Adaptive Traffic Signal Control: A Novel Modelling Approach

Lubing Li[*1], Ka Fai Ng[1], Jacob Chak Yan Lo[1], and Hong K. Lo[1]

[1] Department of Civil and Environmental Engineering
The Hong Kong University of Science and Technology, Hong Kong, China

SHORT SUMMARY

We develop a novel cell-based two-stage stochastic program to address spatial, dynamic and stochastic features of traffic flow for adaptive signal control. Cell transmission model (CTM) is employed to capture the dynamic feature of traffic flow, with certain CTM cells designated as detector cells to capture real-time spatial queuing effects. We formulate a two-stage stochastic program to address uncertain demand for signal control. In stage 1, a base timing plan (BTP) is determined as the long-term default plan. In stage 2, cycle-based adaptive policies, i.e., green extension/cut-off based on the BTP, are implemented according to the detector cell states. We develop a specialised GA algorithm to search for the optimal BTP and adaptive policies. A case study of Tai Tam reservoir is conducted to elaborate the property of the proposed approach. The adaptive control plan can have 17% delay reduction compared to the optimal fixed-time plan.

Keywords: adaptive signal control, traffic flow theory, two-stage stochastic program

1. INTRODUCTION

To develop a demand-responsive traffic signal control system, traffic detectors play a vital role in collecting traffic information for making signal control decisions. For vehicle actuated signal control, detectors are deployed near the stop lines of all or some of the junction approaches. According to the vehicle detection information, the green times of certain stages are extended or cut off. The question of how long the green time ought to be extended or cut off is not addressed explicitly. The extension/cut-off durations are generally determined according to traffic engineer experiences in practice. Urban traffic control (UTC) signal control system generally produces fixed-time plans for each identified traffic pattern based on detector information. Appropriate timing plans are selected by the time of day, day of the week, or special event situations. Once selected, the fixed-time plan is implemented for that period. Albeit detectors provide seconds/minutes level sensing data, the traffic variations within the period are neglected. For adaptive signal control systems, such as SCOOT (Robertson and Bretherton, 1991), detectors are deployed at the entry to the network links to predict the time and shape of the flow profiles at the stop line. Optimal signal timing variables are calculated with the incremental change algorithm. The optimality of the signal timing plans may be hampered by the restricted computational time budget. Because of platoon dispersion and lane changing effects, the estimated flow profiles are likely biased toward the arrival patterns at the stop line. In this paper, we utilize the vehicle detection data from first principles and incorporate dynamic detector status information into a mathematical model to derive the optimal adaptive control policies.

Our study aims to address three characteristics of traffic flow, i.e., spatial, dynamic, and stochastic, for adaptive signal control. To capture spatial and dynamic features, we adopt the cell transmission model (CTM) (Daganzo, 1994) as the underlying traffic flow model. Certain cells in the CTM network are selected as the detector cells. Cell occupancy information is collected to indicate queue presence status at the detector locations. To capture the stochastic traffic demand feature, we adopt a two-stage stochastic program method. In stage 1, a base timing plan, including cycle time, base green time, and offset, is determined as the long-term default plan or 'fallback' plan. In stage 2, upon the traffic demand realization scenarios, cycle-based adaptive control policies are determined to address residual queues. At the end of each signal cycle, adaptive policies are selected according to the status of the detector cells. Each detector status pattern corresponds to a certain adaptive policy. The selected adaptive policy will be implemented in the next cycle. We develop a specialized GA algorithm to determine the optimal base timing plan and adaptive policies. A case study at Tai Tam reservoir is provided to indicate the properties of the proposed adaptive signal control method.

