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Dynamic Electric Vehicle Routing with Mid-route Recharging and Uncertain Availability

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1 Introduction

As we shift towards sustainable transport, electric vehicles (EVs) are becoming more popular in supply chain distribution functions. However, EVs pose operational challenges to which their conventional petroleum-based counterparts are immune. For instance, EVs' driving ranges are often only 25 percent that of conventional petroleum-based vehicles' (CVs), charging infrastructure is still relatively sparse compared to the network of refueling stations for CVs, and the time required to charge an EV can range from 30 minutes to 12 hours depending on charging technology - orders of magnitude longer than the time needed to refuel a CV.

There are two general approaches to overcoming these operational challenges. The first is a simple approach in which routes are restricted to the vehicle's autonomy. That is, the EV is routed back to the depot when its battery nears depletion so it may charge overnight in preparation for the subsequent day's deliveries. In the second approach, the EV is allowed to perform mid-route recharging by taking advantage of charging infrastructure in the field.

In their 2016 study, Montoya, et al. showed that the second approach offers cost savings, because mid-route recharging allows for a decrease in the total distance traveled and an increase in the utilization of a single EV, thereby reducing the number of vehicles and drivers needed [1]. However, like the others that consider mid-route recharging (e.g., [2]),

the Montoya study makes the assumption that the charging stations (CSs) are always available to the EV when it arrives to charge. In reality, this is often not the case. Because charging station infrastructure is limited and EVs require significant time to charge, charging stations will often be unavailable when an EV arrives and the EV may be forced to queue. This discrepancy between modeling assumptions and reality has thus far prohibited logistics companies from implementing mid-route recharging, despite the suggested cost savings.

Our work aims to reduce this discrepancy by more realistically modeling both the uncertainty in availability and the queuing processes at public charging infrastructure. We model the EV Routing Problem with Mid-route Recharging and Uncertain Availability (E-VRP-MRUA) as a Markov decision process and implement a stochastic dynamic programming (SDP) solution for which we propose four routing policies. Further, using an information relaxation and information penalties, we establish a lower bound for the value of the optimal policy. Our results show that for a subset of our problem instances, our policies perform within approximately 5% of the optimal policy, providing encouragement for logistics companies to take advantage of the increases in capacity offered by mid-route recharging and thus extend the utility of EVs as delivery vehicles.

2 Problem description

The E-VRP-MRUA consists of a set of known customers $\mathcal{N}$ and charging stations $\mathcal{C}$ and a single EV. At time 0, the EV begins at the depot. It then traverses the complete graph on $\mathcal{N} \cup \mathcal{C}$. The vehicle must visit each customer $i \in \mathcal{N}$ and then return to the depot.

Between customer visits, the EV may elect to visit a CS $c \in \mathcal{C}$. The vehicle may charge if there are available charging terminals ("chargers"), or it may elect to join the queue if all chargers are in use. Let the number of chargers at CS c be ψ_c. We assume that the ψ_c chargers at the CS are identical, although charging technology may differ between charging stations. We further assume that the depot is always available for charging but all other charging station queue lengths are unknown prior to arrival.

We model waiting line dynamics at a CS c as M/M/ψ_c – a pooled first-come-first-served queue with a system capacity of $\ell_c \geq \psi_c$, where ℓ_c is chosen such that the system capacity is practically infinite. We consider a continuous-time Markov model on the state-space $\{0, 1, \ldots, \ell_c\}$ and assume that the the inter-arrival time of vehicles to c and the service times of the chargers at c are exponential random variables with known parameters $p_{c,x}$ and $p_{c,y}$, respectively. When a station is available, the vehicle may restore its charge to full capacity Q or to an intermediate capacity.

The problem terminates when the EV has visited all customers and returns to the depot. The objective of the E-VRP-MRUA is to find the routing policy that minimizes

the total expected time for the EV to visit each customer in $\mathcal{N}$, including travel time, charging time, and queuing time.

3 Solution methods

3.1 Heuristic policies

We have constructed four policies to solve the SDP: a myopic policy, a one-step rollout of the myopic policy, a static fixed-route policy, and a post-decision rollout of the fixed-route policy. For the fixed-route policy, we construct a route by computing the minimum-length Hamiltonian path from the current location to the depot that visits all remaining unvisited customers. If this route is not energy-feasible, we solve the fixed-route vehicle charging problem (FRVCP) using the labeling algorithm described in [3], which performs optimal insertion of charging stations and charging decisions.

