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Critical Path Identification for Network Signal Coordination Control Using Connected Vehicle Data Based on Analytic Hierarchy Process Method

Jiarong Yao, Chaopeng Tan, Hao Wu, Yumin Cao, Keshuang Tang*

Abstract— **Network signal coordination control is a crucial means to improve the traffic operation efficiency of the overall roadway network. Accurate identification of critical paths does play an important role in determining the scope of network coordination control. Therefore, this paper proposed the definition of critical path from the perspective of traffic control and management. Under the detection environment of connected vehicle (CV), a comprehensive quantitative indicator system for path criticality evaluation from three aspects, supply side, demand side and operation side, which are arranged in the form of a tower structure. A critical path identification method (CPIM) was then proposed based on the analytic hierarchy process (AHP) theory, which was hereinafter referred to as AHP-CPIM. In order to evaluate the feasibility and effectiveness of the proposed method, a case study set in an urban network in Tongxiang, Zhejiang Province in China, is conducted through simulation models built through VISSIM and Synchro. Two scenarios were set, one is coordination control based on the coordination subarea obtained from Synchro (namely without critical path identification), and another one is coordination control with critical paths obtained from AHP-CPIM. Results showed that, compared with the control of Synchro and Multiband method under the scenario of coordination control without critical path identification, network signal coordination control optimization based on AHP-CPIM improved about 37.9% and 35.9% in average delay, respectively, justifying the effectiveness of CV-driven critical path identification for network signal coordination control.**

I. INTRODUCTION

Network signal coordination control is an important measure to improve the efficiency of urban traffic control and management. Under the circumstance of limited temporal and spatial resources, accurate identification of critical elements (intersection, link, path, etc.) help determine the scale of coordination control, which is thus significant to the optimization of network signal control.

Compared with critical intersection and critical link, current studies on critical path are rarely seen. Existing research generally defines the criticality of roadway network elements based on social network analysis theory, system resilience theory and information transmission theory. The connotation of criticality is three-fold, the first is the importance of network topology characteristics [1][2], the second is the service capability to meet the traffic demand [3][4], and the third is the function reliability against risk and disturbance [5][6]. Based on this, the evaluation and identification methods of critical intersection or links are also derived from these original theories. As intersections and links are both zero dimensional elements from the perspective of topology and they are interchangeable, thus the evaluation and identification methods are similar. The most common method is to propose a criticality index based on several quantitative indicators and thus a ranking of intersections or links can be obtained according to the criticality values. Apart from the method of composite criticality index, different methods have been developed to establish the mapping between the quantitative indicators and the criticality of network elements, such as analytic hierarchy process (AHP) method [2], TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method [7], maximal entropy method [3], clustering method [8]-[10], machine learning method [3][11]-[14]. In essence, such a variety of methods transform the identification of critical intersections or links into classification problems or regression problems. In terms of traffic evacuation under emergence, simulation-based methods are usually used to apply seriatim disturbance analysis for each intersection or link by comparing the overall traffic progression efficiency between normal network situation and the network removing the element of interest. The intersection or link with the largest efficiency difference is thus determined as the critical one [15]-[16]. Whereas, such methods are limited in application as the method of removing certain element from the network is infeasible in reality, and the computation cost may surge once the scale of the network becomes larger, which leads to various designs of the whole network troubleshooting process, including Latin hypercube sampling, Monte Carlo simulation, user optimum assignment iteration, etc.[5][17]-[18].

Regarding research on critical path in signalized network, the definition and connotation is still not unitary. Zain et al. [19] defined the critical path as the combination of critical flows, while Li and Yang [20] further declared that the critical path of an intersection cluster is the path with the larger traffic demand and dominates in the overall traffic efficiency, which should be the prior optimization object of coordination control. From a macroscopic perspective, Hari et al. [21] pinpointed the critical path of a transportation network to be the one with the highest importance in terms of trip cost, trip risk, safety and infrastructure configuration.

