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## On dynamic demand responsive transport services with degree of dynamism

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The operation of a demand responsive transport service usually considers advanced and real-time requests. Previous studies focused on solution algorithms for routing and scheduling challenges of a pickup and delivery problem with time windows, but the operational issues of the overall system performance under a partially dynamic environment have not been investigated. In this article, we explore the operating efficiency of a dispatching system with a degree of dynamism (i.e. a ratio of dynamic requests). It is found that a dispatching system incurs higher transportation costs and accepts fewer requests when the request arrivals are partially dynamic, as compared to static or fully dynamic scenarios. Operational policies are derived for the dispatcher to avoid the inefficient range of degree of dynamism if future demand can be anticipated.

**Keywords:** degree of dynamism; demand responsive transport; dynamic; waiting strategies

### 1. Introduction

Demand responsive transport (DRT) is a form of shared-ride public transportation service that is responsive to the requests of passengers. Passengers are picked-up and dropped-off at specified locations within desired time windows, and the dispatcher plans routes and designs schedules for a fleet of vehicles starting at a common depot to provide transportation services. The problem is analogous to the Dial-a-Ride problem (DARP). A comprehensive review of this problem was given by Cordeau and Laporte (2003a, 2007). If the system accepts dynamic requests, the vehicle routes are updated and modified in real time and the system is dynamic. With the development of telematics and vehicle tracking, dynamic DRT has become more possible and has received greater attention in recent years. Fu (2002b) discussed the concepts and operations of the dial-a-ride transit system with offline and online scheduling.

The DARP problem is NP-hard with high complexity, and the solution algorithms can be divided into exact and heuristic approaches. The exact approach solves for the exact solution, and usually only works well for small-sized problems (Psaraftis 1980). When the number of requests is large, the problem may not be solvable for an exact solution in polynomial time, and heuristic methods are commonly derived to find approximate or

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near-optimal solutions in reasonable time. Some widely used heuristics for static problems are insertion heuristics (Jaw *et al.* 1986, Madsen *et al.* 1995) and regret insertion heuristic (Diana and Dessouky 2004). Metaheuristics have also been developed for certain problems (Cordeau and Laporte 2003b).

The solution approaches for dynamic problems are very different from those developed for static problems. The solution of a static problem is the sequence of requests to be visited and the routing of vehicle stops. In a dynamic setting, the schedule of a route, defining the arrival and departure times at each stop along the route, has to be determined. Some researchers have contributed to the model simulation and solution methodology in routing and scheduling problems, with the objective of increasing demand acceptance rates, improving levels of service and reducing operating costs (Fu and Tepy 1999, Fu 2002a, Coslovich *et al.* 2006). The passenger-oriented DRT problem also shares similar formulation with pick-up and delivery problems with time windows (PDPTW), which consider commodity transportation and allow for longer travel times and storage of up to several days. Berbeglia *et al.* (2010) gave a recent review on dynamic pickup and delivery problems, and pointed out that some properties and algorithms that are common between DARP and PDPTW.

For a dynamic dispatching problem, as the temporal pattern of the request arrivals is of concern, the scheduling of the routes is important to overall operating efficiency. Mitrovic-Minic and Laporte (2004) developed several waiting strategies to improve the scheduling of vehicles, taking into consideration the arrival of future requests. The main principle governing a waiting strategy is to hold a vehicle to wait at a location before dispatching to the next location, so as to increase the possibility of accepting a dynamic request and reduce the associated additional routing costs. Waiting strategies were also investigated for dynamic vehicle routing problems (Branke *et al.* 2005) and dynamic DARPs (Yuen *et al.* 2009). Pureza and Laporte (2008) proposed a vehicle waiting strategy and a request buffering strategy for PDPTW. While the waiting strategy delays the dispatching of vehicles, the request buffering strategy postpones the assignment of non-urgent requests to vehicles in later route planning. For the public transport system operation, Sáez *et al.* (2011) developed a real-time control strategy for transit where uncertain passenger demand was treated as a disturbance, and actions such as holding and expressing (station skipping) of transit vehicles were demonstrated to be effective. These headway control strategies can be effective if incorporated with arrival time prediction models for transit vehicles at stops (Yu *et al.* 2011).

Most of the previous studies assumed fully dynamic systems in which all requests are real-time and unknown, and few of them discussed the operation strategy when the demand arrival pattern is partially dynamic and predictable. Notably, Lund *et al.* (1996) defined the degree of dynamism (i.e. the ratio of immediate requests to the total number of requests for service) and categorised vehicle routing problems for their impacts and responses. Residential utility repair services are classified as weakly dynamic, whereas taxi services and emergency services are strongly dynamic. With the degree of dynamism increasing, the problematic objective shifts from travel cost minimisation toward response time minimisation (Larsen *et al.* 2002).

Recently, there have been several studies into quantifying the value of information and anticipation of future requests (Ichoua *et al.* 2006, Tjokroamidjojo *et al.* 2006). Diana (2006) considered several characteristics of the information flow, including the percentage of real-time requests, the interval between call-in and requested pickup time and the length

of the computational cycle time, in evaluating the effectiveness of how the input is revealed to the algorithm in dynamic systems. Schilde *et al.* (2011) studied a partially dynamic DARP in which an outbound request could cause a corresponding inbound request on the same day. Based on historical data, such stochastic information can be predicted, and they investigated whether this information can be utilised in designing vehicle routes. It was shown that a short look-ahead period of arrival information would be effective (20 min in their case), leading to an average improvement of 15%. These studies suggested that how future requests presenting themselves in dynamic systems should be taken into account in the design of solution algorithms.

The objective of this article is to explore a partially dynamic DRT problem and its operational efficiency under different levels of degree of dynamism, which can represent a form of information regarding future request arrivals. Operational policies such as decisions on vehicle fleet size control and rejection of requests are also proposed, when the arrival of future requests can be anticipated. This article is organised as follows. The problem definition is given in Section 2. Heuristics for the routing and scheduling problems are described in Section 3. Numerical experiments and simulation results are given in Section 4 to explore the problem under several scenarios. Finally, we discuss the findings and implications for the dispatcher and the operator of the DRT system in Section 5.

## 2. Definition of the DRT problem

The DRT problem is a dynamic passenger pick-up and delivery problem. The static version of the problem can be stated as follows.

