Proceedings of 7th Transport Research Arena TRA 2018, April 16-19, 2018, Vienna, Austria

An integrated dynamic ridesharing dispatch and idle vehicle repositioning strategy on a bimodal transport network

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Abstract

In bimodal ridesharing, a private on-demand mobility service operator offers to drop off a passenger at a transit station, where the passenger uses the transit network to get to another transit station, and the service operator guarantees picking up the passenger to drop them off at the final destination. Such collaborations with public transport agencies present a huge potential to increase the ridership. However, most existing studies on dynamic dial-a-ride/ridesharing mainly focus on mono-modal cases only. We consider dynamic bimodal ridesharing problems where real-time information is available to anticipate future demand. A new non-myopic vehicle dispatching and routing policy based on queueing-theoretical approach is proposed and integrated with a non-myopic idle vehicle repositioning strategy to solve the problem. Several experiments are conducted to test the effectiveness of this integrated solution method and measure the benefit of bimodal cooperation. The proposed model and solution algorithm provides useful tools for real-time operating policy design of shared mobility.

Keywords: Mobility-on-demand; ridesharing;idle vehicle relocation; pickup and delivery; multimodal; transportation system

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1. Introduction

Collaborations between public transport agencies and private transport operators present a huge potential for leveraging the obstacles of using mobility-on-demand (MoD) services as suggested by the report (Murphy and Feigon (2016). Collaboration can be achieved by having the private service operator borrow the coexisting transit service's capacity to lighten the operating costs of its fleet of vehicles, as shown in Fig. 1. For example, when a passenger makes a request to a private service operator to be picked up from the "origin" to be dropped off at the "destination", the operator may choose to offer a bundled service option. Under this option, a vehicle would be dispatched to pick up the passenger and drop them off at an entry station in a transit system, where they would take it to get to an agreed upon exit station. Upon arrival, another vehicle would pick them up and drop them off at the final destination. It is a win-win strategy. The passenger gets a seamless service option in which a single fare is paid, likely at a much more discounted rate than if they were dropped off door-to-door by the operator (especially if the distance is far enough and well-served by an existing transit system). The transit system gets higher ridership and can serve riders that may typically be discouraged by the high last mile access costs. Lastly, the operator saves on operating costs for transporting along a path that is already well served by existing transit system capacity.

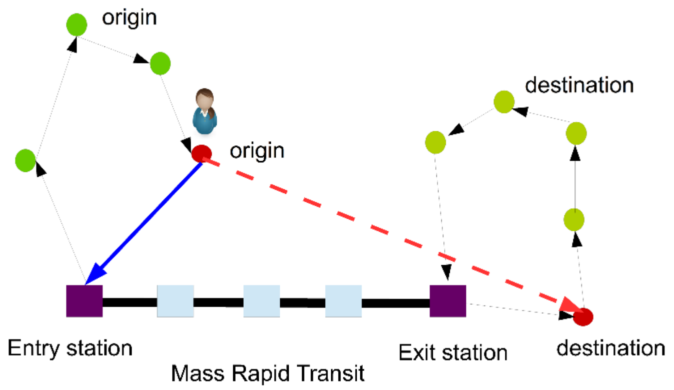

Fig. 1 Illustration of bimodal ridesharing in collaboration with a coexisting transit system

The collaborative system described does not currently exist as an option from private operators yet. However, collaborative partnerships between MoD services and mass transit systems are increasing in number particularly to address the last mile transit problem (Djavadian and Chow, 2017; Wang and Odoni, 2016). These initiatives suggest such partnerships can provide better connectivity and improve the efficiency and flexibility of the coexisting fixed-route transit service. Recently, multimodal ridesharing problems received increasing interests by considering vehicle operations policy design with collaboration of public transport services (Cangialosi et al., 2016; Liaw et al., 1996; Ma, 2017; Masson et al., 2014). In this perspective, Liaw et al. (1996) considered a bimodal dial-a-ride problem and proposed a linear mixed integer programming model to find optimal vehicle routes and schedules for paratransit service. Cangialosi et al. (2016) proposed a mixed integer linear programming model to find multimodal trips which minimize a cost function of riders' desired departure and arrival time deviation, number of intermadal transfers and number of matches between riders and drivers. Masson et al. (2014) considered a static dial-a-ride problem with the presence of a set of transfer points. They proposed an adaptive large neighborhood search metaheuristic to find approximate solutions. However, none of these studies anticipated future states of vehicles and future demand to desgin anticipative online vehicle dispatching and routing policy. For this issue, some authors proposed non-myopic vehcile dispathing using real-time information to anticipate future requests in vehicle dispatching and routing decisions (Bent and Van Hentenryck, 2004; Hyytiä et al., 2012; Ichoua et al., 2006; Sayarshad and Chow, 2015; Thomas, 2007, among others).

