Poster: Data-driven Algorithms for Reducing the Carbon Footprint of Ride-sharing Ecosystems

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ABSTRACT

Urban mobility contributes 40% of CO2 emissions from road transport, which is projected to double by 2050 [6]. Ride-sharing services like Uber and Lyft have transformed urban mobility by providing convenient and on-demand personal transportation through smartphone applications. However, their success has resulted in an increase in traffic and congestion on roads—a type of rebound effect. For example, in New York City, ride-sharing accounts for over 50% of road traffic. Recent studies estimate that a typical ride-sharing trip is less efficient than a personal car trip, mainly due to "deadhead" miles traveled by a ride-share vehicle between consecutive hired rides, resulting in 36-45% higher distance travelled and upto 47% higher CO2 emissions compared to a private car ride [3]. As a result, there is a need to develop emission-aware ride-assignment algorithms that reduce emissions from deadhead miles.

Recent work has used theoretical as well as data-driven and machine learning (ML) approaches to improve the performance of ride-sharing platforms. For example, Abkarian et al. [1] present a model that aims to balance the tradeoff between waiting times and deadhead mileage driven by the vehicles in the fleet. Ke et al. [4] propose a novel spatio-temporal deep learning approach that uses a convolutional neural network (CNN) to model the spatial distribution of demand and a long short-term memory (LSTM) network to model the temporal patterns in ride demand. While these studies focus on improving the performance of ride-sharing services, they do not explicitly target reducing deadhead miles.

The most relevant work to ours targets reducing deadhead miles for individual trips [5]. Authors combine demand predictions with a heuristic approach to driver assignment to demonstrate up to 82% reduction in *trip-level* deadhead miles. However, their approach may not effectively reduce system-wide deadhead miles and emissions, which depend on factors like fuel efficiency and traffic conditions. Furthermore, they neither consider EVs nor do they take equity into account. Our work takes a holistic approach toward designing multi-objective ride assignment optimizations, aiming to reduce emissions from deadhead miles, incorporate equity considerations, and account for EVs in ride-sharing fleets. In this paper, we present a preliminary study illustrating the benefits of emission-aware ride assignment and propose combining data-driven algorithms and machine learning to enhance online decision-making processes.

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1 MODEL AND FORMULATION

We assume a riding ecosystem with $M = M_e + M_g$ cars, where M_e is the number of EVs, and M_g is the total number of non-electric cars. There are N ride requests that are arriving online over time. The ride assignment algorithm aims to minimize the overall emissions by matching ride requests to drivers, considering both passenger rides and the "deadhead" mileage between consecutive pickups. We formulate the Emission-aware Ride Assignment (ERA) as follows.

$$
\begin{aligned}
[\mathsf{ERA}] \quad & \min \sum_{n=1}^{N} \sum_{m=1}^{M_n} \left(e_t(n,m) + e_d(n,m)\right) x_{n,m} \\
& \text{s.t.,} \sum_{m=1}^{M_n} x_{n,m} = 1, \quad n \in [N], \\
& \text{vars.,} \quad x_{n,m} = \{0,1\}, \quad n \in [N], m \in [M_n],
\end{aligned}
$$

where M_n denotes the set of available cars n, $e_t(n,m)$ is the emissions during the trip due to the assignment of passenger n to driver m and $e_d(n,m)$ represents the emissions due to the deadhead mileage for driver m to pickup passenger n. The binary optimization variable $x_{n,m} = 1$ if m is assigned to n; 0 otherwise.

We illustrate the benefits of our system-level emissions-aware deadhead optimization over per-ride optimization approaches (such as [5]), in Figure 1 (left). We have a driver M_1 who is carrying a passenger at time t_0 with an expected drop-off time of t_5. At t_3, two passengers request rides. In a per-ride optimization approach, the driver M_1 is assigned to passenger N_2, due to its close proximity, and the passenger N_3 is assigned to the driver M_2, which leads to total deadhead miles of 61 *units*. However, a system-level view of the ride assignment will assign driver M_1 to the passenger N_3 and driver M_2 to the passenger N_2, despite it not being the optimal assignment for driver M_1. This results in the overall deadhead miles of 40 *units*, which not only reduces the deadhead miles emissions but also the waiting time experienced by the passengers.

2 PRELIMINARY RESULTS

To motivate the proposed research, we conducted a preliminary feasibility study using the RideAustin dataset [7]. The feasibility study aims to maximize emission reduction potential by offline passenger reassignment using complete advance trip request information. For our offline algorithm design, we leverage the existing algorithms for multiple traveling salesman problem (MTSP) [2].