- *Request*: Each request  $i$  is characterised by a pickup location ( $O_i$ ), a delivery location ( $D_i$ ) and a desired pickup time ( $DPT_i$ ).
- *Maximum ride time*: The maximum ride time ( $MRT_i$ ) is the maximum time that a passenger takes to arrive at the delivery location, and can be determined with:

$$MRT_i = \max(\beta + \alpha \times DRT_i, DRT_i + WS), \tag{1}$$

where direct ride time ( $DRT_i$ ) is the direct travel time from  $O_i$  to  $D_i$ , and  $\alpha$ ,  $\beta$  and  $WS$  are parameters specified by the dispatcher for service quality. The parameters  $\alpha$  and  $\beta$  represent the urgency of the transportation services to be provided to the passenger and  $WS$  is the maximum acceptable time that a passenger needs to wait at the pickup location.

- *Request time windows*: Denote the time window of request  $i$  at the origin as earliest pickup time ( $EPT_i$ ) and latest pickup time ( $LPT_i$ ), and denote the time windows at the destination as earliest delivery time ( $EDT_i$ ) and latest delivery time ( $LDT_i$ ). Based on the desired pickup time specified by the request and the service quality parameters specified by the dispatcher, the time windows can be determined with the relations given below and are illustrated in Figure 1:

$$EPT_i = DPT_i, \tag{2}$$

$$LPT_i = EPT_i + WS, \tag{3}$$

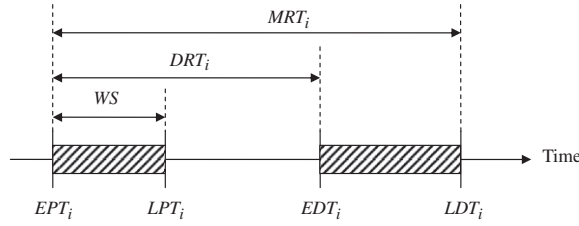


Figure 1. Determining the time window of a request.

$$EDT_i = EPT_i + DRT_i, \quad (4)$$

$$LDT_i = EPT_i + MRT_i. \quad (5)$$

- *Vehicles*: A fleet of identical uncapacitated vehicles are dispatched to satisfy the requests, and each vehicle travels along a single route starting and ending at the same depot.
- *Objective*: The objective of the dispatcher is to design the routes and schedules for the vehicle fleets to satisfy the requests, with the objective of minimising, in the order of importance, (a) the number of vehicles and (b) total travel distances of all vehicles.

The above definitions and settings were used by Jaw *et al.* (1986) and Diana and Dessouky (2004) for static problems.

In the dynamic version of the problem, a number of real-time requests, which are not known to the dispatcher at the time of planning, are revealed gradually over time. All real-time requests are assumed to be immediate requests, to be picked up as soon as possible. When a new request appears, the objective of the problem is to assign this request to a vehicle and serve it at minimum additional cost. This setting of the problem simulation assumes that all passenger requests must be satisfied and that there is no upper limit for the number of vehicles. Another problem setting is that the dispatcher aims to maximise the number of accepted requests if the maximum number of vehicles is fixed and passenger requests can be rejected.

### 3. Heuristics algorithms

A heuristics framework for the DRT service problem is presented in this section. The insertion of requests involves a routing algorithm and a scheduling algorithm. The routing algorithm is the procedure used to decide the sequence of requests to be visited and the insertion of service stops along a vehicle route, while the scheduling algorithm is for determining the arrival and departure times of the stops along the route.

#### 3.1. Mode of operation

In a partially dynamic environment, the dispatching system accepts both static and dynamic requests. The advanced requests are received before the day of operation, and

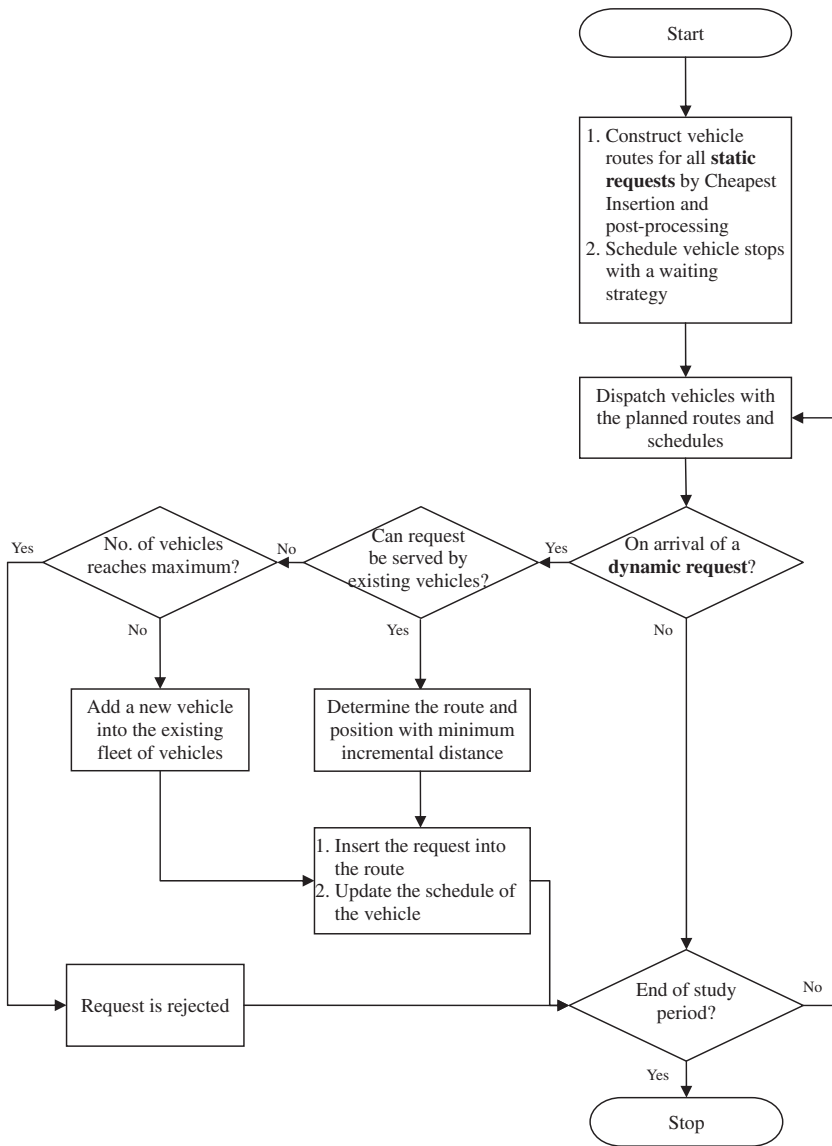


Figure 2. Flow chart of the dispatching operation.

vehicle routes and schedules are initially constructed. During the day of operation, the vehicles are dispatched according to the planned routes and schedules. When a real-time request is received, the dispatcher inserts it into the existing vehicle routes with minimum incremental costs. If the vehicles cannot feasibly accept the request, a new vehicle is dispatched for service, or the request is rejected. Each request insertion will modify the route and schedule of the vehicle for all unvisited stops. As time goes by, the vehicle routes are dynamically updated and the vehicle drivers are informed of their next destinations. The flow of the operation is described in Figure 2.

