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Electric Vehicle Routing with Uncertain Charging Station Availability & Dynamic Decision Making

Nicholas D. Kullman

Justin C. Goodson

Jorge E. Mendoza

1 Introduction

Motivated by environmental concerns and regulations, electric vehicles (EVs) are becoming more popular in supply chain distribution functions (e.g., La Poste [1]). 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 [3].

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.

Montoya 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 capacity of a single EV, thereby reducing the number of vehicles and drivers needed [5]. However, this study, like the others that consider mid-route recharging (e.g., [8][2]), 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 [5].

Our research reduces this discrepancy by more realistically modeling both the uncertainty in availability and the queuing process at public charging infrastructure. We model the EV Routing Problem with Mid-route Recharging and Uncertain Availability (EVRP-MRUA) as a Markov decision process, and we provide a stochastic dynamic programming solution with three different policies. This work aims to enable logistics companies to take advantage of the increases in capacity offered by mid-route recharging, thus extending the utility of EVs as delivery vehicles.

1.1 Related Literature

The literature reports on only two attempts to address charging station availability in EV routing problems. In a recent study, Sassi et al. address an EV routing problem in a semi-public infrastructure context [7]. In their application the infrastructure is owned by several companies. Each company is assigned time slots during which it is allowed to use a given station. The decision

maker must then take into account these time windows when designing the routes. Sweda et al. study a shortest path problem in which a vehicle must travel from an origin to a destination on a network with charging stations positioned at every node [9]. Each station has a probability of being available and expected waiting time until becoming available (known a priori to the planner). In this context, the decision maker must not only select which path to take to arrive at the destination as quickly as possible, but also decide where to recharge and what to do in case a desired charging station is unavailable (i.e., wait or seek an alternative station). The authors propose an approach to determine an adaptive routing and recharging policy that minimizes the sum of all traveling, waiting, and recharging costs. Our work builds on these studies by dynamically routing an EV over a network of customers and charging stations, assuming public infrastructure with unknown availability.

2 Problem Statement

The EVRP-MRUA consists of a set of known customers \mathcal{N} and charging stations \mathcal{C} and a single electric vehicle. At time 0, the EV begins at the depot, which we refer to as node $0 \in \mathcal{C}$. It then traverses the complete graph on $\mathcal{N} \cup \mathcal{C}$.

We assume there exists a Hamiltonian path among the set of CSs such that the edge connecting two charging stations can be traversed with a fully charged vehicle. Further, we assume that the edge from each customer node $i \in \mathcal{N}$ to the nearest CS can be traversed by a half-charged vehicle. These two assumptions guarantee each customer in \mathcal{N} can be serviced by the vehicle. Without loss of generality, we assume travel times are whole numbers and time periods can be indexed via the nonnegative integers.

If the EV elects 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 a CS c be ψ_c . We assume that the ψ_c chargers at the CS are identical, although the charging technology may differ between charging stations. We further assume that the depot is always available for charging and that other charging station queue lengths are unknown prior to arrival.

We model waiting line dynamics at a CS c as 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 discrete-time Markov model on the state-space $\{0, 1, \dots, \ell_c\}$ and assume that the random inter-arrival time of vehicles to the station and the random service time of a single charger are geometric random variables with known parameters p_x and p_y , respectively. After the vehicle joins the queue, it may continue to wait, or it may leave. 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 goal of the EVRP-MRUA is to find a routing policy that minimizes the total expected time of the EV to visit each customer in \mathcal{N} , including travel time, charging time, and queuing time.

3 Problem Formulation

We model the EVRP-MRUA as a Markov decision process and solve it using an approximate stochastic dynamic program (SDP).