2. METHODOLOGY

signal control in CTM

As shown in (1), the green start time $S_{i,j,z}$ of phase-1 (*i=1*) is equal to the initial offset O_j^{ini} at junction *j* plus the lost time *L* plus the z^{th} cycle start time $(z-1)\cdot C$. For other phases (*i>1*), the green start time $S_{i,j,z}$ is equal to the lost time *L* plus the green end time of the predecessor phase $E_{i-1,j,z}$, as shown in (2). The green end time $E_{i,j,z}$ is equal to the green start time $S_{i,j,z}$ plus the green duration $G_{i,j}$, as shown in (3). The signal effects can be captured in CTM by adjusting the inflow capacity of the signal cells (M_1) according to the state of signal light. In (4), when the time step *t* is between $S_{i,j,z}$ and $E_{i,j,z}$ (in green), the inflow capacity of the signal cell, i.e., $Q_{m,1}(t)$, is set to be the saturation flow rate *s*; otherwise $Q_{m,1}(t)$ equals zero.

$$S_{i,j,z} = O_j^{ini} + L + (z-1)\cdot C, i = 1, \forall j, z, \tag{1}$$

$$S_{i,j,z} = L + E_{i-1,j,z}, i > 1, \forall j, z, \tag{2}$$

$$E_{i,j,z} = S_{i,j,z} + G_{i,j}, \forall i, j, z, \tag{3}$$

$$Q_{m,1}(t) = \begin{cases} s, \; S_{i,j,z} \; < \; t \le E_{i,j,z} \\ 0, \; otherwise \end{cases}, \forall i, j, z, m \in M_1. \tag{4}$$

detector cell settings

We designate certain CTM cells as detector cells to mimic real-time traffic detector deployment. Adaptive signal control policies are triggered based on detector states. We employ indicator functions in (5) to represent whether the state of a detector is active or inactive. Denote $d_{i,j}(t)$ as the state of detector cell at time *t* for phase *i*, junction *j*. Denote set $\boldsymbol{\Phi}_t = \{d_{i,j}(t), \forall i \in I', \forall j \in J'\}$ as the set that includes all the detector cell states in the target network. I' is the phase set, for which phase detectors are deployed. J' is the junction set, for which junction detectors are deployed. In (5), if the occupancy of detector cell $c^{d_{ij}}$ is greater than or equal to the critical occupancy κ_f at time *t*, $d_{i,j}(t) = 1$; otherwise, $d_{i,j}(t) = 0$. (5) can be applied to represent queue presence detection. For instance, if the occupancy of detector cell is full or almost full, e.g., $\kappa_f > 0.9$, vehicle queue is regarded as reaching to the detector location.

$$d_{i,j}(t)=\begin{cases}1, & occ_t(c^{d_{ij}})\geq\kappa_f\\0, & occ_t(c^{d_{ij}})<\kappa_f\end{cases} \tag{5}$$

two-stage signal control formulation

With the CTM model embedded, we formulate a cell-based two-stage stochastic program to optimize the traffic signal control plan (Li et al., 2018; Li et al., 2021). In stage 1, the expected total delay $E_{\Omega}[D(C,\boldsymbol{G}^b,\boldsymbol{O}^{ini})]$ is minimized with respect to the base timing plan, i.e., $\left\{C,\boldsymbol{G}^b,\boldsymbol{O}^{ini}\right\}$, shown in (6). It is subject to CTM dynamics constraints. (7)-(10) are constraints for signal control variables.

In stage 2, given the base timing plan $\left\{C,\boldsymbol{G}^b,\boldsymbol{O}^{ini}\right\}$ from stage 1, adaptive policies, $\Delta\boldsymbol{G}$, hence, the actual green time $\boldsymbol{G}^a$, are determined to minimize the total delay D_k upon the realization of traffic demand $\hat{\boldsymbol{v}}_k$ in scenario k, as shown in (11). $\Delta\boldsymbol{G}$ is the set that includes all the adaptive policies, i.e., $\Delta\boldsymbol{G}=\{\{\Delta G_{i,j}^c,\forall i\in I,\forall j\in J\},\forall c\}$. $\Delta G_{i,j}^c$ is the adaptive policy *c* for phase *i* at junction *j*. Denote $\boldsymbol{\Lambda}$ as the set that includes all the detector state combinations, i.e., $\boldsymbol{\Lambda}=\{\{d_{i,j}^c,\forall i\in I^{'},\forall j\in J^{'}\},\forall c\}$. $d_{i,j}^c$ is the state of detector (either 1 or 0, as shown in (5)) for adaptive policy *c* for phase *i* at junction *j*. Each adaptive policy *c* corresponds to a specific detector state combination, i.e., $\Delta\boldsymbol{G}(c)\rightarrow\boldsymbol{\Lambda}(c)$. For adaptive policy *c*, the summation of ΔG^c over all phases for junction *j* should be zero to maintain the common cycle time, as shown in (12). The adaptive policy ΔG^c is selected according to the state of detector cells $\boldsymbol{\Phi}$. If the detector state combinations for adaptive policy *c*, i.e., $\boldsymbol{\Lambda}(c)$, are the same as the state of detector cells, i.e., $\boldsymbol{\Lambda}(c)=\boldsymbol{\Phi}$, indicator function $1_{\boldsymbol{\Phi}}(\boldsymbol{\Lambda}(c))$ returns 1, as shown in (13); otherwise, $1_{\boldsymbol{\Phi}}(\boldsymbol{\Lambda}(c))=0$. In (14), the actual green time $G_{i,j}^a$ for phase *i* junction *j* equals the base green time $G_{i,j}^b$ plus the selected adaptive policy $\Delta G_{i,j}^c$. (15) is the range of actual green time. (16) is the actual green end time constraint.

