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A signal coordination algorithm for two adjacent intersections based on approximate dynamic programming

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Abstract: To reduce vehicle emissions in road networks, a new signal coordination algorithm based on approximate dynamic programming (ADP) is developed for two intersections. Taking the Jetta car as an experimental vehicle, field tests are conducted in Changchun Street of Changchun city and vehicle emission factors in complete stop and uniform speed states are collected. Queue lengths and signal light colors of approach lanes are selected as state variables, and green switch plans are selected as decision variables of the system. Then the calculation model of the optimization index during the planning horizon is developed based on the basis function method of the ADP. The temporal-difference algorithm is employed to update the weighting factor vector of the approximate function. Simulations are conducted in Matlab and the results show that the established algorithm outperforms the conventional coordination algorithm in reducing vehicle emissions by 8.2%. Sensitive analysis of the planning horizon length on the evaluation index is also conducted and the statistical results show that the optimal length of the planning horizon is directly proportional to the traffic load.

Key words: signal coordination; approximate dynamic programming; vehicle emissions; planning horizon

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The coordination of traffic signals located along urban arterials is one of the most effective methods to improve traffic flow movements. In view of the importance of signal coordination, a number of such algorithms have been developed[1-3]. Among these algorithms, traffic responsive coordination is the most widely implemented algorithm at present. The responsiveness to traffic means that timing parameters such as offsets are adjusted according to real-time traffic information. The real-time traffic data are usually detected by inductive loops. Following these ideas, some famous control systems such as SCOOT[4], SCATS[5] and PRODYN[6] have been successively developed and implemented in cities worldwide.

In recent years, a new type of the traffic responsive control algorithm[7-8] has been developed. It is accomplished on a phase-by-phase basis, without any explicit reference to the notion of cycle length or green allocation. Detectors are placed upstream of the stop line and the given planning horizon is split into discrete small stages. At the start of each stage, the downstream signal controller optimizes the starting and ending time of the coordination phase to facilitate the movements of the traffic flow that departs from the upstream intersection and arrives at the downstream stop line in the next planning horizon. Since the optimization needs the cooperation of the upstream information and the downstream controllers, it can thus be called as another type of signal coordination.

The above type of signal coordination can be expressed as a multi-stage optimization process because the planning horizon consists of multiple discrete stages. Dynamic programming (DP) developed by Bellman is so far the only solution for optimization over stages[9]. Nevertheless, the DP implication for traffic responsive control is limited. The computational demand in the recursive calculation of Bellman's equation is exponential to the size of the state space, the information space and the action space. This scenario is often described as the three curses of dimensionality[10]. To overcome the difficulties in applying DP and to preserve the fundamental features of dynamic control, a favorable option is approximation. An approximation to DP usually aims to reduce state space by aggregations or a continuous approximation function. Such an approach is frequently denoted as approximate dynamic programming (ADP).

Therefore, the purpose of this paper is to develop a new signal coordination algorithm and the study differs from previous studies in three ways. First, the ADP technique is applied to solve the multi-stage optimization problem. Secondly, vehicle emission, which is at present one of the most serious problems the public is concerned about, is selected as the optimization objective, instead of delay and stops. Thirdly, the impact of the planning horizon length on algorithm performance is studied, and the relationship between the planning horizon length and the traffic load is developed, which is useful to determine

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optimal planning horizon length.

1 Approximate Dynamic Programming

In this section, we first bring forward the DP algorithm and then introduce the formulation of the ADP.

1.1 Dynamic programming

Take a planning horizon that has N steps as an example, and let $x \subset X$ be the state variable of the system and $u \subset U$ be the decision variable. For current stage t, the one-step cost function is expressed as $g(x(t), u(t), t)$. The DP technique is to solve the decision process for the entire planning horizon and find the optimal decision variable sequence. As illustrated in Fig. 1, the value function J is

$$J[x(t), t] = \sum_{k=t}^{N} \gamma^{k-t} g[x(k), u(k), t] \tag{1}$$

where J is the system value from step t to the ending step of the planning horizon; γ is a discount factor and it ranges from 0 to 1.0. It reflects the system preference to the one-step costs in different steps. If $\gamma = 1.0$, then J is the sum of one-step costs of the steps from t to N and the system gives equal weight to each step. Otherwise J is the sum of the discount costs of the steps.

