PRECOM: A Parallel Recommendation Engine for Control, Operations, and Management on Congested Urban Traffic Networks

Junchen Jin, *Member, IEEE*, Dingding Rong, Yuqi Pang, Fenghua Zhu, *Senior Member, IEEE*, Haifeng Guo, Xiaoliang Ma, and Fei-Yue Wang, *Fellow, IEEE*

***Abstract*— This paper proposes a parallel recommendation engine, PRECOM, for traffic control operations to mitigate congestion of road traffic in the metropolitan area. The recommendation engine can provide, in real-time, effective and optimal control plans to traffic engineers, who are responsible for manually calibrating traffic signal plans especially when a road network suffers from heavy congestion due to disruptive events. With the idea of incorporating expert knowledge in the operation loop, the PRECOM system is designed to include three conceptual components: an artificial system model, a computational experiment module, and a parallel execution module. Meanwhile, three essential algorithmic steps are implemented in the recommendation engine: a candidate generator based on a graph model, a spatiotemporal ranker, and a context-aware re-ranker. The PRECOM system has been deployed in the city of Hangzhou, China, through both offline and online evaluation. The experimental results are promising, and prove that the recommendation system can provide effective support to the current human-in-the-loop control scheme in the practice of traffic control, operations, and management.**

***Index Terms*— Spatial-temporal recommender system, urban traffic control, parallel traffic management, human-in-the-loop system.**

I. Introduction

TRAFFIC congestion is a growing problem in urban areas worldwide, and it causes negative impacts on traffic safety, mobility efficiency as well as environment. A recent report of INRIX stated that traffic congestion, on average, may cost a driver two thousand dollars per year [1]. The most restrictive bottlenecks in urban environments are associated with intersections controlled by traffic signals [2]. Several self-adaptive signal controllers serve as important instruments for maintaining appropriate traffic efficiency, particularly for unsaturated scenarios [3], such as SCOOT [4], SCATS [5], and InSYNC [6]. Additionally, several deep learning-based signal control systems have been proposed for addressing issues in large-scale urban traffic networks [7]–[10]. However, most of the self-adaptive traffic-signal-control systems being deployed have difficulty treating congested traffic conditions of road networks [11], [12]. Reasons for inefficient operation on a congested network are generally classified according to the type of causes: recurrent and non-recurrent event [13]. Recurrent congestion is frequently caused by reasons such as a dramatic increase in traffic flow during peak hours or physical bottlenecks that are already observed. On the other hand, the occurrence of non-recurring congestion is often due to the disruption events, such as traffic incident, temporary road work, bad weather, and crowd-gathering activities [14].

In the practice of signal operation in a large city network with constantly high traffic demand, traffic engineers are often required to manually adjust signal settings in an Adhoc way once congestion is identified. Along with the increasing usage of floating car data as well as the exponential growth in computing power, traffic state can be estimated in real-time and traffic congestion can be rapidly identified [15]. Upon the emergence of a congestion event, traffic engineer needs to analyze the causes of congestion, change signal plans according to their past experiences, and thereafter, post-evaluate the performance of the online adaption [16]. Such a process is cumbersome and time-consuming, and its effectiveness is not necessarily reliable due to the variation of individual experience as well as improper decisions. Furthermore, adjustments of signal plans occur intensively at intersections that congestion frequently appears. Especially, many signalized intersections in the network appear to be simultaneously congested in the rush hours. Hence, one of the major tasks is to expand the spatial context for traffic control operation in the congested urban network. Therefore, a recommendation system was proposed to extract the knowledge base and decision preference of traffic engineers and then imitate their

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Junchen Jin is with Enjoyor Company Ltd., Hangzhou 310030, China, also with the Department of Civil and Architecture Engineering, KTH Royal Institute of Technology, 10044 Stockholm, Sweden, and also with the State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China.

Dingding Rong and Yuqi Pang are with Enjoyor Company Ltd., Hangzhou 310030, China (e-mail: rongdingding@enjoyor.net).

Fenghua Zhu and Fei-Yue Wang are with the State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China.

Haifeng Guo is with the College of Information Engineering, Zhejiang University of Technology, Hangzhou 310013, China, and also with Enjoyor Company Ltd., Hangzhou 310030, China (e-mail: guohf@zjut.edu.cn).

Xiaoliang Ma is with the Department of Civil and Architecture Engineering, KTH Royal Institute of Technology, 10044 Stockholm, Sweden.

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decision making to provide a tuning scheme for the selection of control parameters [16]. This has been proved to be a suitable solution for accelerating the decision-making process.

The manual operation of traffic signal controls may lead to poor performance, especially when a traffic engineer is not sufficiently familiar with the intersections of his responsibility. Meanwhile, such manual operations require immediate evaluation and feedback information to traffic engineers, as the ultimate goal of human involvement is to mitigate non-recurring traffic congestion in reality. The ability of traffic engineers to handle network congestion may continuously develop with incremental practical experience, and it shows that a recommendation system could be enabled for the knowledge development process. The previous work has developed prototype recommendation functions to address the fact that a large number of congested intersections cannot be handled by traffic engineers due to the sparse sensing data [16]. However, the recommender model should be further developed to handle the challenging requirement of providing an appropriate control plan for users who are working in an unfamiliar environment.

This study proposes a parallel recommendation engine for control, operations, and management (PRECOM) of traffic in urban networks to address the aforementioned issues. PRECOM is designed in accordance with the ACP methodological approach and parallel intelligence proposed by Wang [17], [18]. The rest of this paper is organized into five sections. The recent developments in traffic control and management for urban networks are first reviewed in section II, including a brief survey of recommendation systems. Section III then presents the essential components of the proposed PRECOM approach, and section IV illustrates the detailed system implementation of PRECOM. Section V demonstrates a case study, carried out in the city of Hangzhou, China, to validate the efficiency of the recommendation engine when applied for traffic control and operation in reality. Finally, section VI summarizes the study and discusses potential extensions of the recommendation engine in the future.

II. Literature Review

There has been a skyrocket in the number of control instruments developed for reducing traffic congestion of urban road networks in both academic and industrial communities. Many interventions of practice have focused on limiting vehicle trips to reduce traffic congestion. For example, plate-number-based traffic rationing [19], congestion pricing [20], staggering of work hours [14], and carpooling [21] are all measures that have been increasingly deployed worldwide to regulate the aspects of travel demand. To improve the service level of road infrastructure, traffic control is often considered as the main tool that can dynamically handle non-recurrent traffic congestion on a large network.