(Stage 1:)

$$\min_{C,\boldsymbol{G}^b,\boldsymbol{O}^{ini}} E_{\Omega}[D(C,\boldsymbol{G}^b,\boldsymbol{O}^{ini})]=\sum_{k\in\Omega}P_k(\hat{\boldsymbol{v}}_k)\cdot D_k(C,\boldsymbol{G}^b,\boldsymbol{O}^{ini},\hat{\boldsymbol{v}}_k) \tag{6}$$

subject to CTM dynamics constraints and (1)-(4), and

$$\sum_i(G_{i,j}^b+L)=C,\ \forall j, \tag{7}$$

$$G_{i,j}^{min}\leq G_{i,j}^b\leq G_{i,j}^{max},\ \forall i,j, \tag{8}$$

$$C^{min}\leq C\leq C^{max}, \tag{9}$$

$$0\leq O_j^{ini}\leq O_j^{ini,max},\ \forall j, \tag{10}$$

where $D_k(C,\boldsymbol{G}^b,\boldsymbol{O}^{ini},\hat{\boldsymbol{v}}_k)$ is the total delay value in demand scenario *k* in stage-2.

(Stage 2:)

$$\min_{\Delta\boldsymbol{G},\boldsymbol{G}^a} D_k(\Delta\boldsymbol{G},\boldsymbol{G}^a\mid\hat{\boldsymbol{v}}_k)=\sum_l\sum_t d_{l,k}(t) \tag{11}$$

subject to CTM dynamics constraints and (1)-(2), (4)-(5) and

$$\sum_i \Delta G_{i,j}^c = 0, \forall j, c \tag{12}$$

$$1_{\boldsymbol{\Phi}}(\Lambda(c)) = \begin{cases} 1, \ \Lambda(c) = \boldsymbol{\Phi}_t \\ 0, \ \Lambda(c) \neq \boldsymbol{\Phi}_t \end{cases}, t = n \cdot C, n \in \mathrm{N}; \tag{13}$$

$$G_{i,j}^a = G_{i,j}^b + \sum_c 1_{\Phi}(\Lambda(c)) \cdot \Delta G_{i,j}^c, \forall i, j \tag{14}$$

$$G_{i,j}^{min} \leq G_{i,j}^a \leq G_{i,j}^{max}, \ \forall i, j, \tag{15}$$

$$E_{i,j,z} = S_{i,j,z} + G_{i,j}^a, \forall i, j, z \tag{16}$$

The optimal total delay D_k in stage 2 is accrued into the objective function to obtain the expected total delay $E_{\Omega}[D(C, \boldsymbol{G}^b, \boldsymbol{O}^{ini})]$. As shown in (6), the expected total delay $E_{\Omega}[D(C, \boldsymbol{G}^b, \boldsymbol{O}^{ini})]$ equals the summation of the total delay over each demand scenario *k* ($k \in \Omega$). Ω is the space of the realizations of demand scenario. $P_k(\hat{\boldsymbol{v}}_k)$ is the probability of scenario *k* for which the realized demand is $\hat{\boldsymbol{v}}_k$. We assume a finite number of demand scenarios sampled in space Ω and the summation of probability P_k equals 1, i.e., $\sum_{k \in \Omega} P_k = 1$. The whole optimization problem is to determine the optimal solutions for the base timing plan in stage 1 and the set of adaptive policies in stage 2, which will minimize the expected total delay under stochastic demand condition.