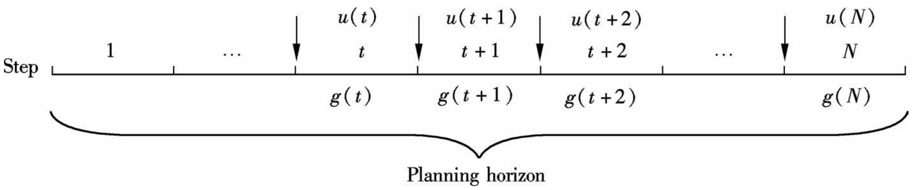

Fig. 1 Illustration of dynamic programming process

Eq. (1) can be expanded as

$$J[x(t), t] = \gamma^0 g[x(t), u(t), t] + \gamma^1 g[x(t+1), u(t+1), t+1] + \ldots + \gamma^{N-t} g[x(N), u(N), N] = g[x(t), u(t), t] + J[x(t+1), t+1] \tag{2}$$

The optimization of DP is to minimize the value function.

$$\min J[x(t), t] = \min_{u(t) \subset U} \{g[x(t), u(t), t] + J[x(t+1), t+1]\} \tag{3}$$

Finally, the optimal decision at step t is $u^*(t) = \arg\min_{u(t) \subset U} \{g[x(t), u(t), t] + J[x(t+1), t+1]\}$.

Eq. (3) offers a simple way of problem solving, but it can be computationally intractable even for very small problems. The reason is that the algorithm has to loop over the entire state space to evaluate the optimal decision at a single step. The computational load, therefore, increases exponentially with additional state spaces[8]. This is often described as the three curses of dimensionality. To solve this problem, an ADP technique is brought forward.

1.2 Forms of approximate dynamic programming

The one-step cost function $g(\cdot)$ can be easily obtained. However, the calculation of $J[x(t+1), t+1]$ will cost much time because it covers the following $N-t$ steps and there are lots of decision branches when approaching the last step. If we find a simple value function $\tilde{J}(\cdot)$ to approximate $J(\cdot)$, the problem of the curses of dimensionality may be solved[11]. Then Eq. (3) can be rewritten as

$$\tilde{J}[x(t), t] = g[x(t), u(t), t] + \tilde{J}[x(t+1), t+1] \tag{4}$$

The calculation of $\tilde{J}(\cdot)$ includes two steps.

Step 1 Selection of approximation value function

Generally, there are four ways to approximate the value function. They are the look-up table method, the basis function method, the polynomial method and the neural network method. Among the four ways, the basis function method is frequently used and in this study it is also employed.

$$\tilde{J}(x(t), t) = \sum_{t=1}^{N} \boldsymbol{\phi}_t^{\mathrm{T}}(x(t)) \boldsymbol{W}_t \tag{5}$$

where $\boldsymbol{\phi}(X) = \{\phi_1(x), \phi_2(x), \ldots, \phi_N(x)\}^{\mathrm{T}}$, and it is the feature-extraction function of the state space. $\boldsymbol{W}_t = \{W_1, W_2, \ldots, W_N\}^{\mathrm{T}}$ is the weighting factor vector.

Step 2 Update weighting factor vector

The determination of W_t is a critical procedure of the ADP because it decides the approximate precision. In this study a temporal-difference (TD) algorithm is employed to update $\boldsymbol{W}_t$ in real time.

The one-step TD is expressed as

$$\delta_t = g[x(t), u(t), t] + \gamma \tilde{J}[x(t+1), t+1] - \tilde{J}[x(t), t] \tag{6}$$

For each time step t, the TD algorithm updates $\boldsymbol{W}_t$ according to

$$\boldsymbol{W}_{t+1} = \boldsymbol{W}_t + \eta_t \delta_t z_t \tag{7}$$

where η_t is the learning factor and it decides the convergence rate of the ADP. z_t is the eligibility trace vector and it records the visited frequency of a state by the recursive method. If a state is visited, then its eligibility will increase, otherwise the eligibility will decrease. z_t can be obtained by

$$z_t = \sum_{k=0}^{t} (\gamma\lambda)^{t-k} \boldsymbol{\phi}(x(k)) \tag{8}$$

where λ is the eligibility trace factor and it represents the dependent degree of historical information, $0 \leqslant \lambda \leqslant 1$.

