Real-time multi-depot dial-a-ride problem considering traffic dynamics and EV fleet

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1 INTRODUCTION

Transportation is a major contributor to pollution, partially due to high congestion levels and inefficient vehicle usage. Ride sharing services such as Dial-A-Ride (DAR) can mitigate these impacts by increasing vehicle occupancy and decreasing total driving time. Dynamic DAR services consider real-time requests so require real-time routing optimisation. However, many studies do not account for the variability of travel times caused by dynamic traffic states (Ho *et al.*, 2018). This is especially important for services with shared rides as users may experience congestion delays during their desired trip and while detouring for other customers. To estimate dynamic travel times Network Macroscopic Fundamental Diagrams (NMFDs) can be used to model traffic states in approximately homogeneous networks (Daganzo & Geroliminis, 2008). To further reduce environmental impacts while also decreasing operator fuel and maintenance costs DAR services can utilise Battery Electric Vehicles (BEVs) (Sperling, 2018). Since the charging time of BEVs is significant compared to refueling this introduces additional constraints for the DARP. As BEVs become more widespread stochastic charging demand may result in queuing at facilities (Tran *et al.*, 2021). This can be considered through estimating queue arrival rates and associated waiting times, but is often not included in DAR routing.

A *real-time shared ride multi-depot DAR service* is presented where vehicle speeds are variable with time. Speeds are estimated through accumulation based NMFDs in statically partitioned regions, similar to Beojone & Geroliminis (2023) with the addition of microscopic modelling of DAR operations. This abstract considers vehicles with internal combustion engines; however, in the full version of the paper, a service fleet of BEVs with charging facility selection and scheduling optimisation will be included. The charging facilities will be capacitated and a queuing model will be used to estimate waiting times at each facility considering stochastic charging demand from private BEVs. The key contribution of the final paper is the joint consideration of the *regional dynamic traffic* model and *stochastic queuing* model at charging stations. The objective function considers conflicting priorities of the operator and users, and sensitivity to objective parameters will be further investigated in the full paper.

2 METHODOLOGY

In this section, we briefly present the mathematical formulations for the proposed DAR framework. Due to the space limit, more details and explanations of the developed methodology will be presented in the full paper. The MINLP formulation is based on the *3-index scheduling* formulation of Cordeau (2006) with the addition of *existing onboard and scheduled requests* inspired by

Hosni *et al.* (2014) and Hua *et al.* (2022). All service vehicles $k \in \mathcal{K}$ are assumed to be homogeneous with capacity Q. Every planning step the DARP is defined on a directed graph $G = (\mathcal{V}, \mathcal{E})$ with relevant nodes $\mathcal{V} = \{\mathcal{O} \cup \mathcal{P} \cup \mathcal{D} \cup \mathcal{F}\}$ and relevant edges $\mathcal{E} = \{(i,j)\ \forall\ i \in \mathcal{V} \setminus \mathcal{F},\ j \in \mathcal{V} \setminus \mathcal{O}\}$. The node sets are the step's initial vehicle locations $\mathcal{O} = \{o_k \mid k \in \mathcal{K}\}$, unserved pick-up nodes $\mathcal{P} = \{1, ..., n\}$, unserved drop-off nodes $\mathcal{D} \supseteq \{1+n, ..., 2n\}$, and candidate depots $\mathcal{F}$. A request with pick-up i and drop-off $i+n$ appears at time e_i with node service duration s_i, passenger pick-up demand q_i, drop-off demand $q_{i+n} = -q_i$, and expected private vehicle trip duration r_i. Requests can be re-assigned until a vehicle is en-route to their pick-up i, $(i, i+n, k) \in \mathcal{P}_\mathrm{S}$, or drop-off j, $(i,j,k) \in \mathcal{P}_\mathrm{O}$ (Eq. 3). New requests $\mathcal{P}_\mathrm{N}$ that arrived since the last simulation step may be rejected and if accepted must be served (Eq. 4 and 5). The two binary decision variables are y_i, whether the request at i is accepted, and $x^k_{i,j}$, whether vehicle k traverses edge i,j. Other variables are w^k_i, the load of vehicle k leaving node i (Eq. 12), and u^k_i, the time vehicle k arrives at node i (Eq. 14). Each edge $(i,j) \in \mathcal{E}$ has length $d_{i,j}$ and predicted travel time $t_{i,j}$.