Self-adaptive urban traffic control systems capable of automatically responding to the prevailing traffic conditions have already been deployed in urban areas [5]. But most of the adaptive signal control systems are designated for under-saturated traffic conditions and are deemed to be inefficient for congested traffic networks. The study of Gayah *et al.* showed that adaptive traffic signals might not improve the network performance in a saturated network, particularly due to non-recurrent traffic congestions [12]. A perimeter signal control is a frequently applied scheme for (over)saturated urban networks, which is deployed at the busiest parts of a network with large traffic demand [22]. Such a control scheme attempts to hold traffic flow from upstream of the links by prolonging the red duration of traffic signals and, therefore, limiting the rate of vehicles entering the area to prevent or alleviate saturation situations. However, a perimeter control scheme belongs to dynamic demand management and does not directly address congested traffic conditions within the region, nor does it systematically address the issues of traffic congestion.

When self-adaptive traffic signals cannot effectively counteract traffic congestion, real-time traffic control, operation, and management strategies are invoked. Previous studies have proposed a signal control system using fuzzy mathematics and neural networks to imitate the reasoning process of the human brain [23]. However, it is still difficult to represent the psychological aspects of the human decision process using lingual rules, especially due to limited cognitive resources and knowledge. Parallel intelligence tries to reduce the uncertainty of complex control systems while being incorporated with control theories [24], [25].On the other hand, reinforcement learning (RL) models were adopted in adaptive traffic signal systems capable of observing, learning, and selecting the optimal traffic phase and timing to monitor and ameliorate traffic congestion [7], [8], [26]–[29]. As mentioned in section I, in many engineering practices, traffic engineers are often involved in the human-in-the-loop traffic management process by manually providing rights-of-way to dissolve congestion based on their professional experience [16].

A recent study incorporated professional knowledge of individual human beings into a recommendation system, which proved of being able to save the time and effort of traffic engineers in their decision-making process when operating urban traffic signal systems [16]. With the development of recommendation models and techniques, recommendation systems have increasingly offered great opportunities for different domains, including e-government, e-commerce, e-shopping, e-learning, and e-tourism [30]. Especially, some of the recommenders have been recently applied to spatial-temporal applications, such as on-demand cinemas [31] and V2X communication [32]. Recommendation systems have already shown to be valuable for facilitating people to make good choices and decisions in some application domains [33]. Few studies have investigated the human-in-the-loop decision process in depth for traffic management and control large-scale congested urban networks.

III. The PRECOM Methodology

A. Overall Framework

The PRECOM approach is developed in accordance with the conceptual framework of ACP [17] and parallel intelligence. ACP stands for artificial systems, computational experiments, and parallel execution, and its evolving approach, parallel

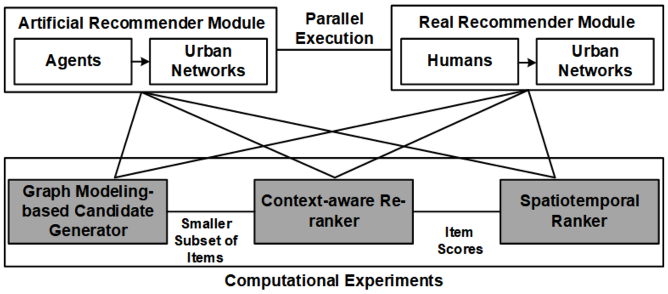


Fig. 1. The overall design of PRECOM in accordance with the ACP conceptual framework.

intelligence, has been applied to autonomous driving [34], [35] and other fields. As shown in Figure 1, the PRECOM framework contains two simultaneously performing modules: artificial and real recommender modules. The recommendation model represented by an artificial module is considered an alternative possible realization of the target recommender system where humans are involved. Both of them provide recommended items via computational experiments sharing three core functioning stages: a graph modeling-based candidate generator, a spatiotemporal ranker, and a context-aware re-ranker. In the parallel execution process, the operations of the real recommender module are gradually improved through comparison, evaluation, and interaction with the artificial module.

The PRECOM is defined as an information processing system that aims to recommend "items" to "users" based on their preferred "rates". In particular, Figure 2 depicts the essential components and an operational process of PRECOM. The recommendation engine can evolve by itself according to the parallel execution process. The system performance is evaluated and further improved by a large number of computational experiments based on the feedback information. At first, a traffic analysis module collects and stores large data streams of historical traffic states, traffic infrastructure, and human regulation data. A user–item-rate processor transfers the collected data into a format that is recognized by recommender modules.

Starting from the first stage, the candidate generator incorporates a graph embedding model to select a smaller subset of candidates from the most similar signalized intersections in a region. Next, a spatiotemporal ranking model scores all the available items with regards to the generated candidates by leveraging spatial and temporal information. The ranking process relies on a more precise and complex modeling approach. In the re-ranking process, the context information is taken into consideration to enhance the novelty of recommendations.

Thereafter, an item filter determines whether the item should be delivered to users. From the very beginning, users always need to be involved in the recommendation process to justify the effectiveness of the recommended items according to their professional experience. If the traffic control schemes being recommended achieve a certain level of confidence according to predefined assessment criteria, they can be directly applied to the traffic management system for a large urban network through an intelligent agent. Such an automatic recommendation process analyzes and evaluates the performance of the recommendation engine in different traffic environments. The final control schemes being applied are stored in a traffic analysis module for a large-scale network to gradually update the recommendation engine via the user-item-rate data processor.

B. Graph Model Based Candidate Generator

The candidate generator tries to solve a proximity search problem by sorting out the available items from the intersection candidates, which are similar to the intersection being queried. Let $\mathcal{C}_{can}$ denote the set of candidate nodes of the linkage graph with the size of N_{can}. The similarity measure between two candidates, c and c', is quantified by

$$f_{sim}(\mathbf{h}_c, \mathbf{h}_{c'}) = \frac{\mathbf{h}_c \cdot \mathbf{h}_{c'}}{||\mathbf{h}_c||||\mathbf{h}_{c'}||}, \tag{1}$$

where $\mathbf{h}_c$ is a concatenation of node embeddings associated with the intersection, i.e.,

$$\mathbf{h}_c = \&_{n=1}^{N_{can}} \mathbf{h}_n, \tag{2}$$

and & denotes the concatenation operator. $||\mathbf{h}_c||$ is the Euclidean norm of vector $\mathbf{h}_c$, and $\mathbf{h}_n$ denotes the embedding for the node n.

The similarity between intersections is estimated based on node-embedding vectors derived from a graph model, GraphSAGE [36]. GraphSAGE is an efficient inductive unsupervised learning algorithm that is capable of quickly generating node embedding for unseen or entirely new (sub)graphs, instead of exhaustively scoring every potential node in a graph. Here, we denote each link as a node for GraphSAGE, and Figure 3 shows five essential steps to build a graph model enabled by the GraphSAGE approach.