solution algorithm

In this study, we develop a specialised solution approach based on genetic algorithm (GA) to solve the proposed adaptive signal control problem. We have introduced GA into solving signal control optimisation problem and elaborated the effectiveness of GA in generating quasi-optimal signal control solutions (Lo et al., 2001; Lo and Chow, 2004). In GA, signal control variables are transformed into 0-1 binary representations. The duration of each variable is coded as a series of chromosomes. An example of the gene structure of the cycle-based two-stage signal control is shown in Figure 1. The head part is the common cycle time for the junctions in the network, following with the control variables of each junction. Junction control variables consists of the base timing plan (including initial offset O_j^{ini}, base green time $G_{i,j}^b$) and adaptive policies $G_{i,j}^a$. The actual green time $\boldsymbol{G}^a$ is coded as the adaptive decision variables in the gene since the range of $\Delta \boldsymbol{G}$ includes negative domain which is not operable in GA. The population of genes are manipulated with three operators, i.e., reproduction, crossover, mutation, to search for optimal signal control solutions. The gene (signal plans) with the best delay performance will be selected as the optimal solution.

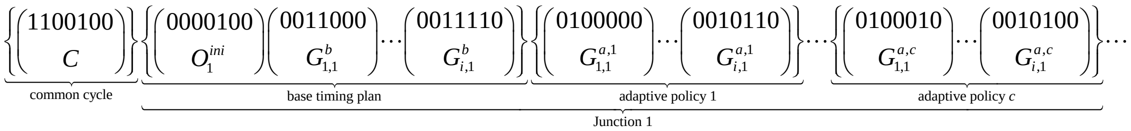

Figure 1. Gene structure of the cycle-based two-stage signal control

3. RESULTS AND DISCUSSION

We select Tai Tam reservoir as the test site to illustrate the performance of the proposed adaptive signal control method. Tai Tam reservoir road is a section of Tai Tam road located at eastern

Hong Kong Island, which is a bi-directional two-lane road connecting Stanley and Chai Wan, as shown in Figure 2. Since the construction of the reservoir was completed in 1918, the width of the road is too narrow to accommodate bi-directional traffic passing through the reservoir simultaneously. A two-phase signal is deployed on the reservoir. Only one direction of traffic is allowed going through per phase. The vehicle clearance time (all red time) of 45 seconds is set for every phase switch. Due to the long all red time, frequent phase switches may incur severe delay deterioration. The key question is how to effectively assign green time of the two phases so that the total delay is minimised under uneven traffic arrivals of the two directions. We apply the data set collected in three days (June, 2019) for signal optimisation. The data set of each day includes three-hour PM peak bi-direction traffic arrivals to the Tai Tam reservoir. We code the CTM network for Tai Tam reservoir as shown in Figure 2. The parameters of the CTM network are calibrated with the real data.

We assign northbound traffic (to Chai Wan) to phase 1 and southbound traffic (to Stanley) to phase 2. The minimum phase duration is 60 seconds. We first optimise an optimal fixed-time plan for the reservoir via the conventional GA (the gene structure without the adaptive policy chromosomes). The optimisation is performed on Intel i7-3370 computer with 32GB RAM. The parameters of the GA include 10 generations, 100 population size. The expected total delay over three demand scenarios is minimised with respect to signal control variables. The optimal fixed-time signal plan is listed in Table 1.