### 3.2. Routing algorithm

Let  $i \in N_s$  and  $i \in N_d$  be the sets of static and dynamic requests, respectively, and  $k \in K$  be the set of the vehicle fleet. The routing sub-problem assigns the pickup location  $O_i$  and the drop-off location  $D_i$  of request  $i$  to the route of vehicle  $k$  with stop  $j \in J_k$ . In this study, the classic cheapest insertion (CI) heuristic method (Jaw *et al.* 1986) is adopted. CI is a quick and simple algorithm, and the basic procedure is to assign each request sequentially into a vehicle route for a minimum cost. For each request  $i$ , each vehicle  $k$  is examined for all feasible ways in which the request can be inserted into the route of the vehicle, and the corresponding additional costs are recorded. The request is then inserted into the vehicle at a point where costs are minimised. If it is infeasible to insert the request into any existing vehicles, a new vehicle is added or the request is rejected. Details and extensions of the algorithm can be found in Diana and Dessouky (2004). Vehicle capacity constraints can also be considered in the route construction. However, in the case of the passenger transportation problem, vehicle capacity is not binding in all tested instances, since the feasible solutions are constrained by time window requirements which are relatively stronger (Wong and Bell 2006).

The advantage of insertion heuristics is its high computational efficiency. It is also suitable for dynamic requests since decisions regarding request acceptance and route updating have to be made with a quick response. However, CI is myopic and the solution may be enhanced when extra computing time is allowed. Therefore, the solution of static problems based on CI can be further improved by using a post-processing phase. Several post-processing schemes were suggested by Toth and Vigo (1997). In our study, an exchange-based procedure is employed after all static requests are inserted, and we iteratively remove a planned request from its route and find the best position for reinsertion with a smaller overall cost among all feasible routes. Each move of request removal and insertion should reduce the total distance travelled. The procedure is also able to reduce the number of vehicles used by merging a short route into another route.

Real-time passenger requests are usually immediate. When a call is received, a vehicle must be assigned without a buffer time or the call is rejected. In dynamic implementation, CI simply assigns the real-time request to a feasible position in an existing route for minimum additional costs. However, we do not reorder the unserved static requests, which have already been assigned to vehicle routes. This is because reshuffling pre-planned requests between vehicles is computationally time-consuming, and in some operations, the license plate number of the vehicle is notified to the passengers for security reasons if the appearance of vehicle fleets is not unique.

### 3.3. Scheduling algorithm

Once the sequences of stops to be visited in a route are determined using the routing algorithm, the scheduling strategy determines the arrival and departure times for each stop. With the sequence of stops in a route, we convert the request time windows (i.e.  $[EPT_i, LPT_i]$  for the pickup location and  $[EDT_i, LDT_i]$  for the drop-off location) into the service time window  $[a_j, b_j]$  for each stop  $j$  of the vehicle route. The service time window is the constraint acting on the scheduling problem, and the algorithm determines the arrival time  $A_j$  and the departure time  $D_j$  at stop  $j$ , which must overlap the service time window in order to satisfy the time window constraints of requests. Figure 3 illustrates a feasible

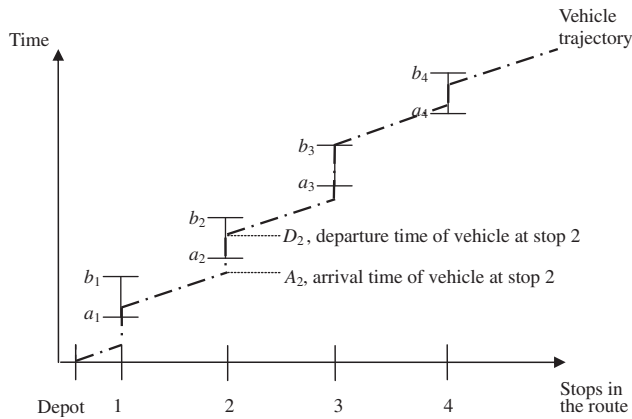


Figure 3. Trajectory of a vehicle with service time windows and arrival and departure times at stops.

vehicle trajectory, which passes through the service time windows for all stops. The schedule is not unique, and the dispatcher has the flexibility to allocate the idle times of the vehicle to different stops for the same travel distances.

The possibility of accepting a dynamic request is dependent on the schedule of the route, and several scheduling algorithms are introduced and compared. Three waiting strategies, namely the Drive First (DF) strategy, the Wait First (WF) strategy and the Modified Dynamic Wait (MDW) strategy, are employed in this study. These waiting strategies were presented in Yuen *et al.* (2009) for the dynamic DARP, and they are briefly described below.

**DF strategy:** Dispatch a vehicle to depart from its current location to the next location immediately after the current location is serviced.

**WF strategy:** Hold a vehicle to wait at its current location for the longest feasible duration, provided that subsequent stops in the route can be serviced without violating the service time window constraints.

**MDW strategy:** Hold a vehicle to wait at its current location for a duration before dispatching, such that the vehicle can reach the next location at the beginning of its service time window and the location can be immediately serviced without waiting.

Computing steps and pseudo codes for the three waiting strategies are given in the Appendix. It is noted that the two extreme strategies DF and WF represent the lower bound and upper bound of feasible scheduling, i.e. the earliest possible arrival and latest possible departure times for all stops without violating the service time window constraints. Any schedule between the lower and upper bounds is feasible.

Both DF and WF are intuitive dispatching rules, and it has been shown that the DF solution requires longer travel distance but fewer vehicles as compared to WF (Mitrovic-Minic and Laporte 2004, Yuen *et al.* 2009). With DF, a vehicle only waits at locations which are not serviced (i.e. the service time window has not started). So when a vehicle is idle and a dynamic request is received, the vehicle diverts to the new request pickup and returns to the previous location which has not yet been serviced. This diversion may incur



extra travel distances. MDW is a modification of DF by holding the vehicle at the current served location for a certain duration before dispatching it to the next planned location, and waiting times should only be allocated to locations after service but not before service. Therefore, a schedule employing the MDW strategy is expected to increase the feasibility of accepting a future request and reduce travel distances.