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For critical path evaluation and identification, Li et al. [20][22] and Song [23] transformed it into a similarity matching problem for the time-varying flow curves of critical flows. Using the 5-min loop flow data as input, a clustering method is applied to the high frequency coefficients obtained by flow data processed by discrete wavelet transform, the combination of flows classified as the same type were thus identified as the critical path. However, the method only applied to arterial intersection cluster. Liu et al. [24] defined a relevance indicator as the sum of path discreteness and retardation. Based on the real-time origin-destination (OD) path set detection, the path discreteness index was calculated using the OD flow and time headway, while the path retardation index was calculated using the queue length of each link along the path. The critical path was identified as the one with the largest relevance. Identification methods using relevance indicator have been developed, with a variety in the generation of path set, like Bayesian network [25], depth-first search [26][27], etc. Moreover, the relevance indicator is also used for sub-area division and network coordination control optimization, which control idea is to realize significant improvement by optimizing the signal timing of only several intersections [28]. Hari et al. [21] adopted an AHP method to quantify the path criticality through criteria of cost, time, risk, non-availability of facilities and insecurity. Then a ranking method combining TOPSIS and fuzzy decision theory was used to sort all the paths to obtain the critical path. Nevertheless, the method was applicable to long-term evaluation of highway network. Wang et al. [29] quantified the path criticality as the average link relevance which is calculated using the link inflow, outflow and travel time, and identified the critical path as the one with the largest relevance. Shou et al. [30] defined a link impedance index using link length, speed and flow, while the critical path is determined as the one whose link set had the minimal impedance between the path OD using the Dijkstra searching algorithm. Chen et al. [31] conducted a spillover analysis over all the links based on the queue length and quantify the relevance of consecutive links using a frequent pattern growth algorithm. From the perspective of traffic signal control, the critical path is identified as the sub-path consisting of consecutive spillover-prone links according to a predefined threshold of spillover risk.

In summary, current studies on critical path are less mature than those of critical intersections or links, and mostly regard the critical path as the simple combination of critical intersections or links. Identification of critical path is realized through the ranking of a composite criticality indicator without regard to the overall traffic characteristics of the path. The difficulty of critical path evaluation lies in that path is a one-dimension topologic shape, which has more complicated intercorrelation patterns (like merging and diverging) than the simple connectivity pattern of the zero-dimensional intersection and link topology. Thus, the key problem in critical path evaluation and identification is how to select the representative evaluation indicators from both static (spatial topology) and dynamic (traffic operation) aspects.

With the development of techniques like vehicle positioning, smartphone-based navigation and connected vehicles (CVs), substantial real-time trajectory data are becoming available. Compared with fixed detector data, these high-resolution CV data can provide more individual vehicle information, e.g., origin, destination, route choice, etc., which enjoy broad application prospects in traffic operation evaluation [32][33] as well as signal control optimization [34], meanwhile providing a new tool to enrich the study of path-level traffic management.

Therefore, based on the current development of network critical elements, the definition of critical path is proposed. A comprehensive evaluation indicator system consisting of quantitative indexes selected from the aspects of supply, demand and operation is established considering the CV detection environment, and then the critical path identification is realized through an AHP method. Simulation evaluation is conducted based on an empirical network is done to demonstrate the effectiveness of the proposed method through a horizontal comparison of coordination control between with and without critical path identification.

II. Critical Path Evaluation and Identification

Based on the general definition of critical intersection and critical link, a critical path is defined from the perspective of signal control as **the path with important topological characteristic, high relevance with other network elements, large traffic demand and predominant influence in the overall network traffic operation efficiency in the roadway network**. According to this definition, quantitative indicators are selected to describe the path criticality for further evaluation and identification, which is introduced as below.

A. Path Criticality Evaluation Indicator

The definition of critical path not only inherits the connotation of criticality from critical intersections and critical links regarding topological characteristics and service capability, but also reflects the dynamic representation of path flow in temporal and spatial dimensions. Correspondingly, the quantification of path criticality is realized through three aspects, traffic supply, traffic demand and traffic operation, which are further interpreted as follows.