The update process of z_t is

$$z_{t+1} = \gamma\lambda z_t + \boldsymbol{\phi}(x(t+1)) \tag{9}$$

2 Proposed Signal Coordination Model

2.1 Optimization objective

At present, reducing vehicle emissions on road networks is an issue that the public is concerned about. Therefore, developing a traffic signal coordination algorithm to reduce vehicle emissions becomes a difficult task for traffic engineers. In this study, vehicle emission is selected as the optimization index. The amount of emission is affected by vehicular running states. For a vehicle that departs from the upstream stop line and moves towards a downstream signal, its running state can be classified into two groups: complete stop and non stop. To model conveniently, the non complete stop state (such as acceleration and deceleration) is ignored because the proportion of travel time corresponding to the non complete stop state to total travel time on the link is very small, especially in unsaturated conditions. The non stop state in this paper means vehicles running at an even speed.

Vehicle emissions mainly include three gases: NO_x, HC and CO. To obtain the real vehicle emission factors, we conduct field experiments in Changchun Street of Changchun city. The Jetta car is selected as the experimental vehicle and its emission factors in different running states are collected (see Tab. 1).

Tab. 1 Vehicle emission factors of car in Changchun Street

Running state	E_{NO_x}/(mg · s^{-1})	E_{HC}/(mg · s^{-1})	E_{CO}/(mg · s^{-1})
Non stop	0.17	2.60	0.53
Complete stop	0.90	2.05	0.38

The three gases do different degrees of harm to the environment. According to Ref. [11], we define the weights of the three gases as 0.15, 0.70 and 0.15, respectively.

2.2 Traffic arrival pattern prediction

As shown in Fig. 2, loop detectors are placed near the stop lines of the approach lanes. When the green light starts, the passing time of each vehicle in the platoon can be detected.

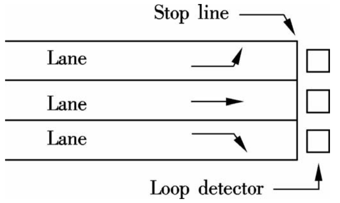

Fig. 2 Illustration of vehicle detector location

Let L denote the distance between two adjacent intersections. Vehicles move downstream at an even speed v, m/s. So the travel time t_a equals L/v. Vehicle data are sampled every Δt s and in this way the platoon departure pattern can be obtained. As shown in Fig. 3, the platoon departure pattern can be projected to the downstream stop line.

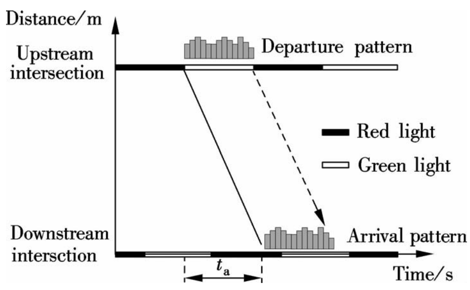

Fig. 3 Projection of upstream platoon pattern to downstream signal

From Fig. 3, we can find that the downstream intersection can obtain arrival vehicle information t_a ahead of their real arrival times. However, the problem is that the length of planning horizon T is usually greater than t_a. For example, when $T = 90$ s and $t_a = 40$ s, the downstream controller can only obtain the real vehicle information of the oncoming 40 s. No vehicle information can be used for the following 50 s. How to obtain the traffic volume for the 50 s is a critical problem for signal coordination. A common way is prediction. As described in Fig. 4, we can divide the planning horizon into two sections. One is the head section, during which the real traffic volume is applied. The other is the tail section, during which the predicted traffic volume is applied.

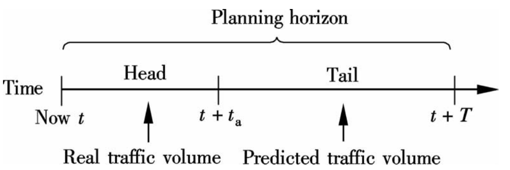

Fig. 4 Division of planning horizon

The OPAC uses the average traffic volume of the past 5 min for the tail section and the results of field tests indicate that this method is effective[7]. So in this study we also use this method. Let q_t denote the traffic volume of the tail section,

$$q_t = \sum_{i=1}^{N_s} \frac{q_i}{N_s} \tag{10}$$

where q_i is the traffic volume of the i-th step, pcu/h; N_s is the number of steps in the past 5 min and it equals $300/\Delta t$; Δt is the time duration of each step, s.