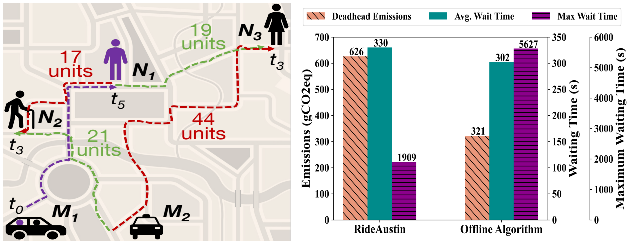

Figure 1: ***System-level optimization of deadhead miles leads to lower deadhead miles (40 units) than per-ride optimization (61 units) (left). Comparison of deadhead miles emissions and waiting time for the default ride assignment and emission-aware ride assignment (right).***

The problem of finding the best ride for N requests and M drivers can be mapped to an MTSP with N cities and M salesmen, where each request and each driver corresponds to a unique city and a unique salesman, respectively. In addition, the distance between city i to city j in MTSP is the distance between the destination point of the ith request and the starting point of the jth request. We modified the branch-and-cut algorithm, used for solving MTSP, to incorporate the emission-aware ride assignment constraint that each driver must visit the requests in a specific order.

The Emission-aware Ride Assignment (ERA) algorithm, shown in Algorithm 1, calculates the near-minimum cost of assigning a set of N requests to M drivers. It begins with an empty assignment for all M drivers (Line 1) and sequentially processes the requests by assigning the new request to any possible driver for any candidate assignments selected for the previous requests (Lines 4-5). Then, it calculates the estimated cost of the recently generated assignments and updates the set of candidate assignments by removing assignments with an estimated cost higher than the lowest estimated cost (Line 6). This algorithm is similar to the brute-force algorithm that evaluates the cost of every possible assignment, but its pruning step (Line 6) allows it to calculate the near-minimum cost faster.

Algorithm 1: ERA: Emission-aware Ride Assignment(N, M)

```
1 assignment_0 = empty assignments to every drivers;
2 𝒜 = {assignment_0};
3 for n ∈ N and a ∈ 𝒜 do
4     remove a from 𝒜;
5     assign n to any possible drivers in a and add new assignments
        to the 𝒜;
6     keep the assignments with lowest calculated cost in 𝒜 and
        remove the rest;
```

Figure 1 (right) presents emissions from the deadhead miles and passenger waiting times for the current assignments in the dataset and the new assignments based on ERA Algorithm. For this preliminary feasibility study, we randomly sampled 142 trips, completed by 14 unique drivers, from the RideAustin dataset [7] on December 2, 2016. The left y-axis presents the total carbon emissions, measured in grams of carbon dioxide equivalent (gCO2eq), for the deadhead miles of all the trips. The y-axes on the right show the waiting time (seconds), measured as the time period between a rider posting the request and the driver picking up, at different scales. Our results demonstrate that our proposed ERA algorithm, albeit offline with complete knowledge of future rides, can reduce the deadhead miles emissions by 48.7% (from 626gCO2eq to 321gCO2eq). Importantly, the average waiting time across all trips also decreased by 8.5% (from 330s to 302s) as ERA reduced the deadhead miles, but the longest waiting time increased by 2.94× to almost 94 minutes from the 32 minutes observed for the default ride assignment.

Takeaway. *Offline emission-aware algorithms can reduce deadhead emissions by 48.7% and decrease average waiting time by 8.5%, but they require future knowledge and increase worst-case wait time.*

3 INITIAL IDEAS FOR ALGORITHM DESIGN

Our preliminary results motivate the design of computationally efficient, data-driven, online algorithms for emission-aware ride assignments. In designing our algorithms, we make three novel and unique contributions. (❶) As a foundational step, we will develop an online, data-driven, and emission-aware ride assignment algorithm that *directly* targets reducing the emissions from the deadhead miles of a ride-sharing fleet consisting of both gas-powered and electric vehicles. (❷) We will extend our algorithm to satisfy EV charging constraints, both w.r.t. charging rate and availability, and incorporate further optimizing emissions by leveraging locational marginal emissions information if, and when, available. (❸) Finally, our multi-objective ride-sharing assignment approach will incorporate the performance constraint on rider's wait time (average or worst) and equity constraints on driver's ride assignment and the deadhead miles travelled by the driver.

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