Another important issue is related to the idle vehicle relocation problem as it presents a considerable running cost for shared mobility systems (Sayarshad and Chow, 2017; Vogel, 2016). This issue has drawn increasing attention in recent years for shared mobility systems (Bruglieri et al., 2017; Nourinejad et al., 2015; Santos and Correia, 2015; Sayarshad and Chow, 2017). The idle vehicle relocation problem can be divided into two vast approaches according to whether or not the system anticipates future states for their relocation decision policy design. If the relocation decision policy anticipates future requests to look ahead, the policy is called non-myopic approach. In this perspective, Sayarshad and Chow (2017) proposed a non-myopic idle vehicle relocation policy based on a queueing-theoretical approach for real-time optimal idle vehicle relocation. The problem is formulated as a mixed integer linear programming (MILP) problem for which a Lagrangian decomposition (LD) heuristic is proposed. The result shows the non-myopic approach can significantly decrease system operating costs in comparison to myopic approaches using New York taxi data. Similarly, Zhang and Pavone (2016) proposed a queueing-theoretical model to rebalance idle vehicles for autonomous MOD systems in a network.

This is the first study to consider non-myopic dynamic dispatch that can assign two vehicles to a passenger by dropping the passenger off at a transit system. This is also the first study to integrate non-myopic dispatch and idle vehicle repositioning in a bimodal network. We study these two methodological contributions using computational experiments to provide insights on how to select algorithm parameters to obtain effective results. The rest of paper is organized as follows. Section 2 presents the methodology for solving non-myopic bimodal dynamic dial-a-ride problem. By extending classical mono-modal dial-a-ride problems, we consider possible bimodal paths using both dial-a-ride operating vehicles and transit services. A non-myopic queueing-theoretical based vehicle dispatching method is applied to take into account additional delays of on-board passengers. In Section 3, we propose a non-myopic idle vehicle rebalancing model to optimize idle vehicle relocation decision by considering delay in the system. Section 4 reports the numerical results of the proposed methods. Several scenarios related to myopic/non-myopic vehicle dispatching policy, variation of demand and idle vehicle relocation policy are tested. Finally, we conclude this study and pave the way to future extensions.

2. Non-myopic bimodal dynamic vehicle dispatching and routing policy

We consider a bimodal dynamic dial-a-ride problem with the presence of one operator for dial-a-ride services. The problem is modeled on a complete graph $G(N, E)$, where N is a set of nodes and E is a set of links. Each node represents the location of a pick-up/drop-off point of ride requests, assumed randomly distributed. Travel time t_{ij} is shortest path travel time from node *i* to node *j*. For each node $i \in N$, we assume request arrivals follow a Poisson process with arrival rate λ_i. Let μ denote the service rate of vehicles, representing number of served trip requests per time unit. Note that μ depends on operator's dispatching and routing policy, arrival rate of customers and vehicles' positions, etc. Both arrival and service rates may be updated over time in an online system. The operation of the system is assumed as follows.

- The operator uses a fleet of homogeneous capacitated vehicles $V = \{v_1, v_2, \dots, v_{|V|}\}$ to serve ride requests. A dispatching center makes decisions according to its operating policy for vehicle dispatching and route planning.
- Following past studied (Hyytiä et al., 2012; Sayarshad and Chow, 2015), we assume there is no time window constraints associated to the requests. All customers' requests need to be served. One can either extend the proposed method by including such constraints (e.g. maximum waiting time or delay of passengers, see Alonso-Mora et al. (2017)) to take into account customer inconvenience or demand elasticity or assume that the demand arrival rate would equilibrate accordingly.
- We consider a generalized bimodal dial-a-ride service in which an operator determines in real-time trip requests to be served by using operating vehicles only (direct trip) or by using both operating vehicles (as last mile feeders) and Mass Rapid Transit (MRT) services. For the latter case, we assume there are at most two intermodal transfers for a customer's origin-destination trip. No transfer is allowed between two different vehicles (Liaw et al., 1996). In this case, a customer initial request is then divided into three segments: a pre-transit trip (from origins to an entry station of MRT system), in-transit trip (from an entry stations to an exit stations), and post-transit trip (from an exit station to a customer's destination). Each pre-transit trip or post-transit trip is supported by one individual vehicle. Travel time estimation of in-transit trips can be based on the headway information of MRT service lines. For simplicity, the capacity constraint of MRT vehicles is not considered in this study.