## 4. Numerical experiments

### 4.1. Simulation settings

To explore the effect of system dynamism of request arrivals on the operating efficiency, the degree of dynamism (dod) is used as an index throughout the numerical simulations. The degree of dynamism is defined as the ratio of the number of dynamic requests to the number of total requests in the system:

$$\text{dod} = \frac{\text{Number of dynamic requests}}{\text{Number of total requests}}, \quad (6)$$

in which the number of total requests is the sum of the number of advanced requests and the number of dynamic requests received within a study period.

In the simulation, we generate passenger requests with several assumptions. The attributes of the passenger requests are randomly generated, such that the pickup and delivery locations are uniformly distributed over a service area of  $20 \times 20 \text{ km}^2$ , and the desired pickup time follows a Poisson distribution over a study period of 480 min. The arrivals of the static and dynamic requests are independent, and given a number of total requests and a dod, the number of static requests and dynamic requests are determined. All of the requests of each type are Poisson arrivals over the study period, and therefore the inter-arrival times of the requests are exponentially distributed with a mean equal to the study period divided by the number of requests of that type.

A constant vehicle speed of  $30 \text{ km h}^{-1}$  and Euclidean distances are assumed in calculating the travel times between locations. To determine the time windows of requests, the parameters  $\alpha$ ,  $\beta$  and WS in Equation (1) are assumed to be 2, 20 and 30 min, respectively. The simulation result shows that the maximum number of passengers on a vehicle at the same time is not greater than 5, and therefore, for a vehicle with a seating capacity of eight seats, it is equivalent to assuming that the vehicles are uncapacitated.

To average out the effects of randomness in request generation, we randomly generate 30 instances with different seat numbers for each problem scenario, and present averaged results of all solutions found for each instance. When we compare the results of the three waiting strategies, the problem instances to be solved by each strategy are identical. Using a PC with an Intel Quad 2.4 GHz processor and 4 GB memory, it takes approximately 2 min to solve a problem instance with 1000 requests, and a problem instance with more static requests will take a longer computational time due to post-processing for static route improvement. On average for all scenarios solved, the post-processing phase improves the solutions by 3.1% for vehicles used and 5.2% for travel distances.

## 4.2. System efficiency and degree of dynamism

We are interested in investigating the efficiency of dispatching strategies and the characteristics of the system under different scenarios in a partially dynamic environment. Two types of simulation analysis are performed. The first simulation is to evaluate the costs of the dispatching systems in order to fulfil a certain number of requests, and the second simulation is to determine the number of requests that can be accepted for a fixed number of vehicles.

### 4.2.1. System costs

For a fixed number of total requests received in the study period, we vary the dod from 0% to 100% to generate different numbers of static and dynamic requests. We also vary the number of total requests at a demand level of 100, 500 and 1000 to see the behaviour of the system under different operation scales. The problems are solved using DF, WF and MDW for scheduling. The incurred system costs, including number of vehicles and travel distances, are shown in Tables 1–3 for different demand levels.

We first compare the performances of the DF, WF and MDW strategies. In general, the results in Tables 1–3 show that the number of vehicles required by the MDW and DF are about the same. MDW requires less distances compared to DF in almost all cases, which is indicated by negative values in the MDW versus DF column in the table, ranging from  $-1\%$  to  $-3\%$ . Furthermore, WF requires more vehicles compared to DF and MDW for all demand levels, which is indicated by positive values in the WF versus DF column and a negative value in the MDW versus WF column. However, WF requires much less distances for the low demand case (i.e. 100 requests), which implies that WF can be useful when the demand intensity is low and the inter-arrival time between request arrivals is large.

We also look at the number of vehicles and distance travelled at different levels of dod for each of the strategies. For the case of 100 demand requests, as shown in Table 1, the required vehicles and distances are generally increasing for dods of 0% to 60%, and then the values fluctuate slightly for dods of up to 100%. The solutions for the three waiting strategies show similar trends. At a demand level of 500, as seen in Table 2, the number of vehicles and the distance travelled increase from a dod of 0% up to a peak at 70% (for DF and MDW) and 80% (for WF), and decrease afterwards. Specifically, for the MDW strategy, both  $\text{veh}(\text{dod}=100\%)$  and  $\text{dist}(\text{dod}=100\%)$  are about 5% less than  $\text{veh}(\text{dod}=70\%)$  and  $\text{dist}(\text{dod}=70\%)$ , respectively. This phenomenon also exists at the high demand level of 1000 requests.

Suppose that pre-booking is a piece of information available in advance. For a fixed number of requests, an increase in the dod means fewer requests are known beforehand and therefore less information is known to the system. Therefore, a common intuition that ‘more resources are needed when less information is known’ (and vice versa) does not apply in this situation, as less vehicles and distances (less resources) are needed when there are more dynamic requests (less information) in the fully dynamic case. In this study, we name this observation the ‘*dilemma zone*’ of the degree of dynamism for describing this counter-intuitive phenomenon. When the system is highly (but not fully) dynamic, there are some pre-booking requests assigned to the routes. A route with assigned stops will be less flexible for rerouting, and the detour to accept dynamic requests is constrained by the locations and time windows of the assigned stops. In contrast, in a fully dynamic system,

Table 1. System costs against the dod for experiments with 100 requests.

dod (%)	DF		WF		MDW		WF versus DF (%)		MDW versus DF (%)		MDW versus WF (%)	
	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.
0	6.83	1130.80	6.83	1130.80	6.83	1130.80	0	0	0	0	0	0
10	7.47	1205.77	8.07	1188.66	7.40	1190.83	8.03**	-1.42**	-0.94	-1.24**	-8.30**	0.18
20	7.63	1277.18	8.40	1245.09	7.70	1264.01	10.09**	-2.51**	0.92	-1.03**	-8.33**	1.52**
30	8.20	1373.95	9.27	1291.17	8.13	1346.44	13.05**	-6.02**	-0.85	-2.00**	-12.3**	4.28**
40	8.23	1408.84	9.90	1323.76	8.17	1361.65	20.29**	-6.04**	-0.73	-3.35**	-17.47**	2.86**
50	8.60	1463.05	10.07	1330.31	8.70	1428.63	17.09**	-9.07**	1.16	-2.35**	-13.60**	7.39**
60	8.70	1488.08	10.53	1367.46	8.63	1456.39	21.03**	-8.11**	-0.80	-2.13**	-18.04**	6.50**
70	8.50	1532.66	10.73	1388.47	8.60	1494.73	26.24**	-9.41**	1.18	-2.47**	-19.85**	7.65**
80	8.67	1531.72	11.03	1373.32	8.53	1502.26	27.22**	-10.34**	-1.61	-1.92**	-22.67**	9.39**
90	8.73	1556.73	10.80	1367.86	8.53	1525.28	23.71**	-12.13**	-2.29	-2.02**	-21.02**	11.51**
100	8.60	1538.55	11.03	1339.02	8.60	1539.06	28.26**	-12.97**	0.00	0.03	-22.03**	14.94**

Notes: \*Significantly different between the two strategies at 90% level of confidence.

