Real-time Ride-matching and Vehicle Dispatching in a Flexible Mobility-on-demand Bus System

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

April 12, 2024

Keywords: mobility-on-demand bus, ride-matching, real-time dispatching, graph neural network, reinforcement learning

1 INTRODUCTION

In recent decades, the ridership of urban buses in many cities has seen a significant decline due to low levels of service and competition from emerging travel modes. To upgrade mass transit systems, it is necessary to improve operational flexibility to cater to time-varying travel demand. With the rapid development of communication technologies, real-time information interchange is becoming increasingly efficient, introducing opportunities to enhance the service quality of travel systems through the provision of demand-responsive services. Most existing literature on demand-responsive transits (DRT) focuses on door-to-door services such as dial-a-ride and ride-sharing, which are suitable for low-demand scenarios due to their extreme flexibility. For high-demand scenarios such as commuting trips or travel corridors, the mobility-on-demand bus service, which combines the characteristics of fixed routes and stops from traditional buses with ride-matching from DRT, can be a promising solution (Errico *et al.*, 2021). With passengers' travel demand precisely collected via mobile applications, mobility-on-demand buses can operate flexibly to satisfy travel demands to the greatest extent. To our best knowledge, dynamic ride-matching and flexible dispatching methods for mobility-on-demand bus networks are yet to be studied.

This study focuses on real-time dispatching of a flexible mobility-on-demand bus (FMDB) system, where multi-type buses operate along fixed bus lines and stops. Flexible dispatching strategies, such as stop-skipping, speed adjustment, and bus holding, can be implemented to enhance service quality by assigning collected requests to specific bus trips. In our previous work (Wu *et al.*, 2022), passengers who book trips in advance are responded in batches and bus dispatching schemes are optimized in a rolling horizon framework. This study aims to further address real-time requests by investigating dynamic dispatching methods and extending the operational scenario to a network level. As depicted in Figure 1, FMDB buses adhere to the operation scheme planned for prebooked requests. Matching multiple real-time requests to bus trips of different bus lines is vital for fully utilizing bus capacities, especially in overlapping bus lines. To capture the complex spatial correlations among bus lines, stops, and requests, the FMDB network is modeled as a heterogeneous graph. A Deep-Q-Network (DQN) algorithm integrated with attention-based Graph Neural Networks (GNN) is employed for real-time decision-making. Numerical studies validate the performance of the proposed dispatching algorithm compared to a well-known on-demand ride-sharing (ODRS) system proposed by Alonso-Mora *et al.* (2017).

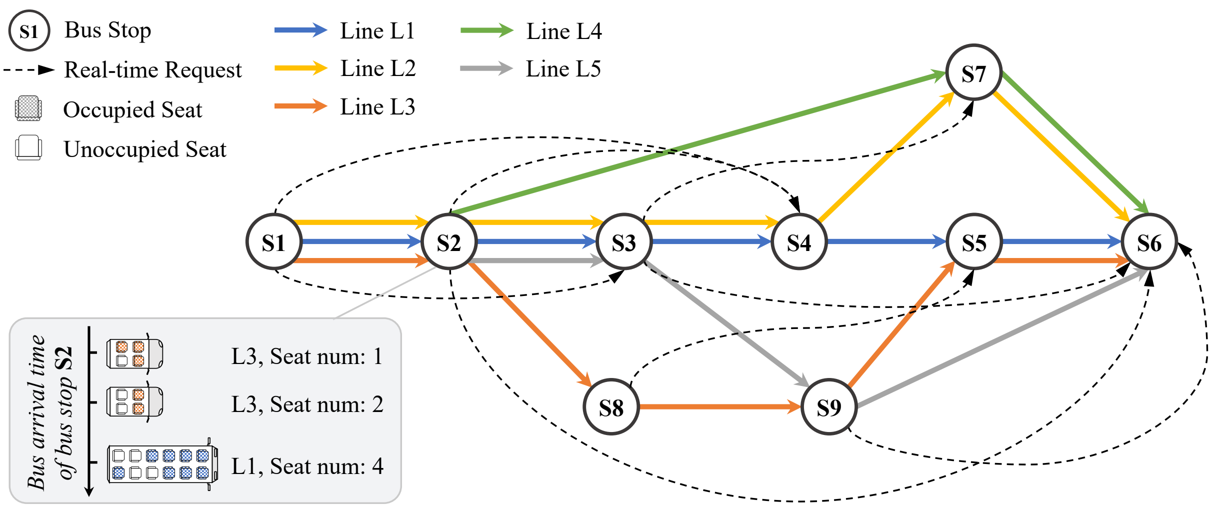


Figure 1 – *Illustration of the real-time dispatching problem in an FMDB network.*