State We denote the state of the system at decision epoch k by s_k . s_k is the vector containing all information necessary to make a routing decision at epoch k and consists of the EV's current charge level in kWh $q_k \in [0, Q]$, the time $t_k \in \mathbb{N}$, the EV's current location $i_k \in \mathcal{N} \cup \mathcal{C}$, the set of customers that the EV has not yet visited $\bar{\mathcal{N}}_k \subseteq \mathcal{N}$, and the vehicle's position at the current node z_k . We assume that at customer nodes and at the depot, the EV is always in the first position $z_k = 1$, while at public charging stations, the position depends on demand at the CS, so $z_k \in \{0, \dots, \ell_{i_k}\}$. Thus, $s_k = (q_k, t_k, i_k, \bar{\mathcal{N}}_k, z_k)$. The initial state is $s_0 = (Q, 0, 0, \mathcal{N}, 1)$, and the problem terminates at some decision epoch K with $s_K \in \{(q_K, t_K, 0, \emptyset, 1) \mid q_K \in [0, Q], t_K \in \mathbb{N}\}$.

Action space At each decision epoch $k \in \{0, 1, \dots, K\}$, we begin in a pre-decision state s_k and select an action x from the action space $\mathcal{X}(s_k)$. Actions are location-charge pairs, $x = (i', q')$. The action space consists generally of queuing, moving, and charging decisions. We impose the following restrictions on the action space: the vehicle may only queue if it resides at a CS with no available chargers; the vehicle may only make moves to nodes $i' \in \bar{\mathcal{N}}_k \cup \mathcal{C}$ that are energy-feasible, with the additional requirement that if $i' \in \bar{\mathcal{N}}_k$ it must have sufficient charge to subsequently reach a CS from i' ; finally, the vehicle may only charge if it resides at a CS with available chargers, it may not charge in two consecutive epochs, and it must at least charge to an energy level sufficient to reach the nearest CS.

Transition to post-decision state Following the selection of an action $x = (i', q')$, we transition to the post-decision state s_k^x . In this transition, we update the location $i_k^x = i'$ and charge $q_k^x = q'$. We also update the set of unvisited customers: $\bar{\mathcal{N}}_k^x = \bar{\mathcal{N}}_k \setminus \{i'\}$ if $i' \in \bar{\mathcal{N}}_k$, and $\bar{\mathcal{N}}_k^x = \bar{\mathcal{N}}_k$ otherwise.

Transition to pre-decision state From the post-decision state s_k^x , we transition to the subsequent pre-decision state s_{k+1} . This transition involves updating the remaining components of s_k : the EV's position at the current location z_{k+1} and the time at which the next epoch occurs t_{k+1} .

Position: If the EV now resides at the depot or a customer, then $z_{k+1} = 1$; however, if the EV resides at a CS $c \neq 0$, then z_{k+1} is probabilistic. Let $G_{c,k+1}$ be a random variable that represents the queue length of CS c at time $k+1$, and let $g_{c,k+1}$ be a realization of $G_{c,k+1}$. Then $z_{k+1} = g_{c,k+1} + 1$.

Time: If the action x selected in decision epoch k was a charging or moving action, then the time of decision epoch $k+1$ is deterministic. Specifically, $t_{k+1} = t_k + \tau_{ii'}$ for moving actions and $t_{k+1} = t_k + \bar{u}(q, q')$ for charging actions, where $\tau_{ii'}$ is the time required to travel between locations i and i' , and $\bar{u}(q, q')$ is the time required to charge from charge level q to q' . For queuing actions, the time of the next epoch is probabilistic and equal to either the time of the next departure from the queue or after a predetermined amount of time δ has elapsed, whichever comes first.

Costs When we are in state s_k and choose action $x = (i', q')$ we incur a cost of $C(s_k, x)$, measured in time. The cost for moving and charging actions is $\tau_{ii'}$ and $\bar{u}(q, q')$, respectively, the time required to perform these actions. If the vehicle elects to queue at a charging station, the cost is the expected waiting time until the next decision epoch. Let ψ_c be the number of chargers at the CS c , κ be a realization of the waiting time until a departure, and γ be a realization of the number of departures

that occur at time $t_{k+1} = t_k + \kappa$. Then the expected waiting time is

$$C(s_k, x) = \delta \Pr(\text{no departures}) + \sum_{\kappa=1}^{\delta} \sum_{\gamma=1}^{\psi_c} \kappa \Pr(\gamma \text{ departures at time } \kappa). \quad (1)$$