NMFDs for each time step were pre-calculated across eight static regions as in Tran *et al.* (2024). The operator is assumed to have more accurate traffic information than the users so $t_{i,j}$ is calculated at each step from the regional NMFD velocities v_r while r_i is calculated from the average network NMFD velocity v at e_i. Regional travel times are calculated for every link in the real network with $t = v_r/d$, then Dijkstra's algorithm is used to find the shortest travel time $t_{i,j}\ \forall\ i,j \in \mathcal{E}$. For the expected travel time of user i velocity is constant across all links so Dijkstra's algorithm is used to find the shortest distance $d_{i,i+n}$, then $r_i = v/d_{i,i+n}$. Vehicles may finish their route at any of the candidate depots with available capacity (Eq. 10 and 11). The multi-depot constraints are based on the formulation of Bongiovanni *et al.* (2019) in preparation for integrating the BEV fleet.

$$\text{Maximise } M + \sum_{i \in \mathcal{P}_\mathrm{N}} y_i (f_0 + f_1 d_{i,i+n} + f_2 t_{i,i+n}) - \sum_{k \in \mathcal{K}} \sum_{i,j \in \mathcal{V}} \delta\, t_{i,j} x^k_{i,j} \tag{1}$$

$$\text{Minimise } N + \sum_{k \in \mathcal{K}} \sum_{(i,j,-) \in \mathcal{P} \cup \mathcal{P}_\mathrm{O}} \sum_{(z,v) \in \mathcal{E} | z=i} \phi\, x^k_{i,v} q_i \left(u^k_j - e_i - r_i\right) + \sum_{i \in \mathcal{P}_\mathrm{N}} \gamma (1 - y_i) \tag{2}$$

$$\text{s.t.} \quad \sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i,j} = 1 \qquad \forall\ (-, i, k) \in \mathcal{P}_\mathrm{S} \cup \mathcal{P}_\mathrm{O} \tag{3}$$

$$\sum_{k \in \mathcal{K}} \sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i,j} - y_i = 0 \qquad \forall\ i \in \mathcal{P}_\mathrm{N} \tag{4}$$

$$\sum_{k \in \mathcal{K}} \sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i,j} = 1 \qquad \forall\ (-, i, -) \in \mathcal{P}_\mathrm{O} \cup \mathcal{P} \setminus \mathcal{P}_\mathrm{N} \tag{5}$$

$$\sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i,j} - \sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i+n,j} = 0 \qquad \forall\ i \in \mathcal{P},\ k \in \mathcal{K} \tag{6}$$

$$\sum_{(z,j) \in \mathcal{E} | z=i} x^k_{j,i} - \sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i,j} = 0 \qquad \forall\ i \in \mathcal{P} \cup \mathcal{D},\ k \in \mathcal{K} \tag{7}$$

$$\sum_{(z,j) \in \mathcal{E} | z=o_k} x^k_{o_k,j} = 1 \qquad \forall\ k \in \mathcal{K} \tag{8}$$

$$\sum_{k \in \mathcal{K}} \sum_{(z,j) \in \mathcal{E} | z=i} x^k_{i,j} = 1 \qquad \forall\ i \in \mathcal{O} \tag{9}$$

$$\sum_{j \in \mathcal{F}} \sum_{i \in \mathcal{D} \cup o_k} x^k_{i,j} = 1 \qquad \forall\ k \in \mathcal{K} \tag{10}$$

$$\sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{D} \cup o_k} x^k_{i,j} \leq 3 \qquad \forall\ i \in \mathcal{F} \tag{11}$$

$$w^k_j \geq x^k_{i,j} (w^k_i + q_j) \qquad \forall\ (i,j) \in \mathcal{E},\ k \in \mathcal{K} \tag{12}$$