The integrated algorithm and new contributions made are highlighted in Fig. 2. The strategy is initiated by three different events. Each time a new passenger makes a request, the system runs a nonmyopic dynamic dispatch that considers the option of loading passengers onto the transit system, using a proposed algorithm defined as **P1**. If the passenger is routed to a transit system, then when that passenger arrives at the exit station the service will run another dispatch algorithm (without the option of re-assigning to transit station), which is essentially the dynamic dispatch algorithm from Hyytiä et al. (2012). Vehicles that have completed their service become idle. Initiate **P2** at each idle vehicle relocation interval (e.g. 5 minutes) to determine an optimal zone to assign idle vehicles. The nonmyopic idle vehicle repositioning is based on the model proposed in Sayarshad and Chow (2017).

*4.1. **P1**: Non-myopic vehicle dispatching policy on a bimodal transport network*

The considered problem is a bimodal dynamic dial-a-ride problem in the presence of a MRT network. When a new request arrives, a decision needs to be made by considering passengers' origin-destination travel times over two options: a direct trip served by an operating vehicle or a bimodal trip served by using vehicles and the MRT system.

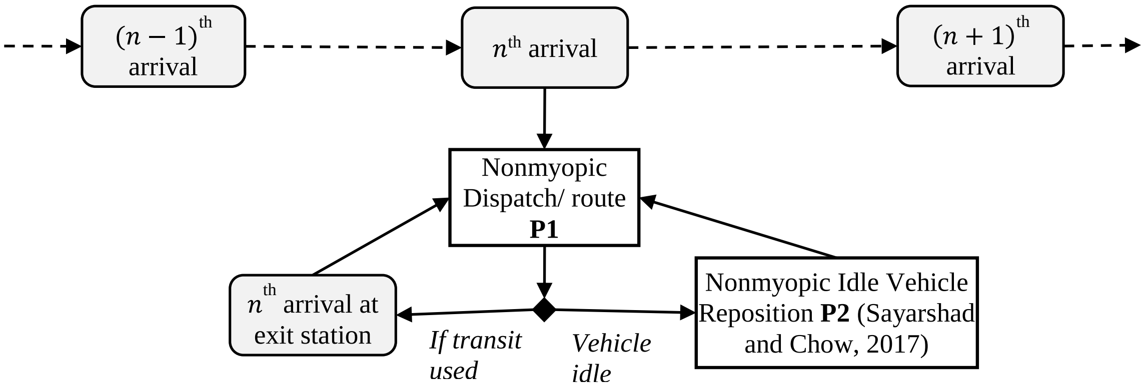

Fig. 2 Integrated strategy with functional components (rectangles) and initiating events (gray rounded rectangles)

We assume full compliance of passengers for the proposed routing policy of the operator. Given the pick-up and drop-off locations of requests, we propose a new non-myopic vehicle dispatching and routing approach derived from Hyytiä et al. (2012) for solving the dynamic DARP problem. In the new model, we also consider the option of routing to a transit station. Before explaining the new model, we provide an overview of the original model.

In the dynamic DARP, vehicles' dispatching and routing is updated in real-time to respond new arrival requests. To anticipate future states of the system and make optimal routing decision, Markov decision process provides a theoretical framework to model DARP and determines optimal operating policy under stochastic demand (Howard, 2007). Let x_t^v be the state of vehicle v at time t, characterized by the remaining route assigned to it. The state of all vehicles constitutes the state of the system at time t, denoted as x_t. The optimal assignment of a new arrival request to a vehicle can be formulated as the Bellman equation as follows (Howard, 2007; Sayarshad and Chow, 2015):

$$V_t(a_t) = \min_{x_t}(C_t(a_t, x_t) + \alpha E[V_{t+1}(x_{t+1})|x_t]) \quad (1)$$

where V_t is the negative value of operating policy at time t. C_t is the immediate cost of taking action a_t under current state x_t. $E[V_{t+1}(x_{t+1})|x_t]$ is the expected value of futre state x_{t+1}. α is a discount coefficient. The difficulty is determining the exact expected value of future states necessities full knowledge of future states of the system. As it is not possible to enumerate all possible future states conditioned on all possible actions to obtain exact expected value of $V_{t+1}(x_{t+1})$, several approximate methods have been proposed based on the approximate dynamic programming methods (Secomandi, 2001; Ulmer, 2017). However, these approximate methods tend to be limited to one or two step look-ahead (Sayarshad and Chow, 2015). Hyytiä et al. (2012) proposed an infinite horizon approximation of the expected value of future states of the system to solve the DARP. It has been shown the non-myopic vehicle dispatching and routing policy can effectively reduce overall operating cost and passengers' riding time (Hyytiä et al., 2012; Sayarshad and Chow, 2015), although poor performances can also be observed in some cases (Chow and Sayarshad, 2016). The non-myopic vehicle dispatching policy is based on minimizing additional insertion cost of a new request, taking into account approximate delay over long-term time horizon (Hyytiä et al., 2012) in Eq. (2).