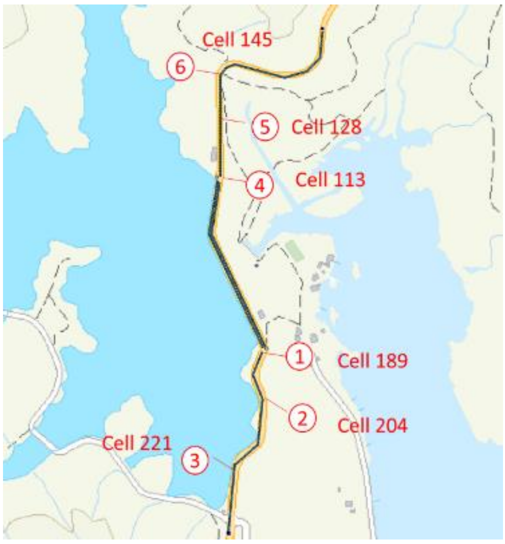

Figure 2. Tai Tam reservoir

Table 1. fixed-time signal plan

	Cycle time (s)	Offset (s)	Phase 1 (s)	Phase 2 (s)
duration	180	130	97	83

For the queue-based adaptive signal control. We deploy three detector cells on each side of the reservoir approaches as shown in Figure 2, (The detector cell ID are marked). The locations of the detector cells are 0 m, 100 m, 200 m, respectively, from the stop lines for both sides. If vehicle queue end is detected at the detector cells (cell occupancy > 90%), the detector state turns 1; 0 otherwise. We adopt the proposed specialised GA algorithm to optimise both the base timing plan in stage 1 and the adaptive control policies in stage 2. Since we deploy six detectors for Tai Tam case, there are $2^6 = 64$ detector state combinations, hence, 64 adaptive policies for adaptive signal control. Table 2 lists all the adaptive polices and the corresponding detector patterns. Detector patterns are counted during the GA simulations. Detector pattern ‘100100’ (policy 37) is the most frequently activated pattern which is counted 50435 times in the simulations. ‘100100’ means that at the end of signal cycle, i.e., end of phase 2, vehicle queues are detected at detector 1 and detector 4 (close to the stop lines), but not at the other detectors. It is noted that only 12 detector patterns are activated and the rest of the detector patterns are never activated. Those non-critical adaptive policies can be eliminated from the gene structure. We further optimise the top 9 frequently activated adaptive policies and the base timing plan via GA. Whenever the detector states not included in the top 9 adaptive policies appear, the base plan will be implemented in the next cycle. The top 9 adaptive policies and the base plan are listed in Table 3.

The base green times are 89 seconds for phase 1 and 91 seconds for phase 2. For pattern ‘100100’ (policy 37), it indicates that there is overflow at the SB approach at the end of phase 2 and vehicle queue at the NB approach. The adaptive plan is to extend 4 sec green time for phase 1 and cut off 4 sec for phase 2 in the next cycle. For pattern ‘111000’ (policy 57), long queue is detected at the NB approach but no queue at the SB approach. The adaptive plan is to extend 27 sec green time for phase 1 to clear the long queue. For pattern ‘100110’ (policy 39), a long residual queue is detected at the end of phase 2. The adaptive plan is to cut off 10 sec green time from phase 1 and extend 10 sec green time for phase 2. The average delay results are listed in Table 4. The average delay of the optimal fixed-time plan is 105 sec/veh. The adaptive plan (86.5 sce/veh) can have a further 17.6% delay reduction compared to the optimal fixed-time plan. Even though some of the adaptive policies are eliminated from the GA optimisation and only top 9 adaptive policies are optimised, the adaptive plans can still have 17.0% delay improvement, which does not deteriorate too much compared to the full policy adaptive plans.

Table 2. adaptive policies and the corresponding detector patterns

adaptive policy *c*	detector patterns ‘123456’	activated patterns counts	**adaptive policy *c***	detector patterns ‘123456’	activated patterns counts
1	'000000'	1493	**33**	'100000'	34308
2	'000001'	0	**34**	'100001'	0
3	'000010'	0	**35**	'100010'	0
4	'000011'	0	**36**	'100011'	0
5	'000100'	1089	**37**	'100100'	50435
6	'000101'	0	**38**	'100101'	0
7	'000110'	59	**39**	'100110'	1786
8	'000111'	0	**40**	'100111'	0
9	'001000'	0	**41**	'101000'	0
10	'001001'	0	**42**	'101001'	0
11	'001010'	0	**43**	'101010'	0
12	'001011'	0	**44**	'101011'	0
13	'001100'	0	**45**	'101100'	0
14	'001101'	0	**46**	'101101'	0
15	'001110'	0	**47**	'101110'	0
16	'001111'	0	**48**	'101111'	0
17	'010000'	0	**49**	'110000'	15172
18	'010001'	0	**50**	'110001'	0
19	'010010'	0	**51**	'110010'	0
20	'010011'	0	**52**	'110011'	0
21	'010100'	0	**53**	'110100'	27584
22	'010101'	0	**54**	'110101'	0
23	'010110'	0	**55**	'110110'	3099
24	'010111'	0	**56**	'110111'	0