GraphSAGE simultaneously learns the topological structure of each node's neighborhood and makes use of structural features that are present in all graphs. The feature information of a node is aggregated from a node's local neighborhood in an iteration through a search of K aggregator functions. The embedding of the node n's neighboring nodes are aggregated into a single representation using a specific aggregator function. The k^{th} iteration of the updated neighboring embedding for node n, $\mathbf{h}^k_{nei,n}$, is

$$\mathbf{h}^k_{nei,n} = F^k_{agg}(\mathbf{h}^{k-1}_e), \quad \forall e \in f_{nei}(n), \ \forall k \in \{1, \ldots, K\} \tag{3}$$

where $f_{nei}(\cdot)$ and $F^k_{agg}(\cdot)$ define the neighborhood function and the k^{th} aggregator function, respectively. Next, the node's k^{th} neighboring representation is updated by the following formula using a fully connected layer, where the neighborhood-wide aggregated representation and node representation at the previous iteration are regarded as the model inputs.

$$\mathbf{h}^k_n = f_{nn}(W^k, \mathbf{h}^k_{nei,n}, \mathbf{h}^{k-1}_n), \tag{4}$$

where $f_{nn}(\cdot)$ denotes a neural network layer, and W^k is the trainable matrix corresponding to the k^{th} aggregator model.

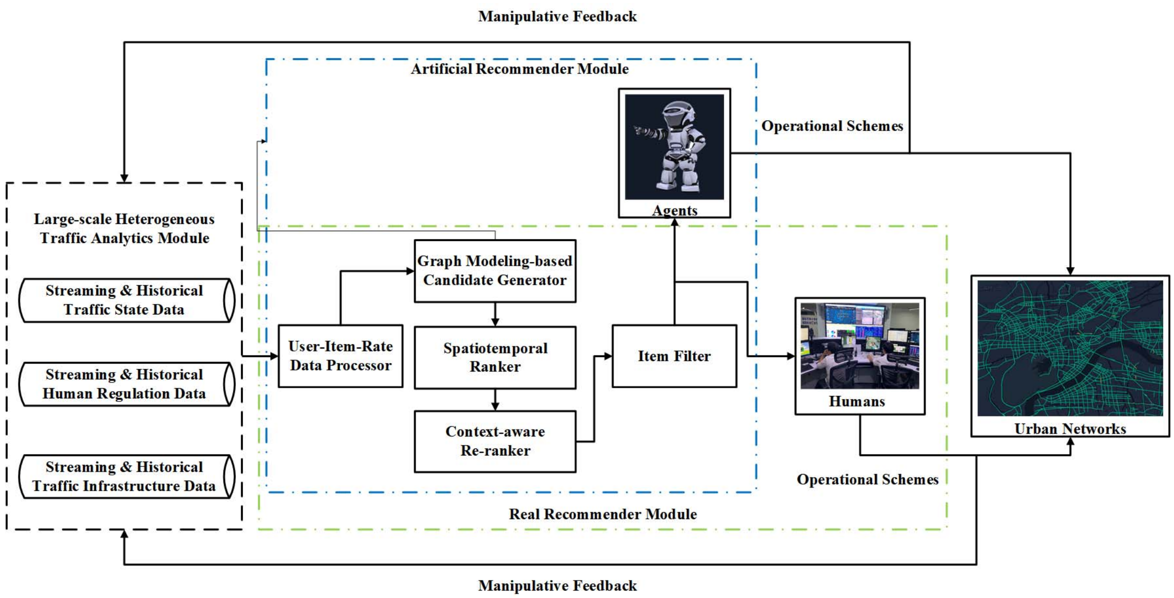


Fig. 2. The essential components and operational process of the proposed PRECOM approach.

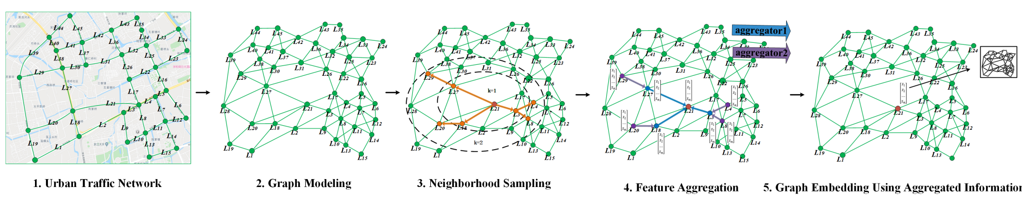


Fig. 3. The graph-modeling steps enabled by the GraphSAGE approach for an urban traffic network.

After processing all nodes, the representation of $\mathbf{h}_n^k$ is normalized by

$$\mathbf{h}_n^k = \frac{\mathbf{h}_n^k}{\sqrt{\sum_{\forall n' \in \mathcal{N}} \mathbf{h}_{n'}^k}}. \tag{5}$$

where $\mathbf{h}_n^K$ denotes the final node representation obtained at the end of the K iterations of aggregator functions. The GraphSAGE model is trained by optimizing a negative sampling-based loss function to ensure that disparate nodes are made to be highly distinct, while nearby nodes in a graph are encouraged to have similar representations. Assume node e co-occurs near the node n on a fixed-length random walk. The task is to distinguish the target node n from samples drawn from a negative distribution, $P(\cdot)$, where there are q negative samples drawn out of each dataset. The objective function is defined as follows:

$$J_{\mathcal{G}}(\mathbf{h}_n) = -\log\left(\sigma\left(\mathbf{h}_n^T \mathbf{h}_e\right)\right) - q \cdot \mathbb{E}_{\hat{e}\sim P(e)}\left[log\left(\sigma\left(-\mathbf{h}_n^T \mathbf{h}_{\hat{e}}\right)\right)\right] \tag{6}$$

where $\log(\cdot)$ refers to a log-likelihood function, and $\sigma(\cdot)$ is the activation function e.g., sigmoid function. $\mathbb{E}(\cdot)$ is the expected value function. $\hat{e}$ and $\mathbf{h}_{\hat{e}}$, respectively, denote a node drawn from the negative distribution of node e, $P(e)$, and its final node embedding.

C. Spatiotemporal Ranker With Automated Model Selection

After processing the candidate generator, the selected candidates are further modeled as user-item pairs in the PRECOM framework. Given a user-item pair (u, i), the ranking problem is generally defined as

$$\hat{r}_{u,i} = f_{recom}(\mathbf{x}_{u'}, \mathbf{x}_{i'}), \quad \forall u', i' \in \mathcal{C}_{can}, \mathcal{I}_u, \tag{7}$$

where $\hat{r}_{u,i}$ denotes the predicted rate corresponding to the queried user-item pair u and i. $\mathcal{I}_u$ is the item set available to user u. $\mathbf{x}_u$ and $\mathbf{x}_i$ are user features and item features, respectively. The spatiotemporal ranker produces a set of items on the order of ten by exploiting the spatiotemporal filter such that the system can use a more precise model taking accounts of additional information. A collaborative filtering-based recommendation approach is performed by relating users' temporal characteristics and the dependencies of traffic control and operation.