- Traffic supply aspect refers to the passage space or right-of-way providing spatial and temporal resources for road users. The contribution of traffic supply to path criticality lies in the service capacity bestowed by its inherent topological structure and traffic rules set by transport departments.
- Traffic demand aspect refers to the traffic demand loaded onto the road network as well as its temporal-spatial distribution within the network. The contribution of traffic demand to path criticality lies in the expected usage of the path resulted from the route choice of all kinds of road user groups.
- Traffic operation aspect refers to the actual traffic flow properties reflecting the interaction between supply and demand within the scale of the road network. The contribution of traffic operation to path criticality lies in the direct illustration visible or perceivable to the road users and traffic practitioners, which is a specialized characteristic from the domain of traffic control and management, different from the supply and demand aspects transferred from other domains.

Based the information provided by CV detection, the following 13 indicators in Table I are selected for quantification of path criticality, including 6 indicators in the traffic supply aspect, 3 indicators in the traffic demand aspect and 4 indicators in the traffic operation aspect. As for the traffic supply indicators, the first three reflect the spatial resource supply information which can be obtained by geographic information system (GIS), while the last three reflect the temporal resource supply information which can be obtained by signal timing scheme data. The indicators of traffic demand and traffic operation aspects can be calculated or estimated using the available CV data.

TABLE I. PATH CRITICALITY EVALUATION INDICATOR

Aspect	No.	Indicator	Meaning
Traffic supply	1	Path length	The travel distance between the origin and destination of the path
	2	Intersection number	The number of intersections in the path
	3	Controlled flow number	The number of signalized flows of each link in the path
	4	Maximal cycle length	The maximum of the cycle lengths of the signalized intersections in the path
	5	Maximal split	The maximum of the splits of the controlled flows at signalized intersections in the path
	6	Path capacity	The minimum of the flow capacity of the flows in the path
Traffic demand	7	Path flow	The actual number of vehicles which travel along the path
	8	Average degree of saturation (DS)	The average value of the ratios between the link flow and the flow capacity of all the links in the path
	9	Flow non-equilibrium factor	The ratio between the path flow (from origin to destination) and the path flow in inverse direction (from destination to origin)
Traffic operation	10	Average travel delay	The average travel delay of all the CVs travelling along the path
	11	Average travel speed	The average travel speed of all the CVs travelling along the path
	12	Average number of stops	The average number of stops of all the CVs travelling along the path
	13	Average queue length proportion	The average ratios between the queue length and the link length of all the links in the path

B. Critical Path Identification

Based on the selected indicators, a tower structure is adopted for the establishment of an evaluation indicator system to describe the parallel relationship of all three aspects. Correspondingly, an AHP method is used to evaluate the criticality of each path and identify the critical path in the network, as shown in Figure 1. Given the path set of the road network and CV data as input, the path criticality is calculated as a weighted sum of the selected indicators through two criterion layers. The detailed steps of AHP-CPIM are given as below.

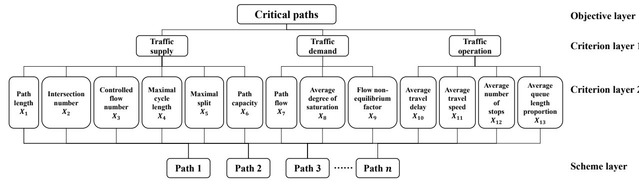

Figure 1 Hierarchical structure for path criticality evaluation

Algorithm 1: AHP-CPIM

Input: Network topology data, signal timing data, CV data
Output: Critical paths

Step 1: Based on the hierarchical structure shown in Figure 1, construct a pairwise comparison matrix $A = [a_{ij}]_{I\times J}$ for criterion layer 1, where a_{ij} denotes the relative importance of i over j. $a_{ij} = 1$ means i and j are equally important.

Step 2: Normalize each column and calculate the average value of each row to obtain the weight vector W, as given by Eq. (1) ~ (2).

$$W = [w_1, w_2, \cdots, w_i, \cdots, w_I]^T \quad (1)$$

$$w_i = \frac{1}{n}\sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad (2)$$

Step 3: Check consistency ratio of the weight vectors. Calculate the maximal eigenvalue of matrix A using Eq. (3), and the consistence index (CI) using Eq. (4). Then calculated the consistency ratio (CR) using Eq. (5) by looking up the value of Saaty random consistency index (RI). If $CR < 0.1$, it means the consistence requirement is met, thus can be used as the weight vector of the criterion layer.