\*\*Significantly different between the two strategies at 95% level of confidence.

Table 2. System costs against the dod for experiments with 500 requests.

dod (%)	DF		WF		MDW		WF versus DF (%)		MDW versus DF (%)		MDW versus WF (%)	
	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.
0	18.77	3784.43	18.77	3784.43	18.77	3784.43	0	0	0	0	0	0
10	21.00	4197.51	22.97	4192.04	21.00	4152.03	9.38**	-0.13**	0.00	-1.08**	-8.58**	-0.95**
20	21.83	4476.77	24.87	4409.73	21.73	4412.61	13.93**	-1.50**	-0.46	-1.43**	-12.63**	0.07
30	22.30	4632.59	25.87	4582.21	22.23	4554.84	16.01**	-1.09**	-0.31	-1.68**	-14.07**	-0.60**
40	23.00	4774.60	27.13	4754.86	22.87	4689.26	17.96**	-0.41	-0.57	-1.79**	-15.70**	-1.38**
50	22.63	4877.18	27.17	4854.57	22.80	4812.00	20.06**	-0.46**	0.75	-1.34**	-16.08**	-0.88**
60	22.87	4911.93	28.47	5012.85	22.70	4861.65	24.49**	2.05**	-0.74	-1.02**	-20.27**	-3.02**
70	22.97	4969.06	28.63	5005.46	23.20	4940.45	24.64**	0.73**	1.00	-0.58*	-18.97**	-1.30**
80	22.93	4966.97	28.73	5025.66	22.53	4895.37	25.29**	1.18**	-1.74	-1.44**	-21.58**	-2.59**
90	23.03	4869.43	28.67	4951.60	22.50	4825.07	24.49**	1.69**	-2.30*	-0.91*	-21.52**	-2.56**
100	21.97	4705.46	27.80	4802.33	21.97	4704.89	26.54**	2.06**	0.00	-0.01	-20.97**	-2.03**

Notes: \*Significantly different between the two strategies at 90% level of confidence.

\*\*Significantly different between the two strategies at 95% level of confidence.

Table 3. System costs against the dod for experiments with 1000 requests.

dod (%)	DF		WF		MDW		WF versus DF (%)		MDW versus DF (%)		MDW versus WF (%)	
	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.	Veh.	Dist.
0	30.80	6366.98	30.80	6366.98	30.80	6366.98	0	0	0	0	0	0
10	32.77	7021.39	35.93	7035.06	32.60	6937.32	9.64**	0.19	-0.52	-1.20**	-9.27**	-1.39**
20	33.73	7368.94	38.30	7435.71	33.67	7265.97	13.55**	0.91**	-0.18	-1.40**	-12.09**	-2.28**
30	34.27	7674.07	40.13	7803.05	34.30	7585.74	17.10**	1.68**	0.09	-1.15**	-14.53**	-2.78**
40	35.37	7914.23	41.70	8108.80	35.30	7817.05	17.90**	2.46**	-0.20	-1.23**	-15.35**	-3.60**
50	35.30	7977.75	42.97	8264.52	35.17	7894.65	21.73**	3.59**	-0.37	-1.04**	-18.15**	-4.48**
60	36.00	8072.53	43.53	8406.07	36.10	8000.17	20.92**	4.13**	0.28	-0.90**	-17.07**	-4.83**
70	36.30	8100.61	45.07	8554.40	36.10	8017.16	24.16**	5.60**	-0.55	-1.03**	-19.90**	-6.28**
80	35.73	8117.92	44.50	8625.83	35.70	8039.51	24.55**	6.26**	-0.08	-0.97**	-19.78**	-6.80**
90	35.50	7995.72	44.97	8597.63	35.50	7992.03	26.68**	7.53**	0.00	-0.05	-21.06**	-7.04**
100	34.13	7719.98	43.90	8255.08	34.17	7715.50	28.63**	6.93**	0.12	-0.06	-22.16**	-6.54**

Notes: \*Significantly different between the two strategies at 90% level of confidence.

\*\*Significantly different between the two strategies at 95% level of confidence.

vehicles without any pre-planned stops can be dispatched with higher flexibility. The results of the simulation also show that the dilemma zone phenomenon exists for all three strategies we employed, and thus we will focus on the MDW strategy in the following experiments.

#### 4.2.2. Requests acceptance rate

The dilemma zone can also be demonstrated by an experiment in which the vehicle fleet size is fixed and we evaluate the number of requests that can be accepted. This is closer to a real-world situation. Using the MDW strategy, we simulate the scenarios with 500 requests, assuming maximum vehicle fleet sizes of 10, 15 and 20, and the results are shown in Table 4. The range of maximum vehicle fleets is chosen because the number of vehicles required to satisfy all 500 requests is between 18.77 and 23.20 for different dods, as shown in Table 2.

As the maximum numbers of vehicles are less than the numbers required in Table 2, not all of the requests can be accepted. For instance, with only 10 vehicles, the dispatching system can only accept about 300 requests. The system can accept about 420 requests with 15 vehicles, and about 490 requests with 20 vehicles. In general, the number of accepted requests is higher when the dod is low, and the number decreases as the dod increases to 70% (for Max. Veh. = 20) and 80% (for Max. Veh. = 10 and 15). Consistent with the findings in the previous experiment, the system at full dynamism (i.e. dod = 100%) can accept more requests than a system at partial dynamism (dod = 80%) by about 1–5%. This supports our discussions on the dilemma zone.

The dilemma zone can also be explained by an analogous situation in the market for taxi services (Bell *et al.* 2005, Sirisoma *et al.* 2010), which can be considered as a special case of DRT without shared riding. A taxi driver has customer-searching behaviour aiming to maximise the profit (i.e. the occupied time). A driver is willing to accept a pre-booked request only if the customer demand is low. If the demand level is high, such that a taxi can pick up customers with ease, the driver may not accept pre-bookings as that would increase the customer searching cost (i.e. waiting time and vacant taxi movement).