In the ranking procedure, a combination of algorithm selection and hyperparameter optimization is applied, since there is normally no single model that performs best in all scenarios, and the recommendation technique crucially relies on hyperparameter settings. Therefore, the algorithm and hyperparameter optimization problem is formulated as a joint optimization problem as follows:

$$R^*, \gamma^* = \underset{R_j \in \mathcal{R}, \gamma \in \Gamma_j}{\operatorname{argmax}} \frac{1}{N^{cv}} \sum_{p=1}^{N^{cv}} \mathcal{L}(R_i^{\gamma}, D_p^{train}, D_p^{valid}) \tag{8}$$

where R^* and γ^* are the optimal recommendation algorithm and the corresponding hyperparameter set. N^{cv} denotes the number of cross-validation folds. Γ_j denotes the set of available hyperparameters for the j^{th} recommendation algorithm since each algorithm may have a different hyperparameter domain. $\mathcal{R} = \{R_1, \ldots, R_j, \ldots, R_{N^r}\}$ is a set of recommendation algorithms with the j^{th} algorithm represented by R_i. N^r is the number of available recommendation algorithms. D_p^{train} and D_p^{valid} represent the p^{th} training and validation datasets, respectively. $\mathcal{L}(\cdot)$ defines a performance function for evaluating the recommendation model. The Bayesian optimizer explores the relationship between the hyperparameter settings of the recommendation algorithm and the performance measure by iteratively updating a probabilistic model to find the optimal hyperparameter setting. A comprehensive description of the Bayesian optimizer can be found in [37].

D. Context-Aware Re-Ranker

Context-aware re-ranker filter items based on a post-filtering approach taking into account the explicit criteria of specific contextual situations. The idea behind this is to enhance the exploration ability of the recommendation space. In particular, if a similar item has been previously recommended to or applied by the user within one day, the associated rate will be depreciated to increase the diversity and novelty of the recommendation. The rating value is updated by

$$\hat{r}_{u,i}(t,d) = \frac{1}{|\mathcal{D}_{date}|} \sum_{d' \in \mathcal{D}_{date}} \frac{\sum_{u' \in \mathcal{C}_{can}} f_{sim}(\mathbf{h}_u, \mathbf{h}_{u'}) \hat{r}_{u,i}(t, d')}{\sum_{\sum_{u' \in \mathcal{C}_{can}}} f_{sim}(\mathbf{h}_u, \mathbf{h}_{u'})}, \tag{9}$$

where $\mathcal{D}_{date}$ denotes the set of dates used for checking the similarity between recommended items during the same period of a day on different days. $\hat{r}_{u,i}(t,d)$ represents the rating value associated with user–item pair u, i at time t of date d.

IV. System Implementations

A. User-Item-Rate Definitions

1) Graph Node Features: When there is a user query, similar users are extracted by the candidate generator using the GraphSAGE model as described in section III. The node features can capture both spatial and temporal dependencies. Graph node features, $\mathbf{x}_n$, are represented by the link features, including link length, number of lanes, and link-speed patterns, as follows:

$$\mathbf{x}_n = [\gamma_n, \delta_n^s, \delta_n^l, \delta_n^r, v_n^{avg}, v_n^{min}, v_n^{max}]. \tag{10}$$

where γ_n denotes the level of link length. δ_n^s, δ_n^l, and δ_n^r refer to the levels of the straight, left, and right lane sizes, respectively. v_n^{avg}, v_n^{min}, and v_n^{max} are the levels of mean, minimum, and maximum values of average link speed per day.

2) User Definition: In this study, user features are specially designed to capture different spatial and temporal characteristics instead of being equivalent to those directly describing an intersection or a traffic engineer. Here, a user is identified based on the following four elements: unique intersection id, signalized cycle length, average speed, and speed amplitude of each link for the previous 15 minutes, defined as

$$\left\{id, sig_{id}, \eta^0, \ldots, \eta^l, \ldots, \eta^{N_{id}}, \varphi^0, \ldots, \varphi^l, \ldots, \varphi^{N_{id}}\right\}.$$

where sig_{id} and N_{id}, respectively, denote levels of signalized cycle length and the number of links associated with intersection id. η^l and φ^l are the mean values of average link speed and speed amplitude for the past 15 minutes of the l^{th} link.

3) Item Definition: To make the system implementation of PRECOM compatible with the existing signal control systems from both hardware and software aspects, the basic component of a signal control system, turning movements, is applied for item definition. Then, various signal control systems can be incorporated by transferring turning movements to their employed components, such as stage and phase.

	0	1	2	3	4	5	6	7	8	9	10	11
0	--	0	0	1	1	0	0	1	0	1	1	0
1	0	--	0	1	1	0	1	0	0	1	1	0
2	0	0	--	0	0	0	0	0	0	0	0	0
3	1	1	0	--	0	0	1	1	0	0	1	0
4	1	1	0	0	--	0	1	1	0	1	0	0
5	0	0	0	0	0	--	0	0	0	0	0	0
6	0	1	0	1	1	0	--	0	0	1	1	0
7	1	0	0	1	1	0	0	--	0	1	1	0
8	0	0	0	0	0	0	0	0	--	0	0	0
9	1	1	0	0	1	0	1	1	0	--	0	0
10	1	1	0	1	0	0	1	1	0	0	--	0
11	0	0	0	0	0	0	0	0	0	0	0	--

Fig. 4. A conflict matrix for all twelve turning movements employed at an intersection.

In this paper, we use the term phase as a combination of non-conflict turning movements, which is consistent with the definition of phase in a phase-based signal controller [23]. All items can be enumerated using a predefined conflict matrix. Figure 4 depicts the applied conflict matrix, inferring the permitted right-of-way of two related turning movements, where a value of one indicates two corresponding movements conflict with each other, and a value of zero indicates otherwise. According to the conflict matrix, in total, 271 phases can be generated, and each phase is assigned a unique ID. Therefore, an item is defined as

$$\{\alpha^0, \ldots, \alpha^{id}, \ldots, \alpha^{271}\}. \tag{11}$$

where α^{id} denotes the level value of changed duration associated with phase id. If the value of α^{id} is 0, it means that phase id is not active. In practice, eight phases are usually activated at the same time. The changed green time for each phase is naturally defined as an item in this application.

4) Rate Definition: The rate is determined according to a comparison of the changed speed when the item is applied with the historical changed speed in the same period. "Changed speed" means the difference between the average speed before and after operational schemes are conducted. Assuming that the item i is applied by the user u at t, the rate is updated by

$$r_{u,i} = \Delta s_{u,i,t} - \Delta s_{u,i,hist} \tag{12}$$

where $\Delta s_{u,i,t}$ denotes the instant difference of the average speed within 15 minutes before the item i is applied by the identical user u. $\Delta s_{u,i,hist}$ refers to the corresponding historical value of $\Delta s_{u,i,t}$.

B. Recommendation Algorithms

Several recommendation algorithms are included in the automated model selection process such as *K-nearest* neighbor (KNN)-inspired methods [38], singular value decomposition (SVD), SVD-plus [39], slope-one, co-clustering [40], and lightFM. In addition, a random approach is applied as a benchmarking algorithm to compare with these advanced algorithms. The random approach predicts rates based on the distribution of the training set, which is assumed to be normal.