$$\text{argmin}_{v,\xi}[c(v,\xi) - c(v,\xi')] \quad (2)$$

where ξ' is the current tour of vehicle v. ξ is a new tour after inserting a new request. $c(v,\xi)$ is a cost function taking into account steady state delay in the system, defined as Eq. (3).

$$c(v,\xi) = \gamma T(v,\xi) + (1-\gamma)[\beta T(v,\xi)^2 + \sum_{p\in P_v} Y_p(v,\xi)] \quad (3)$$

where $T(v,\xi)$ is the length (measured in time) of tour ξ. $Y_p(v,\xi)$ is service time (waiting time plus in-vehicle travel time) for passenger p. $T(v,\xi)$ is related to system cost. $\sum_{p\in P_v} Y_p(v,\xi)$ is related to customers' inconvenience. γ is a conversion coefficient between customer cost and system cost. β is the degree of look-ahead parameter: when $\beta = 0$, the methodology becomes purely myopic.

We use the re-optimization-based TSPPD insertion algorithm (Mosheiov, 1994) to solve the pick-up and delivery problem for a new tour $T(v,\xi)$. This algorithm first finds a minimum-cost Hamiltonian tour for all drop-off locations of on-board customers, and then inserts pick-up locations one-by-one with cheapest cost in the

Hamiltonian tour by satisfying a set of constraints. The latter includes: a) a passenger's pick-up point needs to be visited before its drop-off point (ordering constraint), b) number of passengers on board cannot exceed the capacity of vehicles. As we assume all passengers need to be served, there is no time window constraints associated with pick-up and drop-off times. The TSPPD algorithm first uses Christofides's heuristic (Christofides, 1976) to find an approximate of TSP (Traveling Salesman Problem) tour. The obtained solution guarantees a worse case of 1.5 times of cost of best tour. To improve the solution quality, a 2-opt local search (Croes, 1958) is applied. Note that one can apply the state-of-the-art heuristics to obtain better solutions for the DARP (Agatz et al., 2012; Parragh et al., 2010; Parragh and Schmid, 2013). Numerical studies showed using the non-myopic vehicle dispatching approach can effectively reduce total system operation cost and average passengers' riding time (Hyytiä et al., 2012; Sayarshad and Chow, 2015; Zhang and Pavone, 2016).

The proposed non-myopic vehicle dispatching and routing algorithm for solving bimodal dynamic DARP is described in Table 1. The proposed method considers both non-myopic vehicle dispatching policy and non-myopic idle vehicle relocation policy to reduce overall system operating cost and passengers' travel time in the system.

Table 1 Bimodal non-myopic vehicle dispatching and routing algorithm

1.	Upon arrival of a new request n, update positions and service statuses of every vehicle from the time of previous request $n-1$
2.	Compute a fastest option for request n. Two options are considered: direct trip and bimodal trip. For direct trip, travel time between origin and destination of a request is considered. For bimodal option, we first determine k-nearest MRT stations to the origin and to the destination of a request. Travel time on a bimodal path sums up travel time from origin to entry station, waiting time at entry station, in-transit travel time, waiting time at exit station, and travel time from exit station to destination. The least bimodal travel time is the least travel time path connecting origin and destination using one k-nearest entry station and one k-nearest exit station.
3.	Update the drop-off point of request n if that request uses a bi-modal option
4.	For each vehicle, compute a new tour by inserting the request n by the TSPPD algorithm (Mosheiov, 1994). Assign the vehicle with the non-myopic policy (eq. (2) and (3)).
5.	Update ξ_n as the new tour for that assigned vehicle, while keeping the other vehicles' tours the same as before.
6.	Allocate idle vehicles based on the idle vehicle assignment policy (described later) for each relocation time interval (5 min.)

3. P2: Idle vehicle relocation policy in M/M/k queueing systems

Table 2 Notation for the idle vehicle relocation problem

$\bar{N}$	Number of zones
λ_i	Arrival rate at zone i during last relocation epoch h-1, estimated by a three-step moving average method
μ_j	Service rate at zone j during last relocation epoch h-1, estimated by a three-step moving average method
t_{ij}	Travel time from zone i to zone j
r_{ij}	Relocation cost from zone i to zone j
B	Number of total idle vehicles at the beginning of epoch h (index h is dropped)
C_j	Maximum possible number of idle vehicles at zone j
y_j	Number of idle vehicles at zone j at the beginning of relocation epoch h (index h is dropped)
θ	A conversion scalar
ρ_α	Utilization rate constraints for a reliability level α
Decision variable	
W_{ij}	Flow of idle vehicle relocation from zone i to zone j for relocation epoch h (index h is dropped)
X_{ij}	Customers arrive at zone i served by idle vehicle at zone j if set as 1
Y_{jm}	m-th idle vehicle comes to serve customers located at zone j
S_i	Dummy variable representing the supply of idle vehicles from zone i
D_j	Dummy variable representing the demand of idle vehicles to zone j