#### 4.3. Scale of operation

We further explore the effects on costs due to changes in the scale of operations of the dispatcher, where the scale is defined as the number of static requests that the dispatcher typically receives in a day. For a given operation scale, a stress test is performed for the dispatcher to accept a certain number of dynamic requests, and the required additional costs are evaluated. This can be useful for the dispatching operator to evaluate the marginal operating costs to the system due to the dynamic requests, and to make decisions in adjusting the vehicle fleet size.

We approach this problem by answering the following question with a simulation: what is the additional cost to a dispatching system to accept another 100 unexpected dynamic requests, if the size of the system is designed for a given number of advanced requests? We simulate a scenario with different dods by varying the number of static requests  $N_s$  and the number of dynamic requests  $N_d$ . The scheduling is solved via the MDW strategy, and the results are displayed in Table 5. For instance, a dod of 40% would mean that the system accepts 150 requests in advance and 100 dynamic requests on the day

Table 4. Number of requests accepted against the dod for experiments with 500 requests at different maximum vehicle fleet sizes.

dod (%)	Simulation input						Max. Veh. = 10			Max. Veh. = 15			Max. Veh. = 20					
	$N_s$	$N_d$	Veh.	$N_s$	$N_d$	$N_{total}$	Veh.	$N_s$	$N_d$	$N_{total}$	Veh.	$N_s$	$N_d$	$N_{total}$	Veh.	$N_s$	$N_d$	$N_{total}$
0	500	0	10.0	326.9	0.0	326.9	15.0	465.1	0.0	465.1	18.6	499.8	0.0	499.8	20.0	500.0	0.0	500.0
10	450	50	10.0	319.3	10.1	329.4	15.0	434.4	25.4	459.8	19.9	450.0	48.2	498.2	20.0	400.0	95.8	495.8
20	400	100	10.0	306.0	21.4	327.4	15.0	395.0	57.2	452.3	20.0	400.0	143.7	493.7	20.0	350.0	191.9	491.9
30	350	150	10.0	288.1	34.5	322.6	15.0	349.0	91.3	440.3	20.0	300.0	241.9	490.6	20.0	250.0	290.0	490.0
40	300	200	10.0	267.5	51.6	319.1	15.0	299.9	131.8	431.7	20.0	200.0	339.7	489.7	20.0	150.0	390.6	490.6
50	250	250	10.0	241.4	75.6	317.0	15.0	250.0	178.1	428.1	20.0	100.0	442.6	492.6	20.0	50.0	442.6	492.6
60	200	300	10.0	198.3	110.2	308.5	15.0	200.0	219.7	419.7	20.0	0.0	495.0	495.0	20.0	0.0	495.0	495.0
70	150	350	10.0	150.0	150.4	300.4	15.0	150.0	268.5	418.5	20.0	0.0	495.0	495.0	20.0	0.0	495.0	495.0
80	100	400	10.0	100.0	192.7	292.7	15.0	100.0	317.6	417.6	20.0	0.0	495.0	495.0	20.0	0.0	495.0	495.0
90	50	450	10.0	50.0	242.9	292.9	15.0	50.0	372.1	422.1	20.0	0.0	495.0	495.0	20.0	0.0	495.0	495.0
100	0	500	10.0	0.0	308.3	308.3	15.0	0.0	436.1	436.1	20.0	0.0	495.0	495.0	20.0	0.0	495.0	495.0

Table 5. Extra numbers of vehicles and travel distances for accepting 100 dynamic requests at different operation scales.

dod (%)	$N_{total}$	$N_s$	$N_d$	Costs for all static requests		Additional costs for dynamic requests		Total costs	
				Veh.	Dist.	Veh.	Dist.	Veh.	Dist.
100	100	0	100	0	0	8.60	1539.06	8.60	1539.06
90	111	11	100	1.90	187.88	6.90	1477.00	8.80	1664.88
80	125	25	100	3.03	368.09	6.93	1410.99	9.97	1779.07
70	143	43	100	4.03	561.57	6.60	1404.75	10.63	1966.32
60	167	67	100	5.40	819.91	6.43	1345.64	11.83	2165.55
50	200	100	100	6.83	1130.80	6.03	1307.87	12.87	2438.67
40	250	150	100	8.63	1518.71	6.17	1308.71	14.80	2827.42
30	333	233	100	11.63	2130.66	5.70	1222.98	17.33	3353.64
20	500	400	100	16.40	3214.05	5.33	1198.56	21.73	4412.61

of operation. In addition to the operating costs of handing the advanced requests (8.63 vehicles and 1518.71 km), it would require an additional cost to handle the dynamic requests (6.17 vehicles and 1308.71 km).

The number of static requests can be used as an indicator of the scale of operations of the dispatcher. In general, as  $N_s$  increases, fewer additional vehicles and less distances are needed to handle the dynamic requests. This is because a system with a larger scale of operations (with a higher value of  $N_s$  relative to  $N_d$ ) has greater flexibility in its routes, and this reflects the economies of scale in the dispatching system. Therefore, a dispatcher with a large fleet size has a better capacity to lower its average cost to accept dynamic requests.

**5. Concluding remarks and implications**

In this article, we have investigated how the operational efficiency of a dynamic demand responsive transportation (DRT) system can be affected by the dynamism of demand arrivals. Contrary to fully dynamic dispatching and assignment problems, the DRT system studied is characterised by a partial dynamic environment, in which the dispatching operator accepts static (advanced booking) requests and dynamic (real-time) requests. For dynamic dispatching problems with medium to high intensity of demand, we identified the ‘dilemma zone’ of the degree of dynamism (dod). The transportation cost is not linear relative to the dod; instead, it is highest (and the request acceptance rate lowest) when the system is partially dynamic. In our numerical analysis, this inefficient peak was at around 70% dod, and this observation was consistent across several solution heuristics for the routing and scheduling problem.

The dispatching operator can potentially adjust the dod so as to reduce its transportation costs and increase the total number of requests to be accepted. The dod of the system can be increased by rejecting some static requests and accepting more dynamic requests. Similarly, the dod can be reduced by accepting more static requests and rejecting some dynamic requests. If the predicted dod is above the range of the dilemma



Table 6. Actions for the dispatching operator to avoid the dod dilemma zone.