A KNN-inspired algorithm aggregates the N-nearest neighbors to compute an estimation. In addition, the similarity measure for the nearest neighbors must be positive to avoid negatively correlated neighbors. The similarity between two nodes, u and v, is computed by

$$f_{sim}(u,v) = \frac{\sum_{i\in\mathcal{I}_{u,v}} r_{u,i}\cdot r_{v,i}}{\sqrt{\sum_{i\in\mathcal{I}_{u,v}} r_{u,i}^2}\cdot\sqrt{\sum_{i\in\mathcal{I}_{u,v}} r_{v,i}^2}}. \tag{13}$$

Four variants of KNN inspired models are implemented in this study. They are KNN-basic, KNN-mean, KNN-Zscore, and KNN -baseline. The actual implementations of KNN-based algorithms are presented in [38].

Two versions of the SVD based algorithms are employed in the study, and both try to minimize the following objective function,

$$\begin{aligned} J_{cf}(\mathbf{q}_i,\mathbf{p}_u,\beta_u,\beta_i) = &\sum_{u\in\mathcal{U}_{can}}\sum_{i\in\mathcal{I}_u}(r_{u,i}-\hat{r}_{u,i})^2 \\ &+\lambda_2(||\mathbf{p}_u||^2+||\mathbf{q}_i||^2+\beta_u^2+\beta_i^2). \end{aligned} \tag{14}$$

where $\mathbf{q}_i$ and $\mathbf{p}_u$ represent latent factors while β_i and β_u are two learnable bias parameters. Using the basic version, the predicted rate is

$$\hat{r}_{u,i} = \mathbf{q}_i^T\mathbf{p}_u + \beta_u + \beta_i. \tag{15}$$

Additionally, the upgraded version of SVD, namely SVD-plus, predicts rate by

$$\hat{r}_{u,i} = \mathbf{q}_i^T(\mathbf{p}_u + |I_u|^{-\frac{1}{2}}\sum_{j\in I_n} y_j). \tag{16}$$

Slope-one is a simplified version of a collaborative filtering algorithm that obtains the predicted rate using a precomputation of the average difference between the ratings of one item and another for users who rated both. The predicted rate is obtained according to

$$\hat{r}_{u,i} = \mu_u + \frac{1}{|R_i(u)|}\sum_{j\in R_i(u)}\Delta(i,j), \tag{17}$$

$$\Delta(i,j) = \frac{1}{|U_{i,j}|}\sum_{u\in U_{i,j}}(r_{u,i}-r_{u,j}), \tag{18}$$

where $\Delta(i,j)$ is defined as the average difference between the ratings of item i and those of item j. Co-clustering predicts rates according to user and item co-clusters which can be obtained from a straightforward optimization method such as k-means.

$$\hat{r}_{u,i} = \bar{C}_{u,i} + (\mu_u - \bar{C}_u) + (\mu_i - \bar{C}_i) \tag{19}$$

where $\bar{C}_u$is the average rating of the cluster associated with user u, and $\bar{C}_i$ is the average rating of the cluster associated with item i. $\bar{C}_{u,i}$ is the average rating of co-cluster $C_{u,i}$ with respect to the user–item pair, (u,i). LightFM represents users and items as linear combinations of their feature's latent factors. It is regarded as a hybrid collaborative filtering model, which is promoted for cold-start or sparse interaction data scenarios.

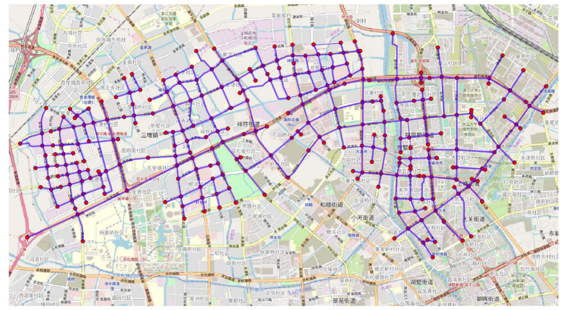


Fig. 5. Layout of the urban area where the PRECOM is employed.

V. Case Study

A. Overview

The recommendation engine, PRECOM, was evaluated for a network of signalized intersections in the city of Hangzhou, where a team of traffic engineers has been recruited since 2018 to tune traffic signal plans in real-time. In Hangzhou, more than 300 thousand vehicles simultaneously drive in the road network consisting of more than 1,500 signalized intersections during peak hours, causing non-recurring traffic congestion events randomly at an arbitrary intersection. The layout of the case study area, as displayed in Figure 5, consists of 309 intersections and 872 road links. SCATS controllers have been deployed in this area, and they work properly in general with optimized time-of-day plans in accordance with the control algorithm [5]. However, the SCATS system itself cannot handle non-recurring congestion events appropriately in real-world traffic engineering practice. Until 2019, the signal plans had to be manually adjusted in real-time according to the experience of traffic engineers when unexpected congestion appeared. The experiments were performed on a computer system with two Intel Xeon E5-2620 CPUs and four TITAN XPascal GPUs.

We consider that a non-recurring congestion event occurs when non-stop vehicle speeds are continuously low within a certain time window. Here, the speed of a non-stop vehicle refers to the moving average of the speed values above 5 km/h such that those vehicles waiting at red lights are eliminated. Specifically, an intersection is considered congested if the maximum value of the associated average vehicle speed over a time window of 15-minutes was below 20 km/h. According to historical statistics, most of the signalized intersections in

TABLE I
THE LEVEL VALUES AND THEIR DESCRIPTIONS OF THE FEATURES USED FOR GRAPH NODE, USER, AND ITEM

Object	Symbol	Level values	Description
Graph node	γ_a	{0, 1, 2, 3, 4}	Link length associated with node a: {[0, 250], (250, 500], (500, 750], (750, 950], (950, inf)}
	δ_a^m	{0, 1, 2}	Number of lanes associated with node a: {0, 1, [2, inf]}
	v_a^{avg}	{0, 1, 2, 3, 4}	Mean value of the average speed in a day associated with node a: {[0, 32], (32, 39], (39, 45], (45, 52], (52, inf)}
	v_a^{min}	{0, 1, 2, 3, 4}	Mean value of the minimum speed in a day associated with node a: {[0, 8], (8, 15], (15, 23], (23, 30], (30, inf)}
	v_a^{max}	{0, 1, 2, 3, 4}	Mean value of the maximum speed in a day associated with node a: {[0, 36], (36, 46], (46, 56], (56, 65], (65, inf)}
User	C	{0, 1, 2}	Signal cycle length: {[40, 90], (90, 140], (140, 190]}
	η_l	{0, 1, 2, 3, 4}	Mean value of average speed (km/h) for the past 15 minutes of the l^{th} link: {[0, 21], (21, 32], (32, 43], (43, 54], (54, inf)}
	φ_l	{0, 1, 2, 3, 4}	Speed amplitude (km/h) for the past 15 minutes of the l^{th} link: {(inf, -23], [-23, -8], (-8, 8], (8, 23], (23, inf]}
Item	α_i	{0, 1, 2, 3, 4}	Changed duration for the i^{th} phase: {(inf, -12], [-12, -4], (-4, 4], (4, 12], (12, inf]}

the network have two peak hours every day, and the top-ten most congested intersections normally suffer from dozens of events every day. In total, more than $3,000$ non-recurrent congestion events happen in the area every day, but 30% of the signalized intersections rarely suffer from non-recurrent congestion. In addition, only a third of these intersections were operated by human beings in real-time due to human resource limitations.