$$\max\{0, q_i\} \leq w^k_i \leq \min\{Q, Q + q_i\} \qquad \forall\ i \in \mathcal{V},\ k \in \mathcal{K} \tag{13}$$

$$u^k_j \geq x^k_{i,j} (u^k_i + s_i + t_{i,j}) \qquad \forall\ (i,j) \in \mathcal{E},\ k \in \mathcal{K} \tag{14}$$

$$e_i \leq u^k_i \leq u^k_{i+n} \qquad \forall\ i \in \mathcal{P},\ k \in \mathcal{K} \tag{15}$$

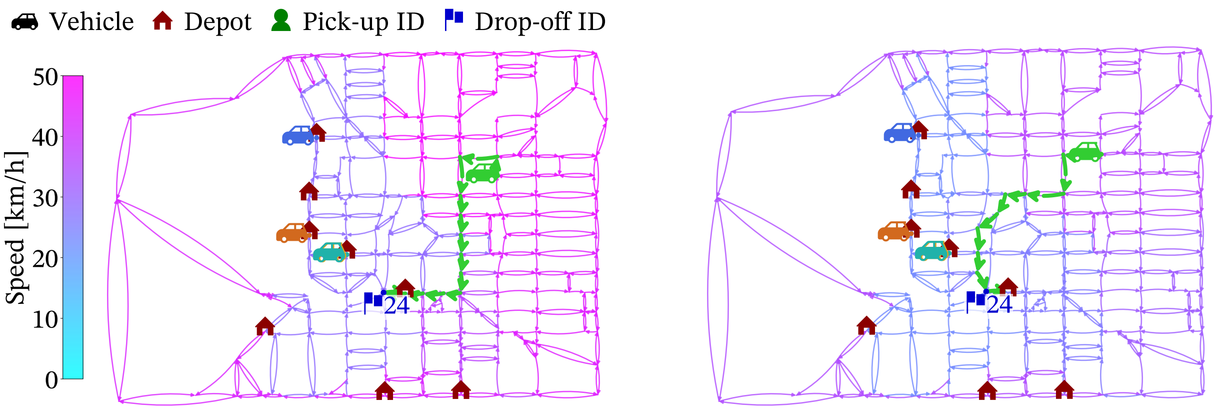
The objective functions maximise the operator's accumulated profit (Eq. 1) and minimise accumulated user dissatisfaction (Eq. 2). The first function is the accumulated profit M plus income from newly accepted requests (comprising flag fare f_0, distance rate f_1, and time rate

f_2) less the operational cost δ [\$/min] of planned driving time. The second function is the accumulated penalty from completed and rejected requests N plus the planned user delay penalty ϕ [\$/min-person], calculated as the time difference between expected ride completion and actual ride completion multiplied by passengers in the request, and a request rejection penalty γ [\$/request]. To solve the DARP these functions are combined with weights ω and $1-\omega$ respectively (Eq. 16). The expanded formulation including battery constraints and queue modelling will be discussed in the full paper.

$$\begin{aligned} \text{Maximise} \quad & \omega(\text{Eq. } 1) - (1-\omega)(\text{Eq. } 2) \\ \text{s.t.} \quad & \text{Eq. } 3 - 15 \end{aligned} \tag{16}$$

3 INITIAL RESULTS

Requests were randomly generated with arrival times following a uniform distribution from 8:00 am to 10:00 am (the entire simulation period) and demands between one and four (vehicle capacity). The scenario size refers to the total number of requests received over the simulation period. Candidate depot locations were chosen as existing publicly available charging stations. The locations of service vehicles at 8 am were randomly selected from these candidates while observing depot capacity. The length of each simulation time step was one minute and was equal to the planning interval. The MINLP was solved using Gurobi with a MIP focus of 1, an acceptable gap of 1e-4, and a solving time limit of 15 seconds to ensure the solution can be implemented in each time step. The computer was running Windows 10 and was equipped with an Intel(R) Core(TM) i7-13700 CPU @ 2.10 GHz and useable RAM of 31.7 GB. Figure 1 shows optimised route plans from the consecutive steps of 8:04 am and 8:05 am. These demonstrate re-routing as the optimal route of the green vehicle changes in response to dynamic regional speeds.