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n} \frac{\sum_{j=1}^{n} a_{ij} * w_j}{w_i} \quad (3)$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

$$CR = \frac{CI}{RI(n)} \quad (5)$$

Step 4: Calculation weight vectors of criterion layer 2 and apply consistence check. Construct a pairwise comparison matrix $B_{i(n\times n)}$ regarding the factors X_i for a certain aspect in criterion layer 2 for n paths in the scheme layer. Similarly, calculate the eigenvectors $w_{i(n\times 1)}$ and CI for each evaluation indicator, Thus the criticality weight of each path can be obtained using Eq. (6).

$$PC_n = \left[w_{1(n\times 1)} \;\; w_{2(n\times 1)} \;\; \cdots\cdots \;\; w_{i(n\times 1)}\right] * W \quad (6)$$

III. EVALUATION

Evaluation of the proposed AHP-CPIM method was conducted using a simulation case built over an empirical roadway network in Tongxiang, China. The criticality indexes of all paths in the network were calculated and sorted to obtain the critical paths in the network. The control performance through coordination control optimization using the identified critical paths was evaluated and compared with that without critical path identification, in order to prove the effectiveness of AHP-CPIM using CV data.

As shown in Figure 2, a simulation network model was built by VISSIM based on a 4×4 network in Tongxiang, Zhejiang, China, which included a total of 26 intersections, 16 of which were signalized intersections and installed with lane-based license plate recognition (LPR) detectors. The LPR data and the corresponding video detector data from 7:00 to 9:00 on December 3rd, 2020, were collected to calibrate demand level of the simulation model. Besides, the floating car data from September 20th to September 27th were also collected to calibrate the OD set and path set of the network, where there were 25 traffic generation points, 28 traffic attraction points and 215 paths under these OD pairs. From empirical detection, the detection rate of LPR system was about 96.5%, which made sure that the simulation was close enough to the real traffic condition.

Figure 2 Topology information of Tongxiang network

The simulation period was set as 9000s while the first 900s and the last 900s were warm-up periods, thus the 7200s in between was used for evaluation. Based on the calibrated traffic demand and route choice, the traffic condition was restored.

A. *Critical Path Identification Results*

Through the simulation, the vehicle trajectory data were extracted and sampled with a penetration rate of 0.1 to simulate the sampled CV data available from car-hailing corporations in reality. Based on the hierarchical structure of path criticality evaluation in Figure 1 and the AHP-CPIM algorithm, the relative weight was determined by the expert scoring method and the criticality weight of each path was calculated. It is noted that the quantity of 215 paths of Tongxiang network was quite a large number, thus the scheme layer was divided into 25 sub-layers according to the origin of the paths. The AHP-CPIM was applied first to the paths in each sub-layer and then the paths with the largest criticality weight were selected from each sub-layer to form a high-level scheme layer for criticality evaluation using AHP-CPIM again. For consistence check of the criterion layer, the number of paths in the high-level scheme layer was set as 7 [35]. Eventually, the paths with the largest criticality weight in all the high-level scheme layers were determined as the critical path set of the study site. As shown in Figure 3, four critical paths (CPs) were obtained eventually. It is noted that apart from CP 2 and CP 3 which are the mainline paths of the arterial North Qinfeng Road, as well as CP 4 which is the southbound path of the mainline of Shiji Avenue, the scale of CP 1 covers two arterials and includes two turning flows along the intersections it passes, which is unlike the default coordination objective of the common arterial or network coordination control strategies.

Figure 3 The critical paths identified through AHP-CPIM

B. *Coordination Control Performance Considering CPs*

To further demonstrate the effectiveness of critical path identification on network coordination control, a comparison was conducted here between the network signal control performance with and without critical path identification.