Historical traffic data from October to December 2019 was used to train the PRECOM system. The data includes detailed dynamic traffic information of the road network such as link traffic speed, traffic signal control plans as well as human intervention records. Link traffic speed was provided by a third-party navigation system, AutoNavi [41], based on floating car data. Traffic signal control data was collected and stored by the SCATS system [5] which is a widely used adaptive traffic signal system. The human intervention data was obtained according to the event occurrence. We used a common time interval, three minutes, to merge and synchronize all data.

B. Analysis of the Candidate Generator

A baseline approach, the note2vec (aka DeepWalk) [42], was also tested for comparison purposes. The mean reciprocal rank (MRR) is the chosen performance metric to evaluate the applied graph embedding approach, i.e.,

$$MRR = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{rank_i} \tag{20}$$

where $rank_i$ is the rank of the positive instance i predicted by the model with respect to the negative samples predefined in the graph-embedding model. If the first returned result is relevant, then the MRR value is 1.0, otherwise, its value is smaller than 1.0. All models share an identical set of minibatch iterators, loss function, and neighborhood samplers (where applicable) to ensure a fair comparison. Adam optimizer [43] was used in the training process for all the tested GraphSAGE models. Five aggregator functions were tested in this study, including mean [36], mean pooling, max pooling, graph convolutional network (GCN) [44], and long short-term memory (LSTM) [45].

TABLE II
VALIDATION RESULTS OF THE TESTED GRAPH EMBEDDING MODELS. BOLD FONT INDICATES THE BEST RESULTS

Graph Embedding	Aggregator Function	Neighboring Size 5	10	15	20
Node2Vec	–	0.561	0.540	0.540	0.533
GraphSAGE	Mean	**0.952**	0.927	0.915	0.902
	LSTM	0.836	0.855	0.831	0.824
	Max pool	0.944	**0.935**	**0.929**	**0.916**
	Mean pool	0.943	0.930	0.922	0.905
	GCN	0.946	0.924	0.915	0.903

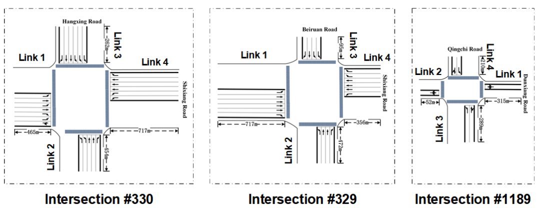
Table II summarizes the performance of GraphSAGE and the baseline embedding models on this dataset using four different tested neighboring sizes, 5, 10, 15, and 20. In general, all of the tested GraphSAGE models outperform the baseline approach by a significant margin. For example, the GraphSAGE model with an LSTM aggregator function can provide a gain of at least 30% compared to the Node2Vec model but it generates the least MRR value among GraphSAGE models using other aggregator functions. The max-pooling aggregator function is reasonably competitive since it achieves the best performances regarding three different neighboring sizes (10, 15, and 20), and its MRR values are all close to 1.0. In the following analysis, the GraphSAGE model with the mean aggregator function was applied, as this generated the biggest MRR value.

Here, an arbitrary intersection, #330, is taken as an example for showing the results of the GraphSAGE model with the mean aggregator function applied. Figure 6(a) shows the layouts of the three intersections: #330 and #329 are almost symmetrical, but the size of #1198 is smaller than the other two. In the tested urban area, the most similar intersection in terms of spatial and temporal characteristics is intersection #329, while #1189 is ranked at 50 according to the similarity measures presented in Equation 1. Figure 6(b) indicates that the mean speeds over one day for intersections #330 and #329 have a relatively similar shape of distribution regardless of which of the four road links is used. However, the range of mean speeds in one day is notably different between #330 and #1189, implying that

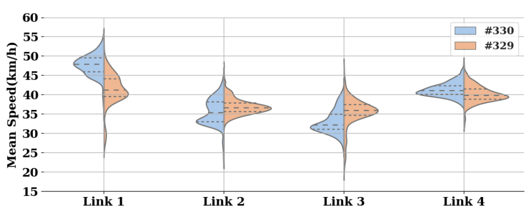
TABLE III

VALIDATION RESULTS FOR THE TESTED RECOMMENDER TECHNIQUES. BOLD FONT INDICATES THE BEST RESULTS

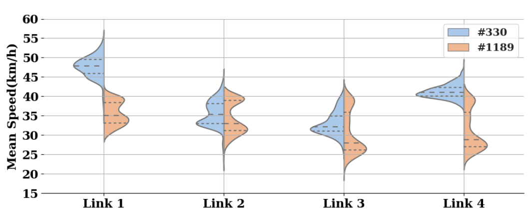
Recommender	Best Model Hyperparameters						Validation Errors		
Technique	k	Learning rate	Regularization	Number of factors	Number of clusters	Loss function	MAE	MSE	RMSE
Random	–	–	–	–	–	–	3.429	19.057	4.309
KNN-basic	60	–	–	–	–	–	2.514	11.197	3.276
KNN-mean	40	–	–	–	–	–	2.503	11.226	3.281
KNN-ZScore	60	–	–	–	–	–	2.512	11.320	3.295
KNN-baseline	60	–	–	–	–	–	2.488	11.042	3.252
SVD	–	0.001	0.005	30	–	–	**2.437**	**10.444**	**3.154**
SVD-plus	–	0.001	0.1	10	–	–	2.483	10.579	3.176
Slope-one	–	–	–	–	–	–	2.575	11.850	3.376
Co-clustering	–	–	–	–	5	–	2.510	11.387	3.304
LightFM	–	0.05	–	–	–	Warp-kos	2.633	12.375	3.457



(a) A comparison of intersection layouts among #330, #329, and #1189.



(b) Daily mean speed distribution comparison of the four road links between intersection #330 and #329.



(c) Daily mean speed distribution comparison of the four road links between intersection #330 and #1189.

Fig. 6. A comparison between the rank 1 and rank 50 intersections obtained from GraphSAGE when intersection #330 is queried.

these two intersections are weakly correlated in a temporal dimension.

C. Performance Evaluations of the Recommender

This section describes the performance evaluation of proposed recommendation model when being deployed in real applications.