2 METHODOLOGY

2.1 Network Modeling

In the FMDB network, any pair of bus stops might be served by more than one bus line, known as the common line problem. Passengers' boarding behavior among common lines significantly impacts each other, as it affects the availability of seats at subsequent bus stops. To better model transit networks with common lines, route section-based methods are commonly adopted (Tian *et al.*, 2021). A route section is defined as a set of bus lines that connects any two bus stops, thereby dividing travelers at a bus stop into different groups based on their destination. The FMDB network can then be modeled as a heterogeneous graph, as illustrated in Figure 2. Each bus stop is divided into several *supply nodes*, with each node representing a bus line serving that stop. Supply nodes are interconnected by *inner-stop edges* and *inner-line edges* according to the network topology. Travel demands are captured by route section nodes, designated as *demand nodes* and *request nodes* for prebooked and real-time requests, respectively. Route section nodes are connected to feasible bus lines at their origin bus stops through *boarding edges*. For example, for a real-time request at node D_5, it can choose either bus line L2 or L3 at stop S2 to reach S4, referred to as *active nodes* $N_{2,2}$ and $N_{2,3}$. Since onboard passengers affect the available seat number along their itinerary, route section nodes are also connected to supply nodes through *passing edges*.

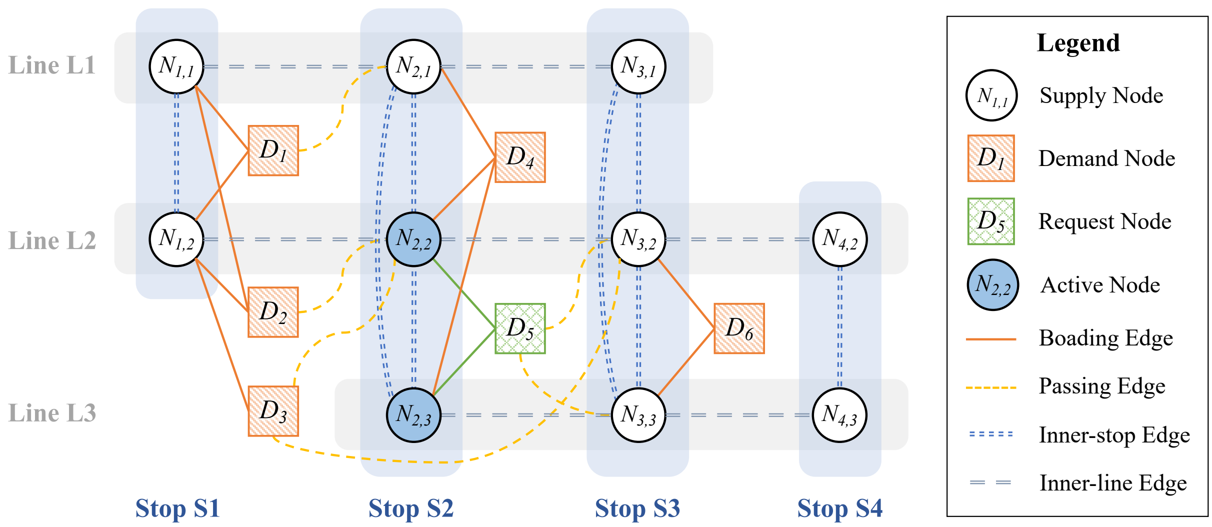


Figure 2 – *Graph for the FMDB network.*

2.2 Markov Decision Process Design

The dynamic FMDB dispatching algorithm assigns a real-time request p to either an existing or a new bus trip once the request is proposed at time t_p. Denote $\mathcal{L}$ as the set of bus lines, $\mathcal{S}$ as the set of bus stops, $\mathcal{R}$ as the set of route sections, and $\mathcal{P}$ as the set of real-time requests, the problem can be modeled as a Markov Decision Process (MDP) as follows.

