Path-Based Network Signal Coordination Control Optimization: Multi-Agent System Modeling

Jiarong Yao, Chaopeng Tan, Fuliang Li and Keshuang Tang

September 6, 2024

Path-based Network Signal Coordination Control Optimization: Multi-agent System Modeling

Jiarong Yao[a*], Chaopeng Tan[b*], Fuliang Li[c], Keshuang Tang[d]

[a] School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, Singapore
jiarong.yao@ntu.edu.sg
[b] Department of Transport and Planning, Delft University of Technology, Delft, Netherlands
c.tan-2@tudelft.nl
[c] Guangdong Key Laboratory of Intelligent Transportation System, Sun Yat-sen University, Guangzhou, China
tjfulianglee@gmail.com
[d] College of Transportation Engineering, Tongji University, Shanghai, China
tang@tongji.edu.cn
* Corresponding author

Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 15, 2024

Keywords: Network coordination signal control, path-based delay modeling, multi-agent system, critical path evaluation, nonconvex optimization

1 INTRODUCTION

With the development of urbanization, urban traffic congestion has been increasingly spreading from big cities to small and medium-sized cities. From the traffic analysis report of in 2021 released by Gaode Map, about 60% of the 361 investigated cities had experienced an increase in the peak hour travel delay (Gaode Map, 2021). To ease traffic congestion, network coordination signal control is an effective measure and plays an important part in cooperative management and control of urban traffic (Li, 2012, Qadri et al., 2020). However, current signal coordination control in practice mainly adopts aggregated traffic flow information such as volume, speed and density as the data input. As for control strategy, arterial coordination control always gives the highest priority to the mainline two-way progression while network coordination control is mostly realized based on control subarea partitioning (Walinchus, 1971, Ke et al., 2022). Such aggregated detector and default optimization priority fail to describe the intrinsic property of traffic demand which is externalized as vehicle paths, thus making it hard to adapt to the dynamic and complicated demand patterns in urban roadway networks. In such case, inevitable deviation between the optimization objective of coordination models and actual traffic demands needed coordination is generated, leading to limited improvement in control effectiveness and efficiency.

The increasingly higher availability of individual continuous detection data like connected vehicle data or license plate recognition data actually brings new ideas to describe and model the traffic flow in path level or trip level (Yao et al., 2023). Compared with control sub-area, path can better represent how traffic demands of different origins aggregate, interact and dissipate. Therefore, this study proposes a path-based network coordination control optimization model under a multi-agent system framework, transforming the network coordination control problem into two subproblems, namely the self-optimization of agents and the traversal of agent optimization in the network scale. Compared with current studies, the proposed method can better characterize the inherent relationship between paths and the whole network, and deal with the dimension explosion problem utilizing the distributed control property of multi-agent systems.

2 METHODOLOGY

2.1 Multi-agent based network coordination modeling

To describe the network traffic dynamics at the path level, a concept, path unit (PU), is defined to be the minimal unit of a path. A path unit refers to a group of two controlled flows from two consecutive intersections to form a spatially connective path. Here the notation of path unit is $PU_{f_i-f_j}^{k_1,k_2}$, $(f_i, f_j \in \{1,2,3,4,5,6,7,8\})$, whose flow index is based on the phase definition of NEMA (National Electrical Manufacturers Association). A path unit can be uniquely represented using the flow indexes (like f_i, f_j) of the upstream and downstream intersection (denoted by the superscripts k_1, k_2).

Based on the definition of PU, an all-way movement path unit intersection cluster (AMPIC) is defined as the intersection cluster constituted by a centric intersection and its four neighboring intersections. Such a standard AMPIC covers all the PUs interacting within the centric intersection, including the inflowing ones and the outflowing ones, either whose upstream movements or downstream movements are the controlled movements of the centric intersection. The AMPIC is used as the agent to model the roadway network as a multi-agent system for network coordination signal control. Thus, a network can be regarded as the assembly of multiple AMPICs, while an AMPIC is autonomous and able to interact with other AMPIC agents. The coordination control of the network thus can be realized through the coordination among all AMPICs in the network considering the coordination occurring at the overlapping components between AMPICs, which can be regarded as the interaction of agents. With this introduction of agent components and the relationship between agents and the system, a multi-agent based framework is built for network coordination modeling.