Objective A decision rule at epoch k is the function X_k^π that selects an action x from the action space $\mathcal{X}(s_k)$. A policy π is a sequence of decision rules. Letting Π denote the set of Markovian deterministic policies, we seek to find an optimal policy $\pi^* \in \Pi$ that minimizes the expected total cost (duration) of the tour, conditional on our initial state. The value of this policy is measured by the expected duration of the resulting tour T^*

$$T^* = \min_{\pi \in \Pi} \mathbb{E} \left[\sum_{k=0}^K C(s_k, X_k^\pi(s_k)) \middle| s_0 \right] = \mathbb{E} \left[\sum_{k=0}^K C(s_k, X_k^{\pi^*}(s_k)) \middle| s_0 \right]. \quad (2)$$

4 Solution Methods and Preliminary Results

To date, we have implemented three policies for the SDP: a simple myopic policy, a one-step rollout of the myopic policy, and a fixed-route policy. We ran each policy on a set of 22 instances that were generated by Montoya et al. [6] to emulate three different types of customer distributions in urban environments: customers randomly scattered throughout the service area (“Random”); customers that form clusters throughout the service area (“Cluster”); and a combination of these two in which most customers are in clusters, but some have been randomly scattered throughout (“Random+Cluster”). For each instance, we ran each policy under nine different assumptions of the average utilization of the charging stations (5% average utilization, 15%, 25%, ..., 85%). We performed 200 simulations for each policy-instance-utilization combination. For the one-step myopic rollout, we simulated the myopic base policy 25 times for each reachable state s_{k+1} from s_k (see Goodson for more on rollout policies [4]). Our results are summarized in Figure 1.

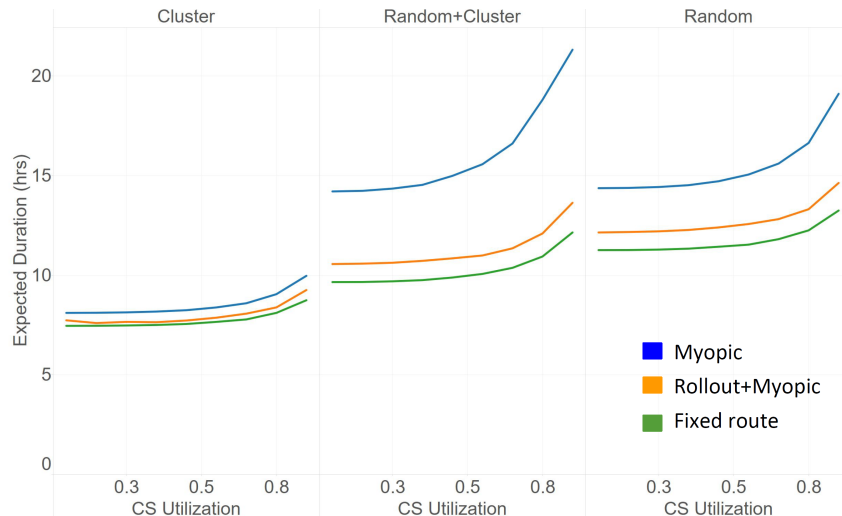


Figure 1: Expected total tour duration across policies, customer distributions, and CS utilizations.

We find that the rollout of the myopic policy performs better than the myopic policy alone, and the fixed-route policy performs better still than both of these, although the extent by which varies by customer distribution and CS utilization. The biggest differences in policy performance are for the Random+Cluster customer distribution at high CS utilizations where the policies differ by more than 75%, while the smallest differences are for the Cluster customer distributions at low CS utilizations where all policies perform within 9% of one another on average. The Cluster customer distribution lends itself to the myopic approach where the EV simply performs the cheapest immediate action, thus resulting in the similarity in performance across policies that we observe. For the other customer distributions, the myopic policy has greater potential to make costly decisions, but these are largely avoided by rolling out the myopic policy.

The improvement in performance that the rollout of the myopic policy offers over the myopic policy alone is encouraging. We are currently in the process of implementing a rollout for the fixed-route policy as well and hope to be able to report on similar improvements.

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