1) Offline Evaluation: After performing the spatiotemporal ranker with an automated model selection module, Table III summarizes the validation errors with regards to all the available recommender techniques, with each using the best model hyperparameters. In more details, SVD is the top performer with the following hyperparameters: a learning rate of 0.001, 30 factors, and a regularization term of 0.05; and this generated the smallest number of errors. Since SVD produces a slight reduction of 2% in errors compared with the SVD-plus and KNN baseline models, the PRECOM system utilized the SVD recommender for its online deployment.

Thereafter, PRECOM was adopted for the historical ground-truth data to measure the accuracy of the system by comparing the recommended item with the items previously selected by users. After performing the spatiotemporal ranker, the top 20 items were extracted to process the context-aware re-ranking procedure. To assess the accuracy of the algorithm, an analysis was carried out to check whether the actual conducted item was within the selected 20 items (P20). Also, both P@10 and P@3 values were computed, and this demonstrated the item divergence and accuracy according to the context-aware re-ranker. The results showed that P20, P10, and P3 were 1.0, 0.67, and 0.29, respectively. The result indicates that the recommender technique applied in the ranker step can yield items that are similar to those previously chosen by the user. Meanwhile, with the inclusion of the context-aware re-ranker, PRECOM is highlighted by its ability to promote recommendations with novelty and diversification.

2) Online Evaluation: To analyze the effectiveness of the recommender when traffic engineers are involved, PRECOM was deployed to facilitate the operation of the tested area in January 2020. The online evaluation was mainly assessed by measuring the click-through rate (CTR), which is the ratio of the clicked items to all recommended items being displayed. User satisfaction is implicitly reflected by the CTR rate. According to the experiment for one month, the resultant CTR was 0.61, and more than two-thirds of the traffic congestion events were handled by PRECOM. It is expected that the acceptance rate of the recommended items might be not high, as traffic engineers might disagree with some of the recommended control plans. This might be also due to the fact that they refuse to accept items that are beyond their knowledge or experience.

Two justification criteria were defined, efficiency (λ_e) and stability (λ_s), to quantitatively analyze the effectiveness of the interventions by PRECOM. Efficiency identifies whether an intervention succeeds in reducing traffic congestion duration while a high stability value represents that PRECOM leads

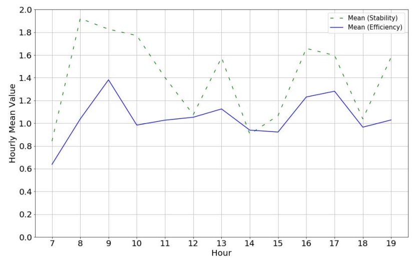


Fig. 7. The values of intervention efficiency and stability between 07:00 and 19:00, as reported by the proposed PRECOM.

to more predictable congestion duration. The two criteria are computed by integrating congestion duration, i.e.,

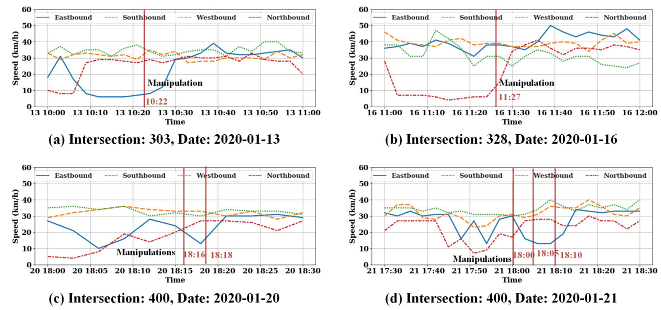
$$\lambda_e = f_{mean}\left(\bar{T}_j^{non}/\bar{T}_j^{man}\right) \quad \forall j \in \mathcal{J} \tag{21}$$

$$\lambda_s = f_{mean}\left(\sigma_j^{non}/\sigma_j^{man}\right) \quad \forall j \in \mathcal{J} \tag{22}$$

where $f_{mean}(\cdot)$ denotes the arithmetic average function. $\bar{T}_j^{man}$ and $\bar{T}_j^{non}$ denote the duration for a congestion event on average when the recommended items are and are not employed, respectively, associated with intersection j. Likewise, σ_j^{man} and σ_j^{non} represent the standard deviation of congestion event duration. $\mathcal{J}$ refers to the set of intersection ids with respect to the tested area.

Figure 7 demonstrates the effectiveness of traffic control operation after the deployment of PRECOM. Such a comparison is made with the deployed SCATS system with optimal settings while traffic engineers are also involved in manual interventions. In general, the positive effect can be easily observed since the efficiency values stay above 1.0 for the majority of the day, indicating a stable reduction of congestion duration. In particular, the travel time performance during rush hours (from 07:00 to 09:00 and from 16:00 to 18:00) was improved by more than 30% when PRECOM was deployed on the congested network. In addition, the stability metric reflects whether the congestion duration is predictable when congestion occurs. Specifically, if the value of stability is above 1.0, the congestion duration is relatively more concentrated distributed before the PRECOM deployment, meaning that the duration of a congestion event is more predictable. When a subarea is in a congestion situation during peak hours, it is often challenging to predict how long the congestion may last. Whereas, PRECOM largely improves the predictability of congestion duration during peak hours resulting in relatively high values of the stability measure. For example, the stability values are all above 1.8 from 08:00 to 10:00.

To illustrate the benefits when PRECOM is implemented in real traffic operation, Figure 8 shows typical examples associated with three intersections. In the plots of Figure 8, at least one link suffered from traffic congestion before an intervention was carried out. The congestion was then alleviated within a reasonable time duration along with the substantial increase of link speeds. For example, average speeds for the congested link, eastbound and northbound respectively, changed from speed value below 10 km/h to above 30 km/h



(a) Intersection: 303, Date: 2020-01-13

(b) Intersection: 328, Date: 2020-01-16

(c) Intersection: 400, Date: 2020-01-20

(d) Intersection: 400, Date: 2020-01-21

Fig. 8. The average link speed before and after the recommended items are applied for the four intersections. A vertical line in right color indicates that an intervention attempts to handle a congestion event for the congested intersection.

within 10 minutes for both intersections #303 and #328 after the execution of the recommended items.

Moreover, if a link is congested, traffic engineer often attempts to address the congestion issue by simply prolonging the green duration of the phase that gives right-of-way to traffic at the link. Such an action may deteriorate the performance of other links associated with the intersection. PRECOM prevents such a negative impact and stops transferring traffic jams from one link to another through multiple interventions. Figure 8(d) shows that, although average speeds associated with eastbound links slightly reduced when the first recommended control plan was applied, the average vehicle speed quickly returned to the speed level of 30 km/h by two additional operations recommended by PRECOM. A human operator can hardly conduct such complicated operations according to the presented traffic states, which demonstrates the prominent advantage of PRECOM over human operator.