2.2 AMPIC Self-optimization

The self-optimization of an AMPIC agent refers to the coordination signal control of all PUs in it, aiming at control delay minimization. Denote this optimization objective as z. the control delay of an AMPIC can be calculated as the sum of the delays of the Centripetal PU set and the Centrifugal PU set, given in Eq. (1). The superscript "k_n" denotes the neighboring intersection of an AMPIC, while the superscript "M" denotes the centric intersection of an AMPIC. Based on the input path flow and shockwave theory, the delay of a PU can be formulated as a piecewise nonconvex multimodal function in terms of control parameter $\boldsymbol{X}_i = [G_i^k,\ g_i^k\ ]^T$, which denotes the of phase time and start timepoint of a controlled flow.

$$\boldsymbol{min}\, z = \sum\nolimits_{i,j\in I} \left(\sum_{n=1}^{4} D\left(PU_{i-j}^{k_n,M}\right) + \sum_{n=1}^{4} D\left(PU_{i-j}^{M,k_n}\right)\right) = \sum_i f(\boldsymbol{X}_i)\,, i,j \in \{1,2,3,4,5,6,7,8\} \quad (1)$$

Therefore, the coordination control problem of an AMPIC is formulated as a constrained high-dimensional nonconvex integer programming problem with constraints on common cycle length, split, offset and phase structure. The formulation of Eq. (1) shows a separable nonconvex optimization problem which separates the decision variable of all controlled movements into the delay summation in terms of $\boldsymbol{X}_i = [G_i^k, g_i^k\ ]^T$. With such separability property of the optimization problem, an alternating direction method of multipliers (ADMM) is proposed to solve the self-optimization of AMPIC.

2.3 Optimization iterator of the network

In a network, an AMPIC can be linked to at least two other AMPICs and at most four other AMPICs. For two AMPICs which are interrelated with one common link, the two intersections at both ends of the common link have a relationship of dependence on each other as the main intersection and the neighboring intersection. Assumed that self-optimization of one AMPIC has been realized, then additional constraints should be considered in the self-optimization model of its neighboring AMPICs. Such interaction between neighboring AMPICs can be regarded as a sequential optimization design.

For the coordination control of the whole network, a PU criticality-based evaluation mechanism using an adaptive neighborhood path searching (ANPS) algorithm is proposed as an optimization iterator to determine the sequence of AMPIC self-optimization in a network. Here the concept of critical PU (CPU) is defined as the PU with the largest improvement in the control delay as well as the correlated delay of its upstream and downstream movement after the optimization of the AMPIC, as given by Eq. (2). The criticality of PU defined here uses the gain of control efficiency to evaluate the degree of criticality, rather than the absolute control efficiency after the optimization.

$$CPU^{*} = \mathbf{argmax}\ \Delta Z_{PU} = Z_{PU}^{*} - Z_{PU}^{0} \tag{2}$$

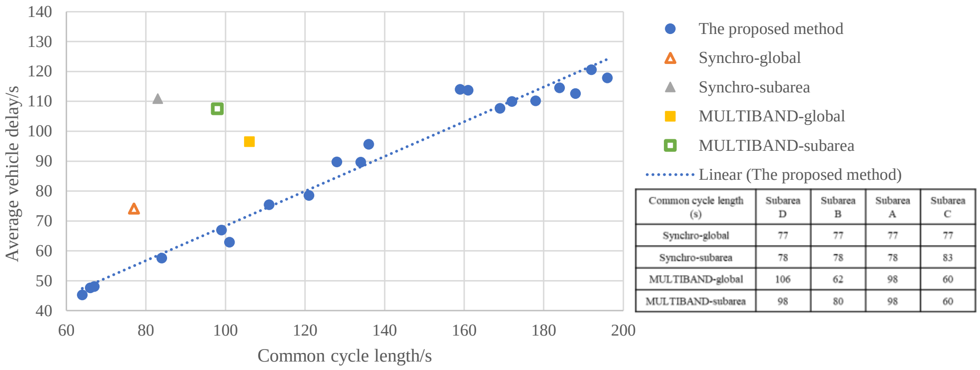
The basic idea of this optimization iterator is that the downstream intersection of the critical PU of an optimized AMPIC will be the main intersection of the next AMPIC to be optimized. Using this ANPS algorithm, the network coordination control can be realized by the traversal of self-optimization of AMPICs driven by the critical PU evaluation for optimization sequence in the network.

3 RESULTS

The proposed model is evaluated using a simulation case. A network is selected from Tongxiang, Zhejiang Province in China as the background of the simulation model which is built through VISSIM software. Empirical license plate recognition data, floating car and signal timing data in the morning peak period from 7:00 to 9:00 on Sept. 29th, 2020, were collected and used for calibration of the vehicle input, the OD set, the path set and the route choice in the simulation model. The simulation period was set as 9000s, while the first 900s was set as a warming-up period, so the control performance in the following 7200s was used for evaluation.