For network signal control regardless of critical path identification, which is actually the common practices, two methods, Synchro and Multiband were selected as the representative of bandwidth-based methods and measure-of-efficiency (MOE) based methods in coordination signal control. As the Multiband model only optimizes the offset and common cycle length, the splits were first optimized using through Synchro to be the given input. For MOE-based method, the sub-area-based optimization strategy was adopted in Synchro, thus the sub-area division scheme was obtained as shown in Figure 4. Based on the divided sub-areas, the signal timing schemes were optimized aimed at the optimal MOE of each sub-area in Synchro. As for the Multiband method, the network signal control was transformed into the arterial coordination control problems of four arterials as the scale of four sub-areas were exactly the scale of four main longitudinal arterials.

Figure 4 Sub-area division scheme obtained through Synchro

By contrast, network signal control considering critical path identification was realized through a divide-and-rule strategy. The intersections of the critical paths (namely CP 1 ~ 4) were optimized using the Multiband model, while isolated intersection control optimization was applied to the remaining intersections (namely Int. 2 ~ 4 in Figure 3) using the Synchro model.

For all three signal control methods, the boundaries of cycle lengths were set as [60s, 200s], and the output optimal signal timing schemes were input into the VISSIM simulation model to test the control performance. Three indicators, average delay, average number of stops and throughput, were selected for horizontal comparison, as shown in Table II. It is obvious that the control performance of network signal control considering critical path identification is better than that without critical path identification by over 30% and 20% in terms of average delay and average number of stops, respectively. Though the improvement in throughput is relatively trivial, the network coordination control scheme using AHP-CPIM has the largest throughput.

Horizontally, the control performance of each sub-area under the Multiband scheme is better than that under the Synchro scheme, whereas the average delay only decreases by about 3.0% and the average number of stops increases by about 13.7%. Such phenomenon proves that the mainline two-way progression takes absolute priority over the other paths in the Multiband model, which inevitably sacrifices the efficiency of other paths. The Synchro scheme aims at the optimum of the sum of MOEs for all the sub-areas, but the gap between the Synchro scheme and the AHP-CPIM scheme shows that the optimization objective of the Synchro method may not be positively associated with the global optimum objective within the scale of the network. The traffic flows of the mainline two-way paths of the four arterials (sub-areas) may not be dominant enough to govern the control efficiency of the whole network through only optimizing the progression of mainline paths, which leads to the limited effectiveness of both the Multiband scheme and the Synchro scheme. Although the performance of AHP-CPIM scheme is not the best in each sub-area, the superiority in terms of global network control performance demonstrates that the identified critical paths can better capture the traffic demand distribution pattern, so that the corresponding divide-and-rule control strategy is able to adaptively optimize their signal control parameters.

In summary, critical path identification using AHP-CPIM is effective for network signal control, especially applicable to scenarios where the traffic demand pattern cannot fit in the default mainline- or sub-area-oriented pattern of the traditional control methods.

IV. Conclusion

This study proposes the definition of critical path from the perspective of traffic control and management, then establishes a quantitative evaluation indicator system covering traffic supply, traffic demand and traffic operation aspects considering a CV detection environment. An analytic hierarchy process-based critical path identification method is proposed, with a divide-and-rule control strategy for network signal coordination control optimization. Through a simulation case study, the effectiveness of the proposed method is evaluated and results show that the control performance based on the identified critical paths is superior over the network control without critical path identification by over 30% in terms of average delay.

Regarding future study, the evaluation indicator system can be extended to include more data sources and be evaluated under more diversified scenarios. Besides, the generality and stability of the AHP-CPIM method is expected to be evaluated using more different control models to explore its applicability and further develop a comprehensive control framework providing fit-for-purpose solutions for different control needs.

