Transportation Research Part C 96 (2018) 144–159

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Vehicle scheduling under stochastic trip times: An approximate dynamic programming approach

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ARTICLE INFO

Keywords:
Vehicle scheduling
Stochastic trip times
Delay propagation
Approximate dynamic programming

ABSTRACT

Due to unexpected demand surge and supply disruptions, road traffic conditions could exhibit substantial uncertainty, which often makes bus travelers encounter start delays of service trips and substantially degrades the performance of an urban transit system. Meanwhile, rapid advances of information and communication technologies have presented tremendous opportunities for intelligently scheduling a bus fleet. With the full consideration of delay propagation effects, this paper is devoted to formulating the stochastic dynamic vehicle scheduling problem, which dynamically schedules an urban bus fleet to tackle the trip time stochasticity, reduce the delay and minimize the total costs of a transit system. To address the challenge of "curse of dimensionality", we adopt an approximate dynamic programming approach (ADP) where the value function is approximated through a three-layer feed-forward neural network so that we are capable of stepping forward to make decisions and solving the Bellman's equation through sequentially solving multiple mixed integer linear programs. Numerical examples based on the realistic operations dataset of bus lines in Beijing have demonstrated that the proposed neural-network-based ADP approach not only exhibits a good learning behavior but also significantly outperforms both myopic and static polices, especially when trip time stochasticity is high.

1. Introduction

Vehicle scheduling plays a key role in public transit operational planning, which consists of line planning, timetabling, vehicle scheduling, and crew scheduling. In a vehicle scheduling problem (VSP), given the detailed information of the timetable of trips, buses are scheduled to finish the tasks (trips on the timetable) with the consideration of practical requirements such as multiple depots and vehicle types, so that each task is completed by a unique bus. In a large-scale transit system, a deadhead trip can be inserted into two adjacent trips to reduce the number of buses used. Recently, because of the growing competition in public transport markets, guaranteeing an adequate service level has become crucial for public transport companies. Many surveys have reported that punctuality is important to bus passengers and considered as one of the key reasons for people's dissatisfaction with bus services (e.g., Passenger Focus, 2014; Department for Transport of UK, 2011).

Traditionally, public transport companies complete vehicle scheduling several weeks before operations, with the objective of minimizing the planned total cost, including the fixed cost of vehicles and the variable cost for idle and travel times. However, on the day of operations, road traffic conditions could exhibit substantial uncertainty, due to unexpected demand surge and supply

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https://doi.org/10.1016/j.trc.2018.09.010
Received 8 November 2017; Received in revised form 23 August 2018; Accepted 12 September 2018
0968-090X/

disruptions, which may appear when road construction and traffic accidents occur (FHWA, 2006). Under stochastic trip times, a bus trip could be directly delayed because of traffic congestion. Moreover, it is also possible that a late arrival of a delayed trip causes a delayed start of its following service trip. In other words, delays can propagate along the adjacent trips fulfilled by the same bus. Consequently, this significant variability of road traffic conditions often makes travelers encounter start delays of service trips, which substantially degrades the performance of an urban transit system. To prevent delays in a transit system, buffer time can be introduced between different trips, which, however, will inevitably increase the bus's idle time and lead to the increase of the system's costs.

Nowadays, bus vehicles in many cities have been equipped with global positioning systems, which enable transit agencies to monitor real-time bus operations. Utilizing the information from this automatic vehicle location system (AVL), many studies have been conducted to enhance the control strategies of bus operations (e.g., Bie et al., 2015; Yu et al., 2016; Berrebi et al., 2017; Du et al., 2017). We envision that the rapid advances of information and communication technologies have also presented tremendous opportunities for intelligently scheduling a bus fleet. Specifically, on one hand, the data gathered through the AVL can substantially contribute to learning how different vehicle schedules affect the operations of a bus fleet under stochastic trip times. On the other hand, within an operations day, we gradually observe the actual arrival times of trips and can thus dynamically schedule the vehicles to fulfill subsequent trips. In practice, this dynamic vehicle scheduling demands an efficient and convenient communication between transit agencies and bus drivers, which is becoming technically feasible thanks to the advances of communication technology.