Horizontal comparison is done by selecting the MULTIBAND model and Synchro model as the representative of bandwidth-based methods and MOE-based methods, respectively. A subarea optimization scheme with subarea division and a global optimization scheme were derived from the Synchro model. Using the global optimum-based splits and the subarea optimum-based splits of the Synchro schemes as input, the MULTIBAND model further optimized the common cycle length and offsets, obtaining two schemes. As for the proposed method, a set of 20 feasible common cycle lengths is first obtained through the time series similarity evaluation of the inflow data of the network boundaries, then input to the network signal control model for optimization of other control parameters, thus obtaining 20 schemes. For all models, the feasible zone of the common cycle length is set as [60,200].

All signal control schemes are run for three parallel experiments under the simulation scenarios. As the optimal cycle lengths obtained by different signal control methods are different, a scatter plot as shown in Figure 1 is used for comparison of the control performance in terms of average vehicle delay. Based on the subarea division obtained by Synchro as shown in Figure 2, four vertical arterials are divided as control subareas, thus cycle lengths of subareas in two MULTIBAND schemes and the subarea optimal scheme of the Synchro model are different, so in the scatter plot, the largest common cycle length of four subareas in such schemes are used as the X-coordinate.



Common cycle length (s)	Subarea D	Subarea B	Subarea A	Subarea C
Synchro-global	77	77	77	77
Synchro-subarea	78	78	78	83
MULTIBAND-global	106	62	98	60
MULTIBAND-subarea	98	80	98	60

Figure 1 Control performance comparison of different signal timing schemes

From Figure 1, the average delays of the 20 schemes obtained by the proposed model show a growing trend with the increase of the common cycle length, while fluctuating around a trendline with a slope of about 0.58, which implies a relatively stable control performance that with every 1s increase in the common cycle length, the network average delay only increase about 0.58s. Horizontally, the proposed method performed best among all schemes as the scattered points of the other schemes are all above the trendline of the proposed method, with a superiority ranging from 25.6% to 47.3%.

Based on the criticality evaluation mechanism, the critical PU set of the optimal timing scheme with a common cycle length of 66s is shown in Figure 3. It can be seen that the proportion of PUs whose upstream and downstream movements are both through movements is only 10.7%, while the proportion of PUs including turning flows dominated in the critical PU set. From this perspective, the simulation scenario is not applicable to the traditional arterial coordination control model targeting at the through paths or the arterial mainlines, which explains the poor performance of the subarea-based Synchro and MULTIBAND schemes, and also implies that the AMPIC self-optimization of the proposed model can better adapt to scenarios where traffic demands of turning flows or several conflicting flows within the intersections are considerable.

Figure 2 Subarea division scheme obtained by Synchro

Figure 3 CPU set obtained by the proposed model

4 CONCLUSION AND RESEARCH SIGNIFICANCE

A path-based coordination control optimization model is proposed based on multi-agent system modeling, where the AMPIC agent is defined to describe the cooperation and competition among paths. Targeted at network delay minimization, the proposed model realizes the network coordination control through the coupling of AMPIC self-optimization and a path searching based optimization iteration driven by critical path unit evaluation. Using a simulation case study, the proposed model shows an improvement of over 25% compared with the Synchro model and the MULTIBAND model.

On the theoretical side, the proposed model refines the analytical modeling from the subarea level to path level, thus enabling more flexibility in different complicated traffic demand scenarios. Using path flow as input, the proposed model and realizes the path-level coordination and evaluation, which lays a solid foundation for methodology system of path-based traffic evaluation and control optimization.

On the practical side, the extraction of the critical path units for each AMPIC agent also makes the proposed model more interpretable in how it manages to fit in the demand pattern of the roadway network, which can become an illustrative reference for practitioners in routine analysis of urban traffic operation management.

References

Gaode Map. Annual traffic analysis report 2021 of major cities in China. Gaode Big Data Platform. https://report.amap.com/home.html. Beijing, China. 2022

Ke S., Wei L., Lu Z., Rao W., An C., and Xia J., 2022. Subarea partition based on correlation analysis with edge-elimination strategy using automatic license plate recognition data. *Transportation Research Record*. 2022, pp. 1-12.

Li S., 2012. A survey of urban traffic coordination controls in intelligent transportation systems. *Proceedings of 2012 IEEE International Conference on Service Operations and Logistics, and Informatics*. pp. 177-182

Qadri S. S. S. M., Gke M. A., Oner E., 2020. State-of-art review of traffic signal control methods: challenges and opportunities. *European Transport Research Review*, 12(1), pp. 1-23.

Walinchus R J., 1971. Real-Time Network Decomposition and Subnetwork Interfacing. *Highway Research Record*, 366, pp. 20-28.

Yao J., Cao Y., Tang K., 2023. An Extended Generalized Least Square (GLS) Model for Estimating Path Flow in Signalized Roadway Network Using Sampled Trajectory Data. *102th Annual Meeting of the Transportation Research Board*, Washington, D.C.