For idle vehicle relocation, we model the problem as a multiple server location problem under stochastic demand (Sayarshad and Chow, 2017). We aim to rebalance the locations of idle vehicles given stochastic demand such that total rebalancing operation cost, customers' inconvenience (travel time) and queueing delay of customers are minimized. The idle vehicle rebalancing is executed at the beginning of each relocation time interval (e.g. 5 minutes). Let us divide the entire service region $\mathcal{A}$ into a number of zones. The objective is to determine flow of idle vehicles rebalancing from zone i to j for each relocation epoch. Note that for simplification of notation, we drop off relocation epoch index h since the problem is solved independently for each relocation epoch. The non-myopic optimal idle vehicle relocation model is stated as follows.

$$Z_1 = min \quad \sum_{i\in\bar{N}}\sum_{j\in\bar{N}}\lambda_i t_{ij}X_{ij} + \theta\sum_{i\in\bar{N}}\sum_{j\in\bar{N}} r_{ij}W_{ij} \tag{4}$$

Subject to

$$\sum_{j\in\bar{N}} X_{ij} = 1, \qquad \forall i \in \bar{N} \tag{5}$$

$$Y_{jm} \le Y_{j,m-1}, \qquad \forall j, m = 2,3,\ldots,C_j \tag{6}$$

$$\sum_{i\in\bar{N}} \lambda_i X_{ij} \le \mu_j \left[Y_{j1}\rho_{\alpha j1} + \sum_{m=2}^{C_j} Y_{jm}\left(\rho_{\alpha jm} - \rho_{\alpha j,m-1}\right)\right], \qquad \forall j \in \bar{N} \tag{7}$$

$$X_{ij} \le Y_{j1}, \qquad \forall i,j \in \bar{N} \tag{8}$$

$$\sum_{j\in\bar{N}}\sum_{m=1}^{C_j} Y_{jm} = B \tag{9}$$

$$\sum_{j\in\bar{N}} W_{ij} = S_i\,, \qquad \forall i \in \bar{N} \tag{10}$$

$$\sum_{i\in\bar{N}} W_{ij} = D_j\,, \qquad \forall j \in \bar{N} \tag{11}$$

$$S_j \le y_j, \qquad \forall j \in \bar{N} \tag{12}$$

$$-D_j - S_j - y_j + \sum_{m=1}^{C_j} Y_{jm} \le 0, \qquad \forall j \in \bar{N} \tag{13}$$

$$X_{ij} \in \{0,1\} \tag{14}$$

$$Y_{jm} \in \{0,1\} \tag{15}$$

$$D_j, S_j, W_{ij} \ge 0 \tag{16}$$

The objective function minimizes total travel time from idle vehicle locations to demand locations and total idle vehicle relocation cost. Eq (5) describes customers at zone i can be served by one and only one idle vehicle. Eq. (6) is an order constraint which states (m-1)-th idle vehicle is relocated before m-th idle vehicle. Eq. (7) is a delay constraint for an idle vehicle representing when a customer arrives at an idle vehicle, there will be no more than b other customers waiting on a line with a probability more than service reliability α. The higher the value of α is, the lower the queue delay for customers. Eq. (8) ensures the allocation of customers to only an idle vehicle. Eq. (9) ensures total available idle vehicles. Eq. (10) and (11) is the dummy variables representing the supply and demand of idle vehicle flows. Eq. (12) ensures initial available idle vehicles at node j must equal or greater than total relocated idle vehicles from j. Eq. (13) ensures total idle vehicle at node j after relocation must be equal or greater than total vehicles from j to serve customers. Eq. (14-16) are binary and non-negativity constraints. Note that given a user-defined reliability α, $\rho_{\alpha jm}$ of Eq. (7) represents the coefficient of the utilization rate constraint for reliability rate α, m servers (idle vehicles) and b customers in a queue, determined exogenously by finding the root of the following equation (Marianov and Serra, 2002, 1998; Sayarshad and Chow, 2017):

$$\sum_{k=0}^{m-1}((m-k)m!\,m^b/k!)\,(1/\rho^{m+b+1-k}) \ge 1/(1-\alpha) \tag{17}$$

The queue delay represents the non-myopic consideration, if we relax Eq. (7) the model becomes myopic.
For comparison purpose, we consider three alternative policies to allocate idle vehicles.

– Waiting policy: idle vehicles stay at their current positions until next customers arrive.