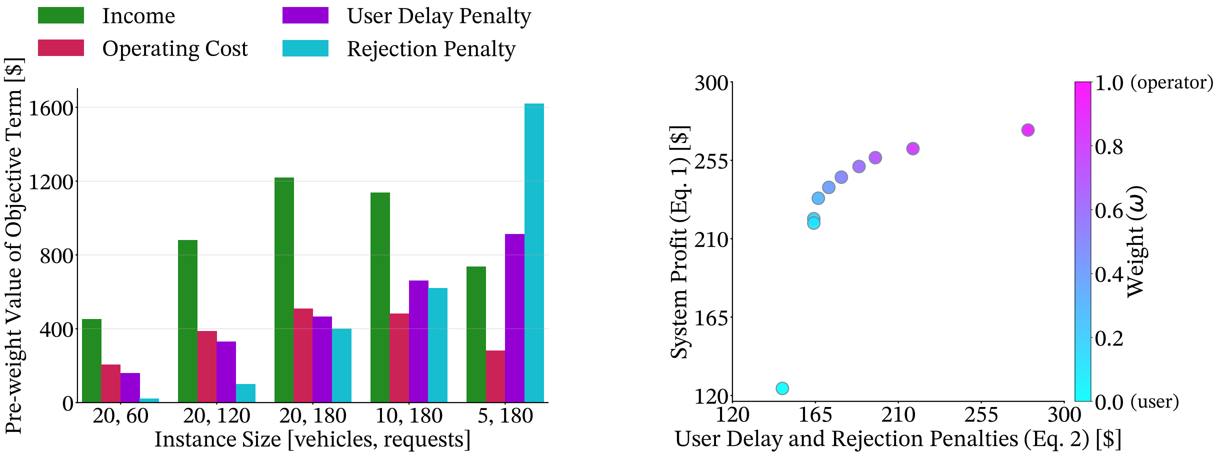
(a) *Optimally planned routes at 8:04 am* (b) *Optimally planned routes at 8:05 am*

Figure 1 – *Optimal DAR routes with 5 vehicles and 60 total requests*

As a preliminary investigation of model scalability five scenarios were tested with three levels of fleet size and total requests. Figure 2a shows the unweighted values of objective function components at 10 am for each scenario. Table 1 gives the mean and 99$^{\text{th}}$ percentile (P_{99}) percentage error and solving time in each step for the same scenarios. The Pareto frontier in Figure 2b was constructed by changing the objective function weight in increments of 0.1.

Table 1 – *Mean and 99th percentile solving times and solution errors per step in each scenario*

	Scenario size [vehicles, requests]				
	20, 60	20, 120	20, 180	10, 180	5, 180
Mean (P_{99}) error [%]	15.2 (281.2)	46.7 (460.0)	202.6 (2514.3)	72.7 (878.8)	50.2 (323.4)
Mean (P_{99}) time [s]	1.2 (15.5)	3.7 (15.6)	5.1 (15.7)	7.8 (15.5)	14.2 (15.6)



(a) *Impact of scenario size ($\omega = 0.5$)* (b) *Pareto dominant solutions (20, 60)*

Figure 2 – *Objective function values across different scenarios and function weightings*

4 DISCUSSION

Initial results presented in this abstract show that the given DAR model is capable of real time solutions considering dynamic travel times with pre-existing onboard and scheduled requests. This means that it is a suitable base model for integrating the BEV service fleet. The contribution of the full conference paper is to consider a BEV service fleet where waiting time at each charging facility will be determined by a stochastic queuing model. This model will thus consider both dynamic travel times from the regional dynamic traffic model and dynamic charging times through the stochastic queuing model. In addition the objective function considers the conflicting priorities of the DAR operator and customers. The full paper will include a sensitivity analysis of the monetary values of the objective function to further refine the Pareto front.

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