, the developed model was validated in this study using the real-time simulation platform that combines VISSIM, Excel, and MATLAB.

The process is described as follows. (1) VISSIM operates the micro-simulation and exports the performance indicators and traffic flow parameters to Excel, including delay, queue length, and traffic volume based on the detected LPR data; (2) MATLAB obtains the necessary data from Excel, completes the online optimization process with the proposed real-time control model based on MPC, and returns the optimized control variable to Excel; (3) VISSIM reads the control variable from Excel and continued the simulation for the next signal cycle. In this simulation and control system, the com interface connected VISSIM and Excel. Exclink connected Excel and MATLAB.

Genetic algorithm is used to solve the optimization problem. This algorithm is a search-based optimization inspired by the process of natural selection. It is commonly used to solve optimization problems with constraints when it is hard to find the analytical solution. The genetic algorithm functions in the global optimization toolbox of MATLAB is used for the case study.

During the simulation process, the following parameters were presupposed based on experience.

(1) Minimum/maximum green time: 8 s/80 s
(2) Minimum/maximum cycle length: 40 s/160 s
(3) Yellow time/all red: 3 s/2 s
(4) Free flow speed: 50 km/h
(5) Saturated flow rate: 2.0 s/veh
(6) Controlled maximum queue length: 350 m
(7) Average occupied space of vehicles: 7.5 m
(8) Propagation velocity of queue dissipation: wave 6 m/s

The simulation period is 4800 s, and the first 1200 s were used as the warm-up period and excluded from the result analysis.

Road network and traffic demand were used to generate the optimized fixed-time timing plans in Synchro for six 10-min intervals, which were further compared with the signal timing plan based on the proposed control model.

In this study, the analysis on queue length focuses on Intersection 1, which has higher traffic demand in the

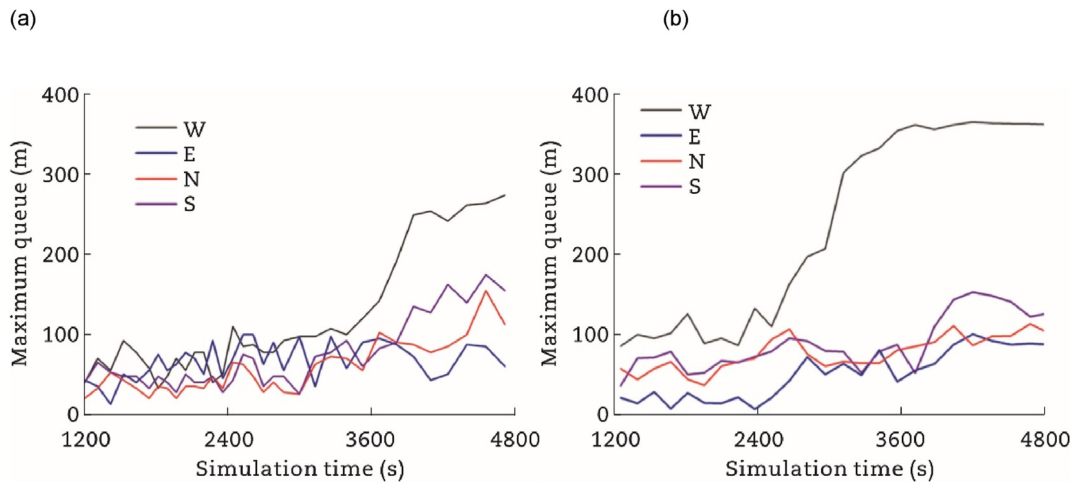

Fig. 7 — Maximum queue length for the through lanes. (a) Real time. (b) Synchro.

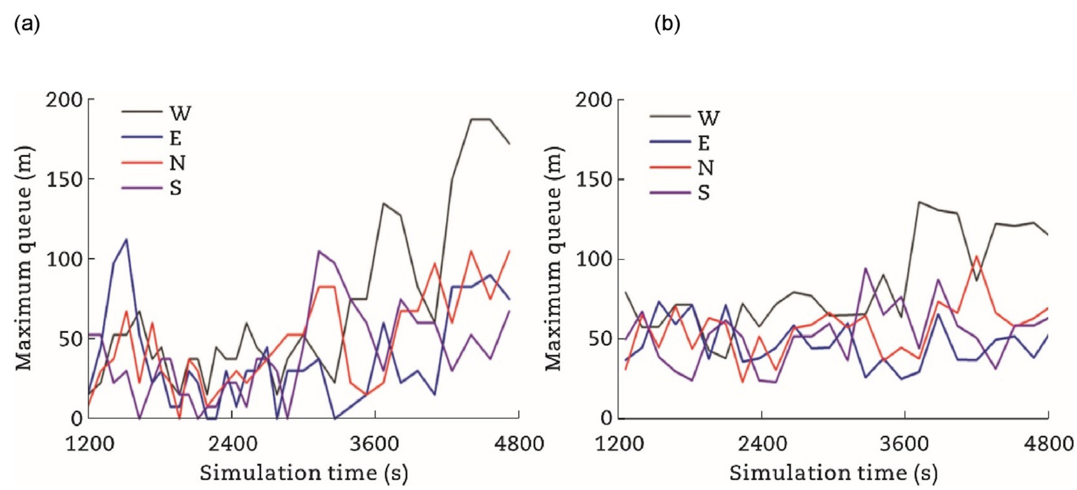

Fig. 8 — Maximum queue length for left-turning lanes. (a) Real time. (b) Synchro.

coordinated direction. A similar conclusion can be drawn from the analysis of Intersection 2.