- Busiest zone policy: idle vehicles move to the busiest zone center (i.e. with highest customer arrival rate in average) with a probability of receiving at least one customer at the busiest zone higher than a threshold (Larsen et al., 2004). The threshold is randomly selected within the range of (0.5,1]. Note that the coordinates of zone centers are calculated based on the center of gravity method (Thomas, 2007).
- P2

4. Computational experiments

To test the effectiveness of the proposed strategy, we conduct a series of experiments on a test instance. The experiments are designed to validate the methodology, compare its performance against varying degrees of myopic strategies, and to evaluate the sensitivity of the strategy to different parameters. Note that we keep MRT system simple at the current stage without simulating the transit time table and vehicle runs. As a result, the passengers' resulting wait times for next arrival train at the entry station is not taken into account.

4.1. Test instance

We consider a bounded region on a plan within a limited square (-10,-10)×(10,10), representing a 20 km × 20 km area shown in Fig. 3. The entire region is divided into 16 identical zones. Ride requests are assumed uniformly distributed in the region following Poisson process for customers' arrivals with different scenarios. The dispatching center uses a fleet of capacitated vehicles for real-time dial-a-ride service requests. All vehicles are initiated at the center depot (0, 0). The fleet size is 40 vehicles. The maximum capacity of vehicle is 4 passengers/vehicle. Vehicle speed is set as 36 km/hr. For transit system, a simple network with two transit lines interconnected via a central station, each line has 11 stations evenly spaced apart. We assume the speed of train is 80 km/hr, and there is no capacity constraint of trains.

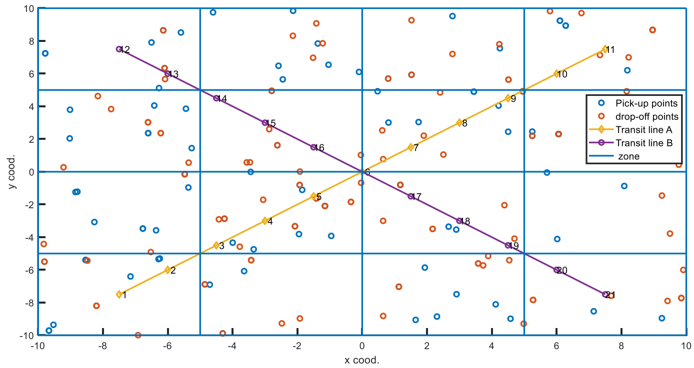

Fig. 3 The test instance for bimodal dynamic dial-a-ride problem

Two performance metrics are used to measure the performance of the proposed methodology: average travel length of vehicles (system operating cost) and average riding time per passenger (passengers' inconvenience). The simulation period is set as 2 hours for all the experiments. The implementation is based by MATLAB using the discrete event simulation technique and the mixed-integer linear programming solver in the Optimization toolbox. The test data contains inter-arrival times of customers, x-y coordinates of pick-up and drop-off points of each request, and the coordinates of the transit stations. The test instance is publicly available on the author's open data library: https://github.com/BUILTNYU and https://github.com/MOBILITY-LISER.

4.2. Experiment 1: influence of look-ahead parameter β for the non-myopic vehicle dispatching policy

Two policy parameters γ and β influence the performance of non-myopic policy in Eq. (3). γ is a trade-off parameter to arbitrate by the operator between operating cost and customers' inconvenience. β is related to the degree of look-ahead in vehicle dispatching, which needs to be calibrated in order to find an adequate value (Hyytiä et al., 2012). Therefore, we set $\gamma = 0.5$ and focus on the test of the influence of β on system performance. We set four sets of data points of β as [1:10]*0.03268, [1:10]* 0.003049, [1:10]*0.0003198, and [1:10]*0.00003153. Note that the reference value 0.03268 is the inverse of mean vehicle travel length. The result in Fig. 4 shows non-myopic vehicle dispatching policy with non-zero β value can effectively improve the system performance.

4.3. *Experiment 2: Influence of policy parameter θ on the performance of idle vehicle relocation*

We test the influence of idle vehicle relocation policy parameter θ (Eq. (4)) on the system performance for arrival intensities of 5/12 and 10/12 customers/minute, respectively. The data points for θ are set from 0 to 1 with an interval of 0.1. The result in Fig. 5 indicates using a small value (0.1 or 0.2) of θ has better performance.