Situation	Policies to avoid dilemma zone	Actions of operator
Approaching dilemma zone from a high dod	Increase dod by accepting fewer static requests	<ul style="list-style-type: none"> <li>• Set an upper bound for the number of static requests to be accepted</li> <li>• Reclassify the rejected static requests as dynamic</li> </ul>
Approaching dilemma zone from a low dod	Increase dod by accepting more dynamic requests	<ul style="list-style-type: none"> <li>• Attract more dynamic requests</li> </ul>
	Reduce dod by accepting more static requests	<ul style="list-style-type: none"> <li>• Attract more static requests</li> </ul>
	Reduce dod by accepting fewer dynamic requests	<ul style="list-style-type: none"> <li>• Keep existing fleet size by not adding new vehicles for dynamic requests</li> <li>• Reject dynamic requests if the system is full, or use rental vehicles (e.g. taxis) instead.</li> </ul>

zone, the operator can increase the dod by accepting fewer advanced calls, and reserve the vehicle capacity of the existing fleet for dynamic requests on the day of operation.

This is useful to operators with limited vehicle capacity to dispatch more efficiently when the arrivals of dynamic requests are more than expected. However, if the demand for dynamic requests is not high, one may reconsider the trade-off between the benefits gained from reduced operating costs and losses due to rejecting some requests. In practice, it may not be feasible to reject advanced requests from a policy viewpoint, and the dispatcher can turn those requests into dynamic ones and reconsider them for possible insertion later. It is worth noting that increasing dod by rejecting advanced requests is an unstable policy, as the average operation cost reduction observed between the dilemma zone and full dynamism was only 5%. In contrast, lowering the dod is a more attractive policy. If the predicted dod is close to the dilemma zone from below, the dispatcher can decrease the dod by rejecting some of the dynamic requests if the system is near capacity.

If the dynamic demand is not high enough, adding new vehicles for the service to accommodate a few dynamic requests could trigger a higher average operational cost to the system, as the added vehicle may not be fully utilised. In this case, it is suggested that no vehicle should be added. Practically, the operation can be in mixed vehicle types, and the rejected static or dynamic requests can be transported by some hired vehicles on trip basis at higher unit costs, such as taxis (Wong and Bell 2006). The discussed policies and actions for the operator to avoid the dilemma zone are summarised in Table 6.

Avoiding the inefficient dilemma zone can achieve a reduction in average operating cost, but the consequences of the suggested policies and actions controlling the fleet size and call rejection have to be considered. Furthermore, for strategic decisions taken by the dispatching service, the uncertainty and predictability of demand arrivals have to be taken into account. The variability of demand under conditions such as weather and seasonal effects can also be considered.

The findings of this study were based on simulation tests. The effects of the degree of dynamism on the operational efficiency could also be dependent on spatial distributions and the temporal arrival patterns of requests. The conclusions of this study are limited by the assumptions of uniformly distributed locations and Poisson arrivals. Cases with other distributions, such as clustered (or scattered) passenger locations and peak arrivals, deserve further investigation.

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### References

- Bell, M.G.H., Wong, K.I., and Nicholson, A.J., 2005. A rolling horizon approach to the optimal dispatching of taxis. In: H.S. Mahmassani, ed. *Transportation and traffic theory: flow, dynamics and human interaction*. Oxford: Elsevier Science Ltd., 629–648.
- Berbeglia, G., Cordeau, J.F., and Laporte, G., 2010. Dynamic pickup and delivery problems. *European Journal of Operational Research*, 202 (1), 8–15.
- Branke, J., et al., 2005. Waiting strategies for dynamic vehicle routing. *Transportation Science*, 39 (3), 298–312.
- Cordeau, J. and Laporte, G., 2003a. The dial-a-ride problem (DARP): variants, modeling issues and algorithms. *A Quarterly Journal of Operations Research*, 1 (2), 89–101.
- Cordeau, J.F. and Laporte, G., 2003b. A tabu search heuristic for the static multi-vehicle dial-a-ride problem. *Transportation Research Part B: Methodological*, 37 (6), 579–594.
- Cordeau, J.F. and Laporte, G., 2007. The dial-a-ride problem: models and algorithms. *Annals of Operations Research*, 153 (1), 29–46.
- Coslovich, L., Pesenti, R., and Ukovich, W., 2006. A two-phase insertion technique of unexpected customers for a dynamic dial-a-ride problem. *European Journal of Operational Research*, 175 (3), 1605–1615.
- Diana, M., 2006. The importance of information flows temporal attributes for the efficient scheduling of dynamic demand responsive transport services. *Journal of Advanced Transportation*, 40 (1), 23–46.
- Diana, M. and Dessouky, M.M., 2004. A new regret insertion heuristic for solving large-scale dial-a-ride problems with time windows. *Transportation Research Part B: Methodological*, 38 (6), 539–557.
- Fu, L., 2002a. Scheduling dial-a-ride paratransit under time-varying, stochastic congestion. *Transportation Research Part B: Methodological*, 36 (6), 485–506.
- Fu, L., 2002b. A simulation model for evaluating advanced dial-a-ride paratransit systems. *Transportation Research Part A: Policy and Practice*, 36 (4), 291–307.
- Fu, L. and Tepy, S., 1999. On-line and off-line routing and scheduling of dial-a-ride paratransit vehicles. *Computer-Aided Civil and Infrastructure Engineering*, 14 (5), 309–319.
- Ichoua, S., Gendreau, M., and Potvin, J.Y., 2006. Exploiting knowledge about future demands for real-time vehicle dispatching. *Transportation Science*, 40 (2), 211–225.
- Jaw, J.-J., et al., 1986. A heuristic algorithm for the multi-vehicle advance request dial-a-ride problem with time windows. *Transportation Research Part B: Methodological*, 20 (3), 243–257.
- Larsen, A., Madsen, O., and Solomon, M., 2002. Partially dynamic vehicle routing – models and algorithms. *Journal of the Operational Research Society*, 53 (6), 637–646.