2.3 Timing plan optimization

In this section, the timing plan optimization process using the ADP technique is introduced. As described in the above section, T denotes the time length of the planning horizon; Δt is the time duration of each step. Traffic data is also sampled every Δt s. So the planning horizon can be divided into N steps, $N = T/\Delta t$.

Before modeling, the following descriptions about the system are given:

1) Vehicles arriving at one step have the same movement states;

2) The start-up lost time is ignored and all the approach lanes are unsaturated;

3) At the start of each step, the system decides to either extend the current green phase or turn the green light to the next phase;

4) The green time duration of each phase should not be smaller than the minimum green time nor greater than the maximum green time.

For an intersection with M approach lanes, its state can be defined by the queue length and the signal light color of each lane. The queue length represents the traffic state and the signal light color represents the control state. The formulation of the control system includes the following five steps.

Step 1 Definition of system state

For $m = 0, 1, \ldots, M$, let $l_t(m)$ denote the number of queue vehicles of lane m and let $s_t(m)$ denote the traffic signal indication during step t. Then,

$$\boldsymbol{l}_t = \begin{bmatrix} l_t(1) \\ \vdots \\ l_t(M) \end{bmatrix}, \qquad \boldsymbol{s}_t = \begin{bmatrix} s_t(1) \\ \vdots \\ s_t(M) \end{bmatrix} \tag{11}$$

$$s_t(m) = \begin{cases} 1 & \text{if signal is green for lane } m \\ 0 & \text{if signal is red for lane } m \end{cases} \tag{12}$$

We denote the arrival traffic by vector $\boldsymbol{w}$ and the departing traffic by vector $\boldsymbol{y}$ as

$$\boldsymbol{w}_t = \begin{bmatrix} w_t(1) \\ \vdots \\ w_t(M) \end{bmatrix}, \qquad \boldsymbol{y}_t = \begin{bmatrix} y_t(1) \\ \vdots \\ y_t(M) \end{bmatrix} \tag{13}$$

The value of each element in $\boldsymbol{w}$ can be obtained by the traffic arrival pattern prediction shown in section 2. 2. The calculation process for $y_t(m)$ is stated in Step 3.

Step 2 System decision

At the start of each step, available decisions of the system are extending the current green phase or switching the green phase to the next phase. Let u_t denote the system decision at step t. Then,

$$u_t(m) = \begin{cases} 1 & \text{switch green to next phase} \\ 0 & \text{extend current phase for one step} \end{cases} \tag{14}$$

Step 3 Transition of system state

Once the system has made a decision on signal status, the state of the intersection will be changed. The transition of the signal state vector $\boldsymbol{s}_t$ can be depicted as

$$s_{t+1}(m) = (s_t(m) + u_t(m)) \bmod_2 \tag{15}$$

The transition of the queue length is determined by the arrival traffic and the departing traffic. So,

$$l_{t+1}(m) = l_t(m) - y_t(m) + w_t(m) \tag{16}$$

$y_t(m)$ is critical for Eq. (16) and the calculation can be classified into three conditions:

$$y_t(m) = \begin{cases} 0 & s_t(m) = 0 \\ q_s(m) & s_t(m) = 1,\ y_{t-1}(m) + w_t(m) \geqslant q_s(m) \\ y_{t-1}(m) + w_t(m) & s_t(m) = 1,\ y_{t-1}(m) + w_t(m) < q_s(m) \end{cases} \tag{17}$$

where $q_s(m)$ is the number of vehicles discharged in saturation flow rate during each step and it equals $\Delta t S_m$. S_m is the saturation flow rate of lane m.