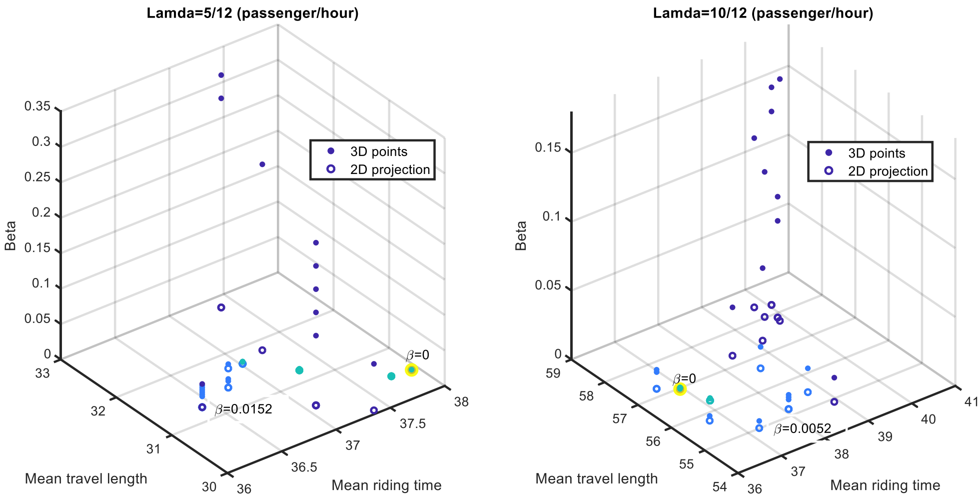

Fig. 4 Influence of policy parameter β on the performance of the system with respect to different customer arrival intensity

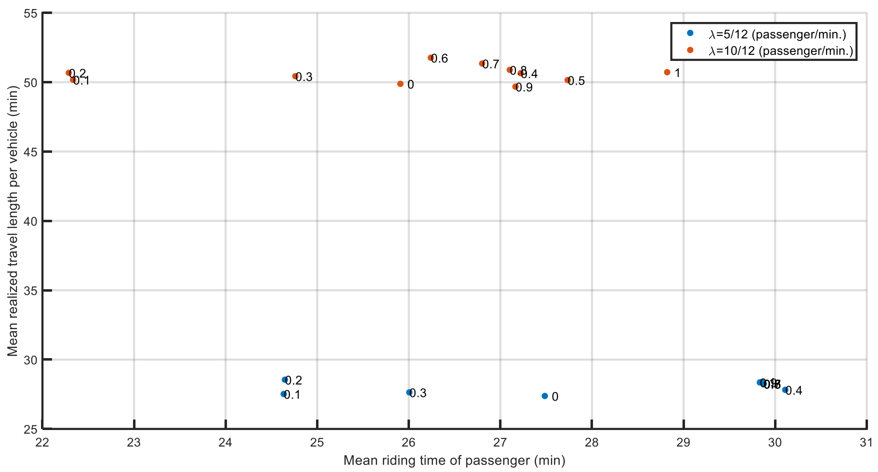

Fig. 5 Influence of policy parameter θ on the performance of idle vehicle relocation

4.4. *Experiment 3: Influence of server utilization rate coefficient ρ_α on the performance of the system*

We test the influence of server utilization constraint coefficient $\rho_{\alpha jm}$ on the performance of non-myopic idle vehicle relocation. 10 data points of $\rho_{\alpha jm}$ are tested: 1.$(\rho_{0.05,j,40}, b = 0)$; 2.$(\rho_{0.05,j,40}, b = 2)$; 3.$(\rho_{0.25,j,40}, b = 0)$; 4.$(\rho_{0.25,j,40}, b = 2)$; 5.$(\rho_{0.5,j,40}, b = 0)$; 6.$(\rho_{0.5,j,40}, b = 2)$; 7.$(\rho_{0.75,j,40}, b = 0)$; 8.$(\rho_{0.75,j,40}, b = 2)$; 9.$(\rho_{0.95,j,40}, b = 0)$; 10.$(\rho_{0.95,j,40}, b = 2)$. We test four arrival intensities as 5/12, 10/12, 20/12, and 40/12 customers/minute. The idle vehicle relocation policy parameter θ is set as 0.2 based on the result obtained in Section 4.3. The result in Fig. 6 shows that using ($\rho_{0.25,j,40}$ with $b = 2$) (label '4' in the figure) has best system performance for non-myopic idle vehicle relocation for three scenarios $\lambda = 10/12$, 20/12 and 40/12. For $\lambda = 5/12$, $\rho_{0.25,j,40}$ with $b = 2$ has very close performance as the best performance ($\rho_{0.05,j,40}$ with b=2). Therefore, we retain $\rho_{0.25,j,40}$ with $b = 2$ to set up Eq. (7) for non-myopic idle vehicle relocation for the experiment 4.