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TABLE II. EVALUATION INIDICATOR COMPARISON OF DIFFERENT CONTROL METHODS

Method		Indicator	Wenhua Road	North Fuxing Road	North Qinfeng Road	Shiji Avenue	Network	Improvement of considering CPs
Without critical path identification	Synchro	Common cycle length (s)	78	78	78	83	/	/
		Average number of stops	1.38	1.28	1.32	1.69	2.40	**21.3%**
		Throughput (veh)	1007	876	1999	753	23591	**2.8%**
		Average delay (s)	55.33	34.45	58.90	33.14	110.89	**37.9%**
	Multiband	Common cycle length (s)	98	80	98	60	/	/
		Average number of stops	1.48	1.19	0.86	0.98	2.73	**30.7%**
		Throughput (veh)	1010	875	2005	756	23799	**1.9%**
		Average delay (s)	38.93	21.5	23.61	14.61	107.5	**35.9%**
With critical path identification	AHP-CPIM + divide-and-rule	Common cycle length (s)	69	69	98	60	/	/
		Average number of stops	2.85	1.84	0.91	0.96	**1.89**	/
		Throughput (veh)	1005	875	2005	755	**24255**	/
		Average delay (s)	59.99	52.31	41.48	23.67	**68.86**	/

VI. REFERENCES

[1] L. Wang. "Study on identification of critical intersection and link in urban network". Jilin University, 2017.

[2] L. Du. "Study on identification of critical intersection and link as well as potential hazards in urban network in operation period". Hebei University of technology, 2017

[3] M. Xu, J. Wu, M. Liu, Y. Xiao, H. Wang and D. Hu. "Discovery of critical nodes in road networks through mining from vehicle trajectories". IEEE Transactions on Intelligent Transportation Systems", vol. 20, no. 2, pp. 583-593, 2019, doi: 10.1109/TITS.2018.2817282.

[4] W. Jiang, Y. Qin, Q. Ji et al. "Study on theory and methodology of critical link identification in roadway network." Road traffic and safety. vol. 2, pp. 38-40, 2010.

[5] S. Yang, F. Hu, R. G. Thompson, et al. "Criticality ranking for components of a transportation network at risk from tropical cyclones." International Journal of Disaster Risk Reduction, vol. 28, pp.43-55, 2018.

[6] W. Tian. "Emergency traffic organization and optimization based on critical link identification of urban roadway network." Lanzhou Jiaotong University, 2016.

[7] F. Su, H. Dong, L. Jia et al. "Critical link identification of urban traffic network based on temporal-spatial correlation." Journal of transportation system engineering and information technology. vol. 3, 2017.

[8] X. Huang, J. Chen, M. Cai, W. Wang and X. Hu. "Traffic Node Importance Evaluation Based on Clustering in Represented Transportation Networks." IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 9, pp. 16622-16631, 2022. doi: 10.1109/TITS.2022.3163756.

[9] H. Jia, M. Guo, Q. Luo, et al. "Critical link identification of urban network using GPS data." Journal of Jilin University Engineering and Technology Edition. Vol. 50, no. 4, pp. 6, 2020.

[10] T. Zhao, W. She, S. Li, Y. Wang, W. Liu, G. Zai, L. Jia, Y. Qin, H. Dong. "Key links identification for urban road traffic network based on temporal-spatial distribution of traffic congestion." Modern Physics Letters B. vol. 33, pp. 1950307, 2019. DOI: 10.1142/S021798491950307X.

[11] M. Xu, J. Wu, L. Huang, R. Zhou, T. Wang, D. Hu. "Network-wide traffic signal control based on the discovery of critical nodes and deep reinforcement learning." Journal of Intelligent Transportation Systems, vol. 24, no. 1, pp. 1-10, 2020. DOI: 10.1080/15472450.2018.1527694

[12] X. Yin, Y. Mo, Y. Lin, et al. "Critical link identification of urban traffic roadway network based on directional weighted complex network theory." Application research on computers. vol. 36, no. 12, pp. 3709-3712, 2019.

[13] H. Feng, B. Shan, Y. Xu. "Identification of critical roads in urban transportation network based on GPS trajectory data." Physica A: Statal Mechanics and its Applications, vol. 535, pp.122337, 2019.

[14] E. Yu, Y. Wang, Y. Fu, D. Chen, M. Xie. "Identifying critical nodes in complex networks via graph convolutional networks," Knowledge-Based Systems, vol. 198, pp. 105893, 2020.