Step 4 One step cost function and value function

For lane m, the cost of one step is the total amount of vehicle emission during step t.

$$g_t(m) = [l_t(m) + w_t(m)] E_{\mathrm{cs}} \Delta t + y_t(m) E_{\mathrm{ns}} \Delta t \tag{18}$$

E_{cs} is the emission for a complete stop vehicle,

$$E_{\mathrm{cs}} = 0.15 E_{\mathrm{NO\_cs}} + 0.7 E_{\mathrm{HC\_cs}} + 0.15 E_{\mathrm{CO\_cs}} \tag{19}$$

where $E_{\mathrm{NO\_cs}}$, $E_{\mathrm{HC\_cs}}$ and $E_{\mathrm{NO\_cs}}$ are emission factors of NO_x, HC and CO for a complete stop vehicle, respectively.

E_{ns} is the emission for a non stop vehicle,

$$E_{\mathrm{ns}} = 0.15 E_{\mathrm{NO\_ns}} + 0.7 E_{\mathrm{HC\_ns}} + 0.15 E_{\mathrm{CO\_ns}} \tag{20}$$

where $E_{\mathrm{NO\_ns}}$, $E_{\mathrm{HC\_ns}}$ and $E_{\mathrm{NO\_ns}}$ are emission factors of NO_x, HC and CO for a non stop vehicle, respectively.

For the intersection with total M lanes, the one-step cost function during step t is

$$g_t(M) = \sum_{m=1}^{M} g_t(m) \tag{21}$$

For current step t, the value function of the system during the planning horizon is

$$J_t[x(t), u(t)] = g_t(M) + J[x(t+1), u(t+1)] \tag{22}$$

The optimization is to find the optimal decision for step t that will minimize the value function, namely,

$$u^*(t) = \arg \min_{u(t) \subset U} \{ g(M) + J[x(t+1), u(t+1)] \} \tag{23}$$

The optimization is conducted at the start of each step, so it can dynamically optimize decision variables every Δt s to adapt to the real time change of the system state.

Step 5 Approximation to value function

The basis function method is selected to approximate the value function. As depicted in Step 1, $\{l, s\}$ can represent the system state. For step t and lane m, the feature-extraction function of the state space $\boldsymbol{\phi}_t(m)$ is

$$\boldsymbol{\phi}_m(t)=\begin{cases}\begin{bmatrix}0\\ l_t(m)\end{bmatrix} & s_t(n)=0\\ \begin{bmatrix}l_t(m)\\ 0\end{bmatrix} & s_t(n)=1\end{cases} \tag{24}$$

The weighting factor is defined as

$$\boldsymbol{W}_m(t)=\begin{cases}\begin{bmatrix}0\\ w(m)\end{bmatrix} & s_t(n)=0\\ \begin{bmatrix}w(m)\\ 0\end{bmatrix} & s_t(n)=1\end{cases} \tag{25}$$

Then the approximated value function is

$$\tilde{J}(x(t+1),t+1)=\sum_{m=1}^{M}\boldsymbol{\phi}_n^{\mathrm{T}}(x(t+1))\boldsymbol{W}_{t+1} \tag{26}$$

3 Case Study

3.1 Simulation environment

The developed algorithm is tested in a Matlab environment. The sketch of the test network and the phase diagrams are shown in Fig. 5. Each intersection contains three phases and phase 1 is selected as the coordinated phase. The minimum green time of the left-turn phase is 10 s and that of the straight phase is 15 s. To compare the benefits of the established algorithm, the base algorithm and the new signal coordination algorithm are tested in this paper. The base algorithm is the conventional signal coordination algorithm. Cycle length is determined by Webster's model and the green split of each phase is optimized based on the equal degree of saturation principle. Offsets among intersections are determined by the numerical method[12]. The new signal coordination algorithm is established in this paper. Parameters of the ADP algorithm are set as follows: $\gamma=0.12$, $\eta=0.001$ and $\lambda=0.3$. The length of the planning horizon is fixed at 90 s.

The input traffic volumes of the six entrances are shown in Tab. 2. T_s is the time point during simulation. Because we want to test the ability of treating the dynamic traffic states of the two algorithms, the volumes of entrance 1 and 2 are set changing with time.