State. Denote $\mathcal{L}_s$ as the subset of bus lines serving bus stop s, and $\|\mathcal{L}_s\|$ as the cardinality of subset $\mathcal{L}_s$. Based on the planned operation scheme and real-time bus locations, the arrival time $\widetilde{t}_p^{s,l}$ and available seat number $\widetilde{c}_p^{s,l}$ of the next arriving bus for each supply node at time t_p can be obtained. The supply state S_p^{veh} comprises the state tuple of each supply node, as shown in Equation (1). Real-time request and prebooked demand distributions are also important references for decision-making. In Equation (2), μ_p^r represents the one-hot encoding of the route section of request p. Denote τ_p as the time slot of t_p, $q_{\tau_p}^r$ represents the number of prebooked requests of each route section in τ_p.

$$S_p^{veh} = \left[\left(\widetilde{t}_p^{s,l}, \widetilde{c}_p^{s,l}\right)\right]_{\Sigma_{s\in\mathcal{S}}\|\mathcal{L}_s\|}, \ \forall p \in \mathcal{P} \tag{1}$$

$$S_p^{demd} = \left[\left(\mu_p^r, q_{\tau_p}^r\right)\right]_{\|\mathcal{R}\|}, \ \forall p \in \mathcal{P} \tag{2}$$

Action. For consistency of the action space, the agent determines which supply node should the requests be assigned to, and then, buses are dispatched accordingly. Define the *coming bus* as a bus with available seats and is expected to arrive within a threshold χ_{arr}. Requests will board the coming buses at their assigned supply node $N_{s,l}$ as soon as possible. If there are no coming buses at $N_{s,l}$, a new bus trip will be dispatched immediately from the depot of bus line l. In this way, the action A_p can represented by the one-hot variable $a_p^{s,l}$ for each supply node in Equation (3). Specifically, $a_p^{s,l} = 1$ if request p is assigned to bus line l at stop s; $= 0$, otherwise. A mask is applied to restrict action selection to active nodes.

$$A_p = \left[a_p^{s,l}\right]_{\Sigma_{s\in\mathcal{S}}\|\mathcal{L}_s\|}, \ \forall p \in \mathcal{P} \tag{3}$$

Reward. The objective of dynamic FMDB dispatching is to minimize the total waiting time of all real-time requests while minimizing increment of supply and delay. Therefore, the reward for request p is designed as Equation (4), where $\bar{t}_l^s$ is the travel time from the depot of bus line l to stop s, and ψ_{new}^l is the penalty for dispatching new bus trips of bus line l. The term $\beta_{skip}^s \psi_{stop}^s$ further penalizes the reward if stop s is skipped in the planned operation scheme, considering the impact on onboard passengers.

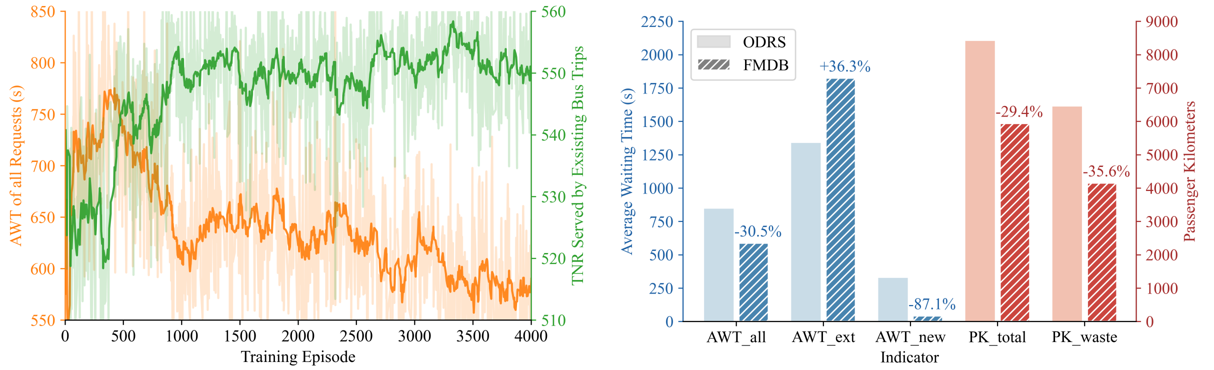
$$R_p = \begin{cases} -\sum_{s\in\mathcal{S}}\sum_{l\in\mathcal{L}_s} a_p^{s,l}\left(\widetilde{t}_p^{s,l} - t_p + \beta_{skip}^s \psi_{stop}^s\right), & if \ \widetilde{t}_p^{s,l} - t_p < \chi_{arr} \\ -\sum_{s\in\mathcal{S}}\sum_{l\in\mathcal{L}_s} a_p^{s,l}\left(\bar{t}_l^s + \psi_{new}^l + \beta_{skip}^s \psi_{stop}^s\right), & otherwise \end{cases}, \ \forall p \in \mathcal{P} \tag{4}$$