[15] F. Li. "Study on critical link identification in urban roadway network and robustness optimization". Jilin University, 2020

[16] F. Li, H. Jia, Q. Luo, Y. Li, L. Yang. "Identification of critical links in a large-scale road network considering the traffic flow betweenness index." PLoS ONE. vol. 15, no. 4, pp. e0227474, 2020. https://doi.org/10.1371/journal.pone.0227474

[17] A. Almotahari, M. A. Yazici. "A link criticality index embedded in the convex combinations solution of user equilibrium traffic assignment." Transportation Research Part A: Policy and Practice, vol. 126, pp. 67-82, 2019.

[18] A. Kumar, K. Haque, S. Mishra, et al. "Multi-Criteria Based Approach to Identify Critical Links in a Transportation Network." Case Studies on Transport Policy, vol. 7, no. 3, 2019.

[19] Z. Adam, M. Abbas, Y. Li. "Critical routes identification method using wavelet filtering." International IEEE Conference on Intelligent Transportation Systems. IEEE, 2010.

[20] Y. Li, J. Yang, X. Guo et al. "Critical Route Identification Method at Related Intersection Group Based on Wavelet Transform." China Journal of Highway and Transport, vol. 1, pp. 139-144, 2012.

[21] A. Hari Ganesh, A. H. Shobana, R. Ramesh. "Identification of critical path for the analysis of bituminous road transport network using integrated FAHP – FTOPSIS method." Materials today: proceedings, vol. 37, no. 2, pp. 193-206, 2020.

[22] Y. Li. "Study on critical path identification of oversaturated intersection cluster and signal control optimization." Southeast University, 2011.

[23] Z. Song. "Study on urban traffic signal coordination control methods based on critical path identification." Qindao University of Science and Technology, 2019.

[24] Y. Liu, L. Fang, J. Shen. "Research of Intersection Groups Optimization Control Method Based on Critical Path Identification." MATEC Web of Conferences. Vol. 173, pp. 03068, 2018. 10.1051/matecconf/201817303068.

[25] J. Yao, P. Wang, Y. Wei, et al. "Identification on urban network critical path based on outage probability." 2020. 10.3969/j.issn.2095-2163.2020.12.017.

[26] X. Guo, Q. Zhang, F. Lv, et al. "A critical path identification method for signalized intersection cluster of urban network." CN106683450A. 2017.

[27] F. Yan, Y. Song, S. Zheng et al. "A critical path identification method for intersection cluster based on improved Cuckoo search algorithm." CN111932875A. 2020.

[28] J. Shi, D. Liu, C. Zhang, Y. Liu, C. Zhou. "Intelligent Subarea Dynamic Division and Line-Axis Cooperative Control Based on "Number-Shape Combination." Open Journal of Transportation Technologies, vol. 8, no. 6, pp. 358-363, 2019. DOI: https://doi.org/10.12677/ojtt.2019.86044.

[29] W. Wang, X. Li, M. Lu. "A critical path identification method for intersection cluster based on depth-first search." CN110097757 B. 2021.

[30] Y. Shou, J. Xu. "A network subarea critical path identification method based on Dijkstra algorithm." CN202210695373.X. 2022.

[31] J. Chen, Y. Zeng, et al. "A critical path signal control optimization method oriented at traffic spillback." CN202211349811.3. 2023

[32] C. Tan, J. Yao, K. Tang, and J. Sun, "Cycle-based queue length estimation for signalized intersections using sparse vehicle trajectory data," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 1, pp. 91–106, 2019.

[33] J. Yao, F. Li, K. Tang, and S. Jian, "Sampled trajectory data-driven method of cycle-based volume estimation for signalized intersections by hybridizing shockwave theory and probability distribution," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 6, pp. 2615–2627, 2019.

[34] J. Yao, C. Tan, K. Tang, "An optimization model for arterial coordination control based on sampled vehicle trajectories: The STREAM model," Transportation Research Part C: Emerging Technologies, vol. 109, pp. 211-232, 2019.

[35] Y. Zhang, J. Qin. "Application of modern statistics information analysis technics to safety engineering—Theory of analytic hierarchy process." Industry Safety and Dust Control. vol. 25, no. 5, pp. 44-48, 1999.