VI. Conclusion

This paper has introduced a recommendation engine, PRECOM, that has been developed to facilitate human-in-the-loop traffic management operations for large-scale urban networks. PRECOM is designated in accordance with the ACP methodological framework and has implemented the conceptual modules of an artificial system, computational experiment, and parallel execution. Three essential components are defined in the system design and implemented to generate online recommendations: a graph model-based candidate generator, a spatiotemporal ranker, and a context-aware re-ranker. A real-world case study was carried out and showed that the proposed recommendation system is capable of extending the spatial coverage for more efficient traffic management and control on an urban network. Meanwhile, the deployment of PRECOM in engineering practice has led to substantial improvement concerning mobility efficiency of traffic networks, compared to the case of online recommendation by human operators. Indeed, the current study is a further extension of the previous work that improves the frequency of recommendation when addressing traffic congestion at intersections [16]. Therefore, both temporal efficiency and spatial converge have been addressed for our recommendation system.

Nevertheless, there are still research questions to be answered in the further development of the recommendation system. For example, how to update the recommendation model according to data of interaction between user and system? Therefore, the recommendation system can be further enhanced by capturing users' preferences and their behavioral patterns after the deployment of PRECOM. In addition, the recommendation system may benefit from developing a real-time online traffic simulator capable of providing a high-fidelity model for human-in-the-loop traffic management operations. Moreover, the proposed recommender may integrate with a reinforcement learning-based signal control system [7] so that the system intelligence and performance can be gradually improved when interacting with an external traffic environment. Last but not least, the proposed recommendation system has not involved management strategies at the city scale, and the current system has to be extended to implement control strategies at a more aggregate level.

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Junchen Jin (Member, IEEE) received the M.Sc. and Ph.D. degrees in transport science from the KTH Royal Institute of Technology, Stockholm, Sweden, in 2014 and 2018, respectively. He was the Vice Director of the Smart Transportation Research Institute, Enjoyor Company, Ltd., Hangzhou, China. He was also a Post-Doctoral Researcher with the State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing. His research interests include intelligent decision-making processes, recommender systems, deep reinforcement learning, simulation and control, and intelligent transport systems.

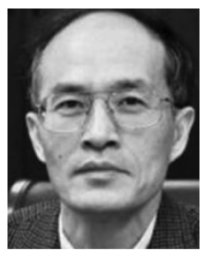
Dingding Rong received the M.Sc. degree in transport engineering from Shanghai Maritime University, Shanghai, China in 2017. She is currently an Algorithm Engineer with the Smart Transportation Research Institute, Enjoyor Company Ltd., Hangzhou, China. Her main research interests include artificial intelligence, deep learning, and reinforcement learning.

Yuqi Pang received the B.Eng. degree in traffic engineering from Tongji University, Shanghai, China, and the M.Eng. degree in transportation planning and management from Zhejiang University, Hangzhou, China, in 2017. She is currently affiliated with Enjoyor Company, Ltd., Hangzhou. Her research interests include intelligent transport systems, traffic control, and artificial intelligence.

Fenghua Zhu (Senior Member, IEEE) received the Ph.D. degree in control theory and control engineering from the Institute of Automation, Chinese Academy of Sciences, Beijing, China, in 2008. He is currently an Associate Professor with the State Key Laboratory for Management and Control of Complex Systems, China. His research interests include artificial transportation systems and parallel transportation management systems.

Haifeng Guo received the Ph.D. degree in traffic information and control from Jilin University in 2008. From 2011 to 2013, he was a Post-Doctoral Research Associate with the Zhejiang University of Technology. He is currently an Associate Professor with the College of Information Engineering, Zhejiang University of Technology, Hangzhou, China. He is also affiliated with Enjoyor Company Ltd., Hangzhou. His research interests include traffic operation and control, smart transportation systems, and traffic AI.

Xiaoliang Ma received the M.Sc. degree in computational science and the Ph.D. degree in infrastructure system from the KTH Royal Institute of Technology, Sweden. He led a research group of System Simulation and Control with the Department of Transport Science, KTH, from 2013 to 2018. He has also been an Industrial Consultant and worked with technologies and development in intelligent transport systems. He is currently a Senior Researcher and a Docent (Associate Professor in ITS research) affiliated with the Department of Civil and Architectural Engineering, KTH. His research interests include system modeling, simulation, and intelligent control with application focus on transport and traffic systems. His academic services include being an Associate Editor of *IET Intelligent Transport Systems* journal and the editorial services for the IEEE Intelligent Transport System Society during the past ten years.



Fei-Yue Wang (Fellow, IEEE) received the Ph.D. degree in computer and systems engineering from Rensselaer Polytechnic Institute, Troy, NY, USA, in 1990.

In 1990, he joined The University of Arizona, Tucson, AZ, USA, as a Professor, and the Director of the Robotics and Automation Laboratory and the Program in Advanced Research for Complex Systems. In 1999, he founded the Intelligent Control and Systems Engineering Center, Institute of Automation, Chinese Academy of Sciences (CAS), Beijing, China, under the support of the Outstanding Overseas Chinese Talents Program from the State Planning Council and 100 Talent Program from CAS. In 2002, he joined the Laboratory of Complex Systems and Intelligence Science, CAS, as the Director, where he was the Vice President of Research, Education, and Academic Exchanges, Institute of Automation, from 2006 to 2010. In 2011, he was a State Specially Appointed Expert and the Director of the State Key Laboratory for Management and Control of Complex Systems, Beijing. His current research interests include methods and applications for parallel systems, social computing, parallel intelligence, and knowledge automation. He was elected as a fellow of INCOSE, IFAC, ASME, and AAAS. He was a recipient of the National Prize in Natural Sciences of China in 2007, the Outstanding Scientist Award from ACM for his research contributions in intelligent control and social computing in 2007, the IEEE Intelligent Transportation Systems (ITS) Outstanding Application and Research Awards in 2009, 2011, and 2015, and the IEEE SMC Norbert Wiener Award in 2014. He was the General Chair or the Program Chair of more than 30 IEEE, INFORMS, ACM, and ASME conferences. He was the President of the IEEE ITS Society from 2005 to 2007, the Chinese Association for Science and Technology, USA, in 2005, and the American Zhu Kezhen Education Foundation from 2007 to 2008. He was the Vice President of the ACM China Council from 2010 to 2011, and the Chair of IFAC TC on Economic and Social Systems from 2008 to 2011. He is currently the President-Elect of the IEEE Council on Radio Frequency Identification (RFID). Since 2008, he has been the Vice President and the Secretary General of the Chinese Association of Automation. He was the Founding Editor-in-Chief of the *International Journal of Intelligent Control and Systems* from 1995 to 2000 and *IEEE Intelligent Transportation Systems Magazine* from 2006 to 2007, and the Editor-in-Chief of the IEEE INTELLIGENT SYSTEMS from 2009 to 2012 and the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS from 2009 to 2016. He is currently the Editor-in-Chief of the IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS and the Founding Editor-in-Chief of the IEEE/CAA JOURNAL OF AUTOMATICA SINICA and the *Chinese Journal of Command and Control*.