25	'011000'	0	**57**	'111000'	22707
26	'011001'	0	**58**	'111001'	0
27	'011010'	0	**59**	'111010'	0
28	'011011'	0	**60**	'111011'	0
29	'011100'	0	**61**	'111100'	20344
30	'011101'	0	**62**	'111101'	0
31	'011110'	0	**63**	'111110'	9520
32	'011111'	0	**64**	'111111'	0

Table 3. optimal base timing plan and adaptive signal plans

adaptive policy *c*	detector patterns '123456'	Phase-1 (sec)	ΔG_1	Phase-2 (sec)	ΔG_2
37	'100100'	93	4	87	-4
33	'100000'	96	7	84	-7
53	'110100'	93	4	87	-4
57	'111000'	116	27	64	-27
61	'111100'	104	15	76	-15
49	'110000'	111	22	69	-22
63	'111110'	89	0	91	0
55	'110110'	87	-2	93	2
39	'100110'	79	-10	101	10
Base plan (0)	--	89	0	91	0

Table 4. signal plans delay performance

	fixed-time plan	adaptive plan (full policy)	adaptive plan (partial policy)
Delay (sec/veh)	105.0	86.5	87.1
reduction	--	17.6%	17.0%

4. CONCLUSIONS

In this study, we developed a novel approach to address dynamic, spatial and stochastic characteristics of traffic flow for adaptive signal control. Our approach was able to map adaptive signal control policies to dynamic traffic detector information and address the closed-loop signal control strategy with a mathematical model. Cell transmission model was adopted as the underlying dynamic traffic flow model. Certain CTM cells were designated as detector cells to indicate the queue presence information. We developed a two-stage stochastic program to address uncertain demand for signal control. In stage 1, the base timing plan is determined as a long-term default plan. In stage 2, various demand scenarios are loaded to CTM to simulate detector cell state patterns and the corresponding adaptive control policies. The case study at Tai Tam reservoir illustrated the performance of the approach. At the end of a signal cycle, we examined the detector states to identify the queuing status. The green extension/cut-off policies were re-adjusted in response to the unbalanced queues for the next cycle. The preliminary simulation results showed that a further 17% delay reduction can be achieved by the adaptive control policies. In the future study, we will further investigate a stage-based adaptive control strategy, i.e., the adaptive policy is adjusted at the end of each signal stage according to the detector states. We anticipate that the stage-based control strategy will exhibit more flexible control impacts to the traffic flow pattern variations.

ACKNOWLEDGEMENTS

The study is supported by General Research Fund #16204518 of the Research Grants Council, and Smart Traffic Fund STF22EG01 of the HKSAR Government.

REFERENCES

Daganzo, C.F. 1994. The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. *Transportation Research Part B: Methodological*, 28(4), 269-287.

Li, L., Huang, W., Lo, H.K. 2018. Adaptive Coordinated Traffic Control for Stochastic Demand. *Transportation Research Part C: Emerging Technologies*, 88, 31-51.

Li, L., Huang, W., Chow, A. H., & Lo, H. K. 2021. Two-stage stochastic program for dynamic coordinated traffic control under demand uncertainty. *IEEE Transactions on Intelligent Transportation Systems*, 23(8), 12966-12976.

Lo, H.K., Chang, E., Chan, Y.C. 2001. Dynamic network traffic control. *Transportation Research Part A: Policy and Practice*, 35(8), 721-744.

Lo, H.K., Chow, A.H.F. 2004. Control Strategies for Oversaturated Traffic. *Journal of Transportation Engineering*, 130(4), 466-478.

Robertson, D. I., & Bretherton, R. D. 1991. Optimizing networks of traffic signals in real time-the SCOOT method. *IEEE Transactions on vehicular technology*, 40(1), 11-15.