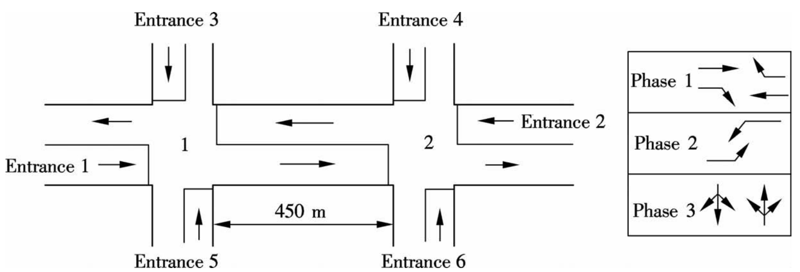

Fig. 5 Sketch and phase diagram of the two intersections

Tab. 2 Input volume of each entrance pcu/h

Entrance	1	2	3	4	5	6
Volume	$1\,000+200\sin T_s$	$1\,000+200\cos T_s$	300	300	300	300

3.2 Simulation results

Total vehicle emissions of the coordinated phases in the network are collected and the data are shown in Tab. 3. From the table we can find that compared with the base algorithm, the new developed coordination algorithm can reduce vehicle emissions by 8.2%.

Tab. 3 Vehicle emissions of coordinated phases in the simulated network g

Tested algorithm	New signal coordination algorithm	Base algorithm
Vehicle emissions	51.216	55.440

3.3 Sensitive analysis of planning horizon length

In previous related studies, the length of the planning horizon is fixed (i.e. 90 s). However, it is known to us that the traffic volumes of the tail section used in the ADP algorithm are predicted volumes and there must be prediction errors. If the length of the planning horizon is long, then the total prediction error will be large and lead to the degradation of control performance. If the planning horizon is set short, the algorithm will not consider the global traffic information and will not respond to the change of traffic state quickly.

Since the prediction error is inevitable, we can avoid the degradation of performance to some extent by setting the optimal length of the planning horizon. In this section, experiments are conducted to discover the relationship between the performance and the length of the planning horizon. The procedure of the simulation includes the following steps.

Step 1 Obtain control performance using real traffic volume

In this step, real traffic data are generated first in the Matlab environment. Then the developed signal coordination algorithm operates using real data over the entire planning horizon rather than over the head section. So there is no prediction error of traffic volume. In such a situation, the longer the planning horizon, the better the signal control. So in this step the planning horizon is set as 120 s. The input traffic volumes of entrances 1 and 2 are ranged from low to heavy and they are shown in Tab. 4.

Tab. 4 Input volumes of entrances 1 and 2 for simulation experiments pcu/h

Scenario	Entrance 1	Entrance 2
1	$500 + 200\sin T_s$	$500 + 200\cos T_s$
2	$600 + 200\sin T_s$	$600 + 200\cos T_s$
3	$700 + 200\sin T_s$	$700 + 200\cos T_s$
4	$800 + 200\sin T_s$	$800 + 200\cos T_s$
5	$900 + 200\sin T_s$	$900 + 200\cos T_s$
6	$1\ 000 + 200\sin T_s$	$1\ 000 + 200\cos T_s$
7	$1\ 100 + 200\sin T_s$	$1\ 100 + 200\cos T_s$
8	$1\ 200 + 200\sin T_s$	$1\ 200 + 200\cos T_s$
9	$1\ 300 + 200\sin T_s$	$1\ 300 + 200\cos T_s$

Step 2 Obtain control performance using predicted volume over tail section

In this step, predicted traffic volumes are applied to the tail section of the planning horizon. To test the impact of the planning horizon on control performance, the length of the planning horizon is increased from 40 to 120 s with a step of 10 s. So simulations are conducted nine times for each scenario.

Step 3 Compare evaluation indices collected in Steps 1 and 2 for the same scenario

Because each scenario is simulated nine times in Step 2, accordingly there are nine indices. Comparing the nine indices to the index in Step 1, the closer the nine indices with the index in Step 1, the better the corresponding planning horizon in Step 2. The optimal planning horizon length for each scenario is found and they are shown in Tab. 5.

Tab. 5 Optimal planning horizon for each scenario

Scenario	Optimal length of planning horizon/s
1	60
2	70
3	70
4	80
5	80
6	80
7	90
8	100
9	110

From Tab. 5, we can find that for the scenarios with low traffic demand (i. e. scenarios 1 and 2), the optimal length of the planning horizon is short. However, with the increase in traffic demand, the optimal length also increases. This phenomenon can be interpreted as follows. When traffic demand is low, the algorithm is sensitive to the prediction error, and the short length of the planning horizon can reduce the errors of the tail section. When traffic demand is high, the length of the arrival platoon at the stop line is also increased and the system is requested to optimize the traffic in a long time period which can cover the entire arrival platoon. In such situation, the long length of the planning horizon is produced.