Fig. 7 shows the change in queue length for the through lanes of each approach in continuous signal cycles under the proposed real-time control model and the Synchro plan. Under the Synchro timing plan (right), the westbound approach of Intersection 1 becomes over-saturated after 3600 simulation seconds. The queued vehicles cannot be released, and the queue length keeps exceeding the queue limit of the link. Moreover, the queue lengths of the other through lanes are less than 150 m. Under the proposed model (left), the maximum queue length of the westbound approach keeps growing after 3600 s, but the queue length is maintained below 300 m. The queue lengths in the other through lanes are slightly longer than those under the Synchro timing plan.

Fig. 8 shows the evident increase in maximum queue length in the left-turning lanes compared with the Synchro timing plan. The negative effects on the left-turning lanes result from the relief of overflow on the eastbound-through lanes. The result indicates the equilibrium of traffic pressure among the different approaches, consistent with the proposed control objective. Overall, one main characteristic of the proposed model in this study is the balance of queued vehicles between approaches, as shown in Eq. (1). The proposed model extremely restrains long queues in particular approaches and narrows the gap of queuing in all approaches. Synchro can generally provide reliable signal timing plans for different traffic conditions. Synchro fails to adapt to the changing system state due to the varying traffic demands and unpredictable disturbances, which may cause the prediction model of Synchro and the actual system to diverge. However, the real-time control model proposed in this study can detect the latest system state and keep updating the prediction model.

Table 3 shows that the proposed model can increase the number of passing vehicles in Intersection 1 and decrease the average delay by 13.0 s in the whole simulation period. In this study, the control objective considers the average delay and the residual queue for the under-saturated and over-saturated conditions, respectively. Table 3 also shows the improvement in the total capacity of two intersections compared with the Synchro timing plan. The intersection average delay also slightly decreases. The analysis of the two intersections shows that the proposed control model based

Table 3 – Comparison between delay and capacity.

Intersection No.	Real time		Synchro		Relative difference compared with synchro	
	Passed vehicles (veh)	Average delay (s)	Passed vehicles (veh)	Average delay (s)	Passed vehicles (%)	Average delay (%)
1	6312	55.2	6187	68.2	2.02	−19.06
2	6362	45.2	6269	49.1	1.48	−7.94

on the MPC can increase the intersection capacity, decrease the average delay, and improve the system operating efficiency.

9. Conclusions

This study proposes a framework for a closed-loop control system based on the LPR data. The emergence of LPR data based on the red light enforcement camera provides a possible data resource for traffic signal control. The control objectives and the queue prediction model are proposed for isolated intersection control based on the concept of MPC. Online rolling optimization and preliminary implementation of feedback in the system are also introduced.

This study proposes practical methods for calculating the arrival rate at the downstream based on the upstream data to extend the isolated intersection control model to a coordinated control model. Moreover, the offset is dynamically optimized with consideration of the downstream queuing. A simulation platform, which combines the application of VISSIM, Excel, and MATLAB, is developed to further validate the developed model. The results show the advantage of the proposed model in controlling extremely long queuing. Moreover, this model is tested to improve the intersection capacity and reduce the intersection average delay compared with the offline timing plan provided by Synchro.

Although the proposed control model may serve as a foundation for further studies on signal control systems with feedback for large-scale networks, this study is only an initial exploration to optimize the traffic signal timing plan based on the LPR data. The weaknesses of the LPR data, such as adverse effects of the weather and a recognition rate of below 90%, can degrade the performance of the proposed control strategy. Future research should consider the development of a traffic control optimization strategy based on multi-source detection data to ultimately take full advantage of the strengths of various traffic detection techniques.

Further work should include a more accurate description of the downstream arrival based on the specific characteristics of history data and real-time detected data for the proposed traffic control strategy. Furthermore, in-depth research should be conducted on the direct feedback of residual queue and average delay. For example, a more effective feedback mechanism may be developed to compensate for prediction delay.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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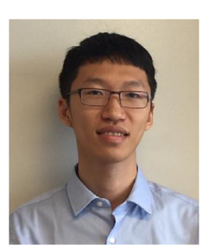

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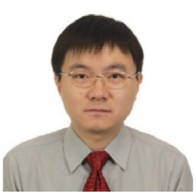

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