2.3 GNN-DQN based Dispatching Algorithm

Learning through interactions with the environment, reinforcement learning methods excel in solving sequential decision-making problems by discovering optimal action policies to maximize cumulative rewards. Due to the inherent advantages of GNNs in utilizing topological information, combining GNNs with other deep learning techniques in the transportation field has proven to be highly effective (Zhou *et al.*, 2022). In this study, a DQN algorithm is employed to solve the MDP for FMDB dynamically. Attention-based GNNs are embedded for feature extraction and value function approximation. To enhance the robustness of the model across various demand scenarios and bus operation schemes, a simulator is designed to generate massive samples of ride-matching and operation schemes for prebooked requests efficiently. During the training stage, the GNN-DQN agent selects a feasible action A_p for each real-time request based on the state $\left(S_p^{veh}, S_p^{demd}\right)$ according to the ε-greedy strategy. Then, the environment executes the action, evaluates the reward R_p, and returns the next state upon the arrival of the next request, i.e., $\left(S_{p+1}^{veh}, S_{p+1}^{demd}\right)$. The training process follows the standard framework of the DQN algorithm, incorporating the experience reply technique and a target Q-network. Detailed introduction of the sampling and network training methods will be provided in the full paper due to page limits.

3 RESULTS

Preliminary tests of the proposed algorithm are conducted on a network consisting of 3 severely overlapping bus lines with 7 bus stops and 17 route sections. Each episode comprises 1,800 real-time requests over a 6-hour period. As the training progresses, the average waiting time (AWT) decreases, while the total number of requests (TNR) served by existing bus trips increases, as shown in Figure 3a. The benchmark algorithm is designed as a combination of a batch optimization model for utilizing existing bus trips and ODRS (Alonso-Mora *et al.*, 2017) for dispatching new bus trips, referred to as ODRS for simplicity. As shown in Figure 3b, the total passenger kilometers (PK_total) of new bus trips dispatched by FMDB reduces by 29.4% compared to ODRS. Moreover, the wasted passenger kilometers (PK_waste) decreases more significantly than PK_total, indicating a higher utilization rate of vehicle capacities. The AWT for requests served by new bus trips (AWT_new) exhibits a remarkable decrease of 87.1%, contributing significantly to the reduction of 30.5% in the AWT for all requests (AWT_all). Since ODRS is a batch-matching method while FMDB makes decisions in response to each request, it's reasonable to observe an increase in the AWT for requests served by existing bus trips (AWT_ext).



(a) *Training Curves* (b) *Comparison of Indicators*

Figure 3 – *Results of numerical studies.*

4 CONCLUSION

This study proposes a learning-based dynamic dispatching model for the FMDB system, which assigns real-time requests to either existing bus trips or new bus trips. The spatial correlation among the service network and requests is captured by an attention-based GNN, which is embedded in a DQN algorithm as value networks. Preliminary results have demonstrated the advantages of the proposed FMDB system over a ride-sharing service in leveraging the capacity of the vehicles. More details about the dispatching model, training methods, and numerical results will be elaborated in the full paper.

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