3.2 Lower bounds

While we seek to produce policies that perform favorably relative to industry methods, gauging policy quality is hampered by the lack of a strong bound on the value of an optimal policy. Without an absolute performance benchmark, it is difficult to know if a policy's performance is "good enough" for practice or if additional research is required to improve the routing scheme. To establish a bound on the value of an optimal routing policy, we combine information relaxation techniques [4] with mixed integer programming (MIP) methods to estimate the expected value of an optimal policy with perfect information, i.e., the performance achieved via a clairvoyant logistics planner.

We do this by granting the decision maker access to perfect information, thereby removing any uncertainty from the problem, and formulating the "perfect information dynamic program" (PIDP). We then formulate and solve a "perfect information MIP" (PIMIP), which we show to be equivalent to the PIDP.

To improve on the perfect-information bound, we develop computationally tractable information penalties, which punish the logistics planner for using information about the future to which they would not naturally have access. We impose these penalties via modifications to the PIMIP, resulting in the "penalized PIMIP" (PPIMIP).

4 Results

We simulated each policy under 50 realizations of uncertainty for 528 different instances. The instances vary in the number of customers and CSs (10-20 and 2-3, respectively), customer location method (random, clustered, and a hybrid), and average CS utilization (10%, 20%, ..., 80%).

Because solving the PIMIP and PPIMIP is computationally expensive, we have only been able to compute these bounds for a small subset of instances to date: those with 10 customers, 2 charging stations, and only 20%, 50%, and 80% average CS utilization.

The results are shown in Figure 1. We find that the implementation of lookahead techniques improves upon the performance of the base policy alone in the case of both the myopic and fixed-route policies, with the rollout of the fixed-route policy being the strongest performing policy. For the subset of instances for which lower bounds were computed, we find that this policy performs within 5% of the optimal policy under high CS utilization and within 2% of the optimal policy under low-to-moderate CS utilization. Additionally, we find that the penalty only serves to improve the lower bound in the case of high CS utilization; for low-to-moderate utilization, the bound is unchanged.

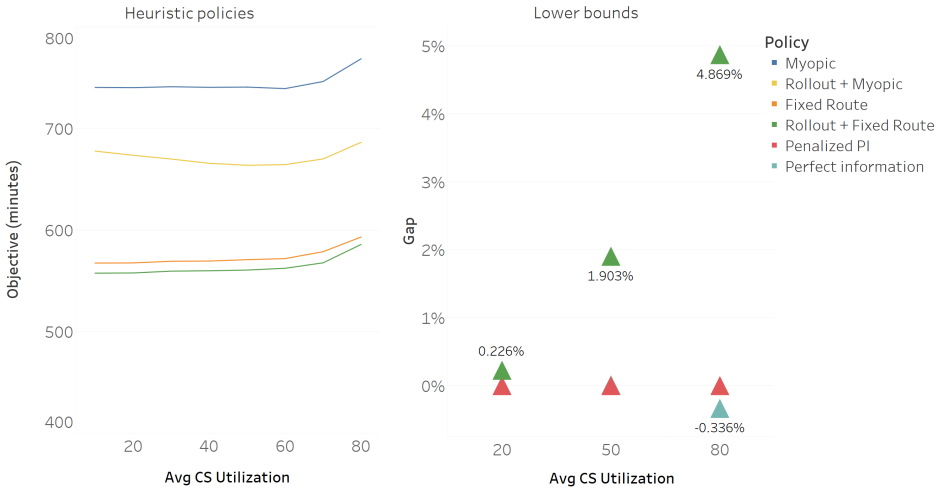

Figure 1: *Left*: Performance of the heuristic policies constructed to solve the SDP. *Right*: Performance of the best policy ("Rollout + Fixed Route") relative to the lower bounds established with information relaxations.

5 Conclusion

We introduce and solve the E-VRP-MRUA, which attempts to more realistically model the uncertainty in EVs' access to charging stations. We also implement information relaxation techniques to obtain lower bounds for the optimal policy and impose information penalties to tighten the bounds; we believe this is a first in the field of vehicle routing. Using the information penalties, we find that for a subset of our problem instances, our dynamic policies perform within 5% of the optimal policy.

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