- Lund, K., Madsen, O. and Rygaard, J.M., 1996. *Vehicle routing problems with varying degrees of dynamism*. Technical report. IMM, The Department of Mathematical Modelling, Technical University of Denmark.
- Madsen, O.B.G., Ravn, H.F., and Rygaard, J.M., 1995. A heuristic algorithm for a dial-a-ride problem with time windows, multiple capacities, and multiple objectives. *Annals of Operations Research*, 60, 193–208.
- Mitrovic-Minic, S. and Laporte, G., 2004. Waiting strategies for the dynamic pickup and delivery problem with time windows. *Transportation Research Part B: Methodological*, 38 (7), 635–655.
- Psaraftis, H.N., 1980. A dynamic-programming solution to the single vehicle many-to-many immediate request dial-a-ride problem. *Transportation Science*, 14 (2), 130–154.
- Pureza, V. and Laporte, G., 2008. Waiting and buffering strategies for the dynamic pickup and delivery problem with time windows. *INFOR*, 46 (3), 165–175.
- Sáez, D., et al., 2011. Hybrid predictive control strategy for a public transport system with uncertain demand. *Transportmetrica*, 8 (1), 61–86.
- Schilde, M., Doerner, K.F., and Hartl, R.F., 2011. Metaheuristics for the dynamic stochastic dial-a-ride problem with expected return transports. *Computers & Operations Research*, 38 (12), 1719–1730.
- Sirisoma, R.M.N.T., et al., 2010. Empirical evidence for taxi customer-search model. *Proceedings of the Institution of Civil Engineers-Transport*, 163 (4), 203–210.
- Tjokroamidjojo, D., Kutanoğlu, E., and Taylor, G.D., 2006. Quantifying the value of advance load information in truckload trucking. *Transportation Research Part E: Logistics and Transportation Review*, 42 (4), 340–357.
- Toth, P. and Vigo, D., 1997. Heuristic algorithms for the handicapped persons transportation problem. *Transportation Science*, 31 (1), 60–71.
- Wong, K.I. and Bell, M.G.H., 2006. Solution of the dial-a-ride problem with multi-dimensional capacity constraints. *International Transactions in Operational Research*, 13 (3), 195–208.
- Yu, B., Lam, W.H.K., and Tam, M.L., 2011. Bus arrival time prediction at bus stop with multiple routes. *Transportation Research Part C-Emerging Technologies*, 19 (6), 1157–1170.
- Yuen, C.W., Wong, K.I., and Han, A.F., 2009. Waiting strategies for the dynamic dial-a-ride problem. *International Journal of Environment and Sustainable Development*, 8, 314–329.

## Appendix

Let  $j \in J_k$  be the stops to be visited by vehicle  $k$  and  $[a_j, b_j]$  be the service time windows of stop  $j$ . The computations of a schedule with the three different waiting strategies are described below.

### A1. DF strategy

Denote  $\underline{A}_j$  and  $\underline{D}_j$  as the arrival and departure times at stop  $j$  planned with the DF strategy, and  $\underline{WT}_j = \underline{D}_j - \underline{A}_j$  as the corresponding waiting time at the stop. If  $\underline{A}_j$  is earlier than  $a_j$ , the vehicle has to wait at location  $j$  until  $a_j$  to start the service and then depart at  $\underline{D}_j = a_j$ . On the other hand, if  $\underline{A}_j$  is later than  $a_j$ , the vehicle starts the service upon arrival and departs immediately without waiting, i.e.  $\underline{WT}_j = 0$ . The vehicle movement has the relationship that the arrival time at a stop equals the departure time of the previous stop plus the travel time between the two stops, i.e.  $\underline{A}_j = \underline{D}_{j-1} + t_{(j-1),j}$ , where  $t_{(j-1),j}$  is the travel time from stop  $j-1$  to stop  $j$ . Starting from the first stop (i.e. the depot) of the route, we can repeat the steps recursively to determine the schedule of all stops. The pseudo code for the DF strategy is given in Table A1.

Table A1. Pseudo code for the DF strategy.

---

```

SET  $N$  = number of stops in the route, with 0 and  $N + 1$  as depot
SET  $\underline{A}_0 = \underline{D}_0 = 0$ 
FOR each location  $j$  ( $j = 1, 2, \dots, N + 1$ )
     $\underline{A}_j = \underline{D}_{j-1} + t_{(j-1),j}$ 
     $\underline{WT}_j = \max(a_j - \underline{A}_j, 0)$ 
     $\underline{D}_j = \underline{A}_j + \underline{WT}_j$ 
ENDFOR
    
```

---

**A2. WF strategy**

Denote  $\overline{A}_j$  and  $\overline{D}_j$  as the arrival and departure times at stop  $j$  planned with the WF strategy, and  $\overline{WT}_j = \overline{D}_j - \overline{A}_j$  as the corresponding waiting time. As the vehicle stays as long as it can, the departure time at the current location  $j$  would depend on the travel time from  $j$  to the next location  $j + 1$  and the latest possible arrival time at the next location, i.e.  $\overline{D}_j = \overline{A}_{j+1} - t_{j,(j+1)}$ , in order to not be late. Using the vehicle movement relationship, the schedule of all stops can be calculated in a backward manner, i.e. from the last stop (i.e. the depot) back to the current stop. The pseudo code for the WF strategy is given in Table A2.

Table A2. Pseudo code for the WF strategy.

---

```

SET  $N$  = number of stops in the route, with 0 and  $N + 1$  as depot
SET  $\overline{A}_{N+1} = \overline{D}_{N+1}$  = end of study period at the depot
FOR each location  $j$  ( $j = N, N - 1, \dots, 0$ )
     $\overline{D}_j = \overline{A}_{j+1} - t_{j,(j+1)}$ 
     $\overline{WT}_j = \max(\overline{D}_j - b_j, 0)$ 
     $\overline{A}_j = \overline{D}_j - \overline{WT}_j$ 
ENDFOR
    
```

---

**A3. MDW strategy**

Denote  $\hat{A}_j$  and  $\hat{D}_j$  as the arrival and departure times at stop  $j$  planned with the MDW strategy, and  $\hat{WT}_j = \hat{D}_j - \hat{A}_j$  as the corresponding waiting time at the stop. MDW is a modification of DF, and the computation of MDW makes use of the results of DF. The schedule of DF allows a vehicle to arrive at a stop and wait before the pickup time of the location (i.e.  $\underline{A}_j < a_j$ ), but MDW reallocates this spare time to the previous stop (i.e.  $\hat{WT}_j = \underline{WT}_{j+1}$ ). With the stated recursive relationships, the arrival, departure and waiting times can be calculated for all stops. The pseudo code for the MDW strategy is given in Table A3.

Table A3. Pseudo code for the MDW strategy.

---

```

CALCULATE  $\underline{A}_j, \underline{D}_j, \underline{WT}_j$  using DF strategy
FOR each location  $j$  ( $j = 0, 1, 2, \dots, N$ )
     $\hat{WT}_j = \underline{WT}_{j+1}$ 
     $\hat{D}_j = \underline{D}_j + \hat{WT}_j$ 
     $\hat{A}_j = \hat{D}_j - \hat{WT}_j$ 
ENDFOR
    
```

---