Though Tab. 5 shows the relationship between traffic demand and the length of the planning horizon, the length is closely related to signal control types, traffic volume prediction errors and so on. The determination of the optimal length should be tried many times by simulations or field tests before it is applied.

4 Conclusion

This paper develops a new signal coordination algorithm for two adjacent intersections based on the ADP technique. Compared with the conventional coordination algorithm, this new algorithm has two obvious characteristics. First, it can optimize timing parameters in real time and the transition between adjacent coordination plans is not requested because there are no common cycle lengths and offsets. Secondly, the conventional algorithm needs to consider the discharged and arrived platoons in both directions. However, the new algorithm only facilitates the arrival platoons, thus, it has a low computational load. Especially when there is large difference between two directional traffic volumes, the new algorithm can also achieve good performance.

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References

[1] Bell M C, Bretherton R D. Ageing of fixed-time traffic signal plans [C]//*Proceedings of the Second IEE Conference on Road Traffic Control*. London, 1986: 77 − 80.

[2] Robertson D I. TRANSYT: a traffic network study tool, RRL Report, LR 253 [R]. Crowthorne: Transport and Road Research Laboratory, 1969: 391 − 394.

[3] Little J D C, Kelson M D, Gartner N H. MAXBAND: a program for setting signals on arterials and triangular networks [J]. *Journal of Transportation Research Record*, 1981(795): 40 − 46.

[4] Hunt P B, Robertson D I, Bretherton R D. The SCOOT on-line traffic signal optimization technique [J]. *Traffic Engineering & Control*, 1982, **23**(4): 190 − 192.

[5] Luk J Y K. Two traffic-responsive area traffic control methods: SCAT and SCOOT [J]. *Traffic Engineering & Control*, 1984, **125**(1): 14 − 22.

[6] Henry J J, Farges J L, Tuffal J. The PRODYN real time traffic algorithm [C]//*Proceedings of the Fourth IFAC-IFIP-IFORS Conference on Control in Transportation Systems*. Baden-Baden, Germany, 1983: 305 − 310.

[7] Gartner N H. OPAC: a demand-responsive strategy for traffic signal control [J]. *Transportation Research Record*, 1983(906): 75 − 81.

[8] Cai C, Wong C K, Heydecker B G. Adaptive traffic signal control using approximate dynamic programming [J]. *Transportation Research Part C*, 2009, **17**(5): 456 − 474.

[9] Bellman R. *Dynamic programming* [M]. Princeton University Press, 1957: 42 − 63.

[10] Powell W B. *Approximate dynamic programming: solving the curses of dimensionality* [M]. John Wiley & Sons, Inc., 2007: 85 - 149.
[11] Guo Dong. Research on vehicle emissions optimization on urban traffic network [D]. Changchun: College of Transportation of Jilin University, 2010. (in Chinese)
[12] Xu Jianmin. *Traffic management and control* [M]. Beijing: China Communications Press, 2007: 172 - 198. (in Chinese)

基于近似动态规划的相邻两交叉口信号协调控制算法

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摘要:为减少路网机动车尾气排放,建立了基于近似动态规划的相邻两交叉口信号协调控制算法.以捷达车作为试验车辆,在长春市长春大街进行实车实验,采集了完全停车以及匀速行驶2种状态下的机动车排放因子;以进口道排队长度、信号灯色作为系统状态的表达变量,以绿灯切换方案作为决策变量集,采用近似动态规划中的基函数方法,建立了规划时间窗内优化目标计算模型;并采用时域差分算法对基函数中的权重向量进行动态更新.在Matlab环境中验证了该算法的有效性,结果表明:所建立的算法较传统协调算法能够减少协调相位机动车排放8.2%.同时仿真验证了规划时间窗长度对协调算法控制效益的敏感性,发现最佳规划时间窗长度随着交通负荷的增加而增加.

关键词:信号协调;近似动态规划;机动车排放;规划时间窗

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