Stochastic dynamic programming (SDP) is considered to be particularly applicable to the problem of sequential decision making under uncertain conditions. With properly chosen state and decision variables, we are capable of formulating the stochastic dynamic VSP for dynamically scheduling a bus fleet. More specifically, in the proposed stochastic dynamic vehicle scheduling framework, each time vehicles are rescheduled, we take into account not only the bus fleet's operations within the current period but also the rescheduling's impact on the fleet's operations in the future, which is captured through a cost-to-go function. However, because of trip time stochasticity, the proposed SDP's state space's augmentation with uncertain travel times easily leads to "curse of dimensionality", which is widely cited as the Achilles heel of dynamic programming (e.g., Powell, 2007). To tackle this challenge, we adopt an approximate dynamic programming (ADP) approach where the cost-to-go function is approximated so that we are capable of stepping forward to make decisions and solving the Bellman's equation through sequentially solving multiple mixed integer linear programs.

The contributions of our paper include: (i) we investigate the multi-depot VSP under stochastic travel times with the full consideration of delay propagation phenomenon; (ii) this study is among the first groups to propose an ADP approach to tackle the trip time stochasticity, mitigate delays and minimize the total cost of a transit system, through dynamically scheduling vehicles; (iii) we do not pre-assume any probability distribution or scenario of trip times and delay propagation, and the impact of scheduling strategies on bus fleet operations under stochastic trip times is directly learned from the multi-day operational dataset; iv) we employ the realistic operations dataset of bus lines in Beijing to test our proposed framework, and it has been shown that our neural-network-based ADP approach not only exhibits a good learning behavior but also significantly outperforms both myopic and static polices.

For the remainder, Section 2 reviews the literature on VSP and ADP. Section 3 formulates the stochastic dynamic VSP. In Section 4, we propose the ADP framework. Section 5 employs the realistic dataset to demonstrate the effectiveness of the proposed ADP framework and derive important insights. Finally, Section 6 concludes the paper.

2. Literature review

2.1. Vehicle scheduling problems in public transport

A public transit planning process starts with collecting and forecasting passengers' demands. According to the demand matrices, local authorities then design the infrastructure of public transport networks and plan lines and their frequencies (timetables). Each trip on a timetable has its own departure and arrival times as well as start and end stations. Next, a public transport company schedules its vehicle fleet to cover these trips and assures that each scheduled trip is served by a unique vehicle, which is widely referred to as VSP. Finally, crew scheduling needs to be performed. It is desirable to plan all the activities above simultaneously for the purpose of maximizing the system's productivity and efficiency. However, because this planning process is extremely complex, especially for medium and large fleet sizes, it requires separate treatment for each activity, with the outcome of one fed as an input to the next (e.g., Ceder, 2007).

Vehicle scheduling has become an important research field for about 40–50 years (Bunte and Kliewer, 2009), which can be divided into two categories based on the number of depots. The single-depot vehicle scheduling problem (SDVSP) indicates that only one depot is considered, whereas the multiple-depot vehicle scheduling problem (MDVSP) considers that vehicles are stationed in multiple depots. In MDVSP, vehicles need to return to their start depots after a day's operation, and some trips have to be assigned to vehicles from a certain set of depots. The SDVSP is solvable in a polynomial time, and a large number of solution methods have been proposed (e.g., Saha, 1970; Gertsbach and Gurevich, 1977; Ceder, 2016). However, the MDVSP is proved to be NP-hard (Bertossi et al., 1987). Various strategies have been proposed to reduce the number of model variables, such as adopting the time-space diagram and column generation approach (e.g., Ribeiro and Soumis, 1994; Bodin et al., 1983). Both exact algorithms (e.g., Kliewer et al., 2006; Oukil et al., 2007) and heuristics (e.g., Ball et al., 1983) have been developed to solve MDVSP. We refer interested readers to Desaulniers and Hickman (2007) and Bunte and Kliewer (2009) for recent reviews.

As previously mentioned, travel time's uncertainty will inevitably cause the delay of service trips. In order to assure a satisfying service level for a bus system, transit system operators should consider delay cost. Huisman et al. (2004) adopted a quadratic function