4.5. *Experiment 4: Influence of different vehicle dispatching and idle vehicle relocation policy on the system performance*

Finally, we evaluate the influence of different vehicle dispatching policy and idle vehicle relocation policy on the system performance. Five scenarios are tested as follows: 1. Mono-modal operating policy: using operating vehicles only, no collaboration with transit services; 2. Bimodal operating policy without idle vehicle relocation policy: we use the bimodal non-myopic vehicle dispatching and routing algorithm (Table 1) without idle vehicle

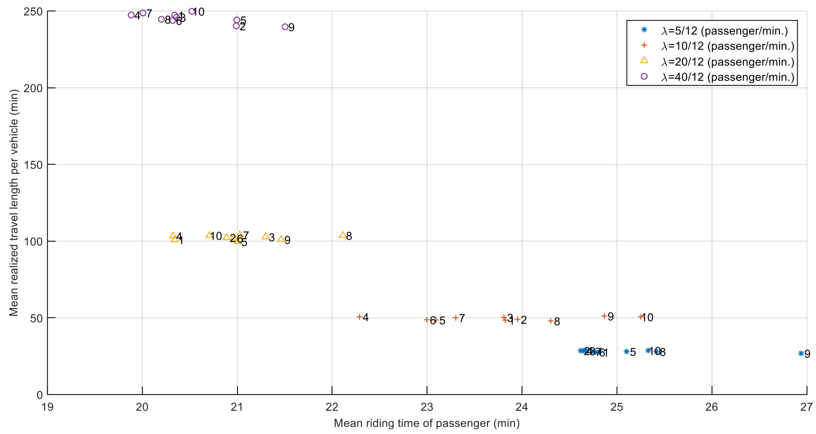

Fig. 6 Influence of $\rho_{\alpha jm}$ on the performance of the system with respect to different customer arrival intensity

relocation. 3. Bimodal operating policy with busiest zone idle vehicle relocation policy; 4. Bimodal operating policy with myopic idle vehicle relocation policy: we relax the queuing delay constraint (Eq. 7) for idle vehicle relocation; 5. Bimodal operating policy with non-myopic idle vehicle relocation policy. We use non-myopic idle vehicle relocation model to rebalance idle vehicles. The policy parameter $\rho_{\alpha jm}$ is obtained by finding the root of Eq. (17) with $\alpha = 0.25$ and b=2 for m=1,…,40 (fleet size in the experiments). The other parameters are set as follows:$\gamma = 0.5$, β is set between 0.000737 and 0.0152 for different arrival intensities of different scenarios. The idle vehicle relocation policy parameter θ is set as 0.2. We test the five scenarios with respect to different arrival intensities. The result in Fig. 7 shows bimodal non-myopic vehicle dispatching and non-myopic idle vehicle relocation policy (label ‘5’ in the figure) has best performance for different arrival intensities.

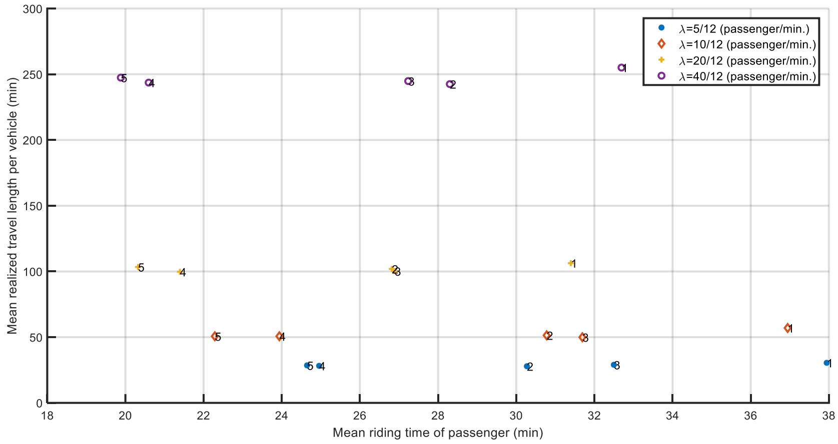

Fig. 7 Influence of vehicle dispatching and idle vehicle relocation policy on the performance of the system

5. Conclusions

In this study, we propose a non-myopic bimodal real-time vehicle dispatching algorithm with idle vehicle relocation to improve operating cost and passengers' riding time on a bimodal network. The proposed non-myopic method is based on a queueing-theoretical approach which estimates the queue delay over infinite horizon. For idle vehicle relocation, we propose a mixed integer linear programming model to take into account customer's travel cost to the server (idle vehicle), spatial queueing delay and relocation cost. The numerical study shows the proposed non-myopic approach in both vehicle dispatching and idle vehicle relocation outperforms the myopic one as well as non-relocation policy and busiest-zone based relocation policy. Moreover, the numerical study shows that bimodal collaboration improves the system performance when using only operating vehicles only. Future extensions includes simulating the transit time table and vehicle runs of the MRT system and using open taxi data and transit networks in New York City to test the performance of the proposed method with real data.

Acknowledgements

The work was supported by the Luxembourg National Research Fund (INTER/MOBILITY/17/11588252), under the MoDLux project (Developing mobility-on-demand solutions for sustainable mobility- the case of Luxembourg). Two of the co-authors were supported by NSF grant CMMI-1634973.

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