A ROUTING AND RESERVATION SYSTEM FOR BATTERY SWAPS FOR ELECTRIC VEHICLES

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EXTENDED ABSTRACT

The environmental, geopolitical, and financial implications of the world's dependence on oil are well known and documented, and much has been done to lessen our dependence on gasoline. One thrust on this issue has been the embracing of the electric vehicles as an alternative to gasoline powered automobiles. These vehicles have an electric motor rather than a gasoline engine, and a battery to store the energy required to move the vehicle. For many electric vehicles, such as the Nissan LEAF or Chevrolet VOLT, the method of recharging the vehicle battery is to plug the battery into the power grid at places like the home or office [1]. Because the battery requires multiple hours to fully recharge, this method has the implicit assumption that vehicle will be used only for driving short distances. Electric vehicle companies are trying to overcome this limited range requirement with *battery-exchange stations*. These stations will remove a battery that is nearly depleted from a vehicle and replace the battery with one that has already been charged [2]. Once the depleted battery is dropped off at the station it is charged until full so that a different vehicle can use it in the future. This method of refueling electric vehicles has the advantage that it is very quick for each vehicle since the driver only has to wait for the battery to be swapped and not for the battery to be charged. The electric vehicle company Tesla Motors Inc., which currently sells plug-in electric vehicles, has recently shown a prototype vehicle with battery-exchange technology [3].

In this research we devise an algorithm for real-time routing of electric vehicles with swappable batteries that balances the desire for drivers to have quick trips with the need for the operating company to balance the battery swap loads across the stations. Further, the algorithm will make reservations for each vehicle at all of the battery-exchange stations on the desired route. Making reservations will remove the possibility that the batteries the vehicle expected to receive are unavailable due to other vehicles taking them. The objective of the routing and reservation algorithm is to minimize the total expected travel times of not only the vehicle being routed, but of future vehicles as well. Because of this objective, part of the routing and reservation process is to understand how a set of battery reservations could affect future arrivals into the system. This objective also creates situations where drivers may be routed in ways that cause them to go slightly out of their way, leaving batteries available at stations for other vehicles to use.

The routing and reservation system would make the route suggestion based on the current battery charge levels at each station along with the pre-existing reservations made by earlier vehicles, which would be stored in the central server. The model in this research assumes that when the vehicle turns on it will be provided with a single route from the routing and reservation system, and that the driver will take the given route exactly. The steps in this routing and reservation process for each vehicle would be:

1. When the electric vehicle is turned on, the driver would input a destination into the vehicle's system unit. This, combined with the origin of the trip determined by the GPS location of the vehicle, would be sent to the central server.
2. The central server receives this origin and destination (OD) pair and, using the current battery levels at the stations and the reservations already made, determines which route the vehicle should take and when and where the vehicle should stop to swap its battery.
3. The central server makes reservations for the batteries at each of the stations for the most convenient times the vehicle would require it, subject to availability.
4. The central server sends the selected route and reservation times to the unit onboard the vehicle, and the driver begins to travel the route.

We model the system as a *Markov Chance-Decision Process* (MCDP) where the states describe the current reservations at the stations and the actions are routing the vehicles that arrive. In the case of routing electric vehicles through a network with reservations, during each interval of time it is unknown whether or not a vehicle will arrive needing to be routed, and if it does arrive what its OD pair will be. When a vehicle does arrive, its OD pair becomes known and the algorithm routes it precisely, and given the routing and reservations made the new state of the system is then exactly known. Then one time step occurs and a new vehicle may arrive; this process is repeated until the end of the day.

While value iteration and other standard Markov decision process techniques can be used on MCDPs, in both cases the algorithms that find the optimal policy become intractable for a large number of states. The problem of routing and reserving batteries for electric vehicles has an immense number of states due to the possible reservations times at each station. Thus, we turn to Approximate Dynamic Programming (ADP) [4] to find a policy for the MCDP that routes the vehicles effectively without being optimal. Here we still attempt to find the value of each state of the MCDP, only now we accept approximate solutions for the values. In the case of the network routing and reservation problem the value of a state represents the estimated delay penalties of all of the future arrivals.

We use the ADP technique of temporal differencing with a linear model. Dynamic programming requires the calculation of the value of the system in each possible state, and each state can have a unique and independently calculated value. If the values of the states are approximated in such a way that we utilize the similarities of the states, the calculation for all of the state values becomes tractable. Thus, by approximating the values of each state future by using a linear combination of basic functions the problem becomes feasible to solve. The temporal differencing allows us to effectively update the values of each state using information generated from simulating the current best policy. For our basis functions we used, for each station and number of batteries up to the total at the station, the amount of time between the current time and the end of the day that the station has at least that number of batteries unavailable.

We tested the algorithm to determine the amount of savings the algorithm would provide compared to the greedy policy and the run time of the algorithm. The test data was the Arizona state highway network from Upchurch et al. [5]. In that paper Upchurch, Kuby, and Lim had a charging station located in each of the 25 cities in the network plus an addition 25 stations located on longer roads between cities. They also used a gravity based demand model to determine the amount of vehicles wanting to traverse each OD pair between cities. The gravity was a function of the population of the OD cities and the length of the shortest path between them. They assumed that the electric vehicles would have a battery that allows them to travel 100 miles before recharging.

Figure 1 shows a comparison of the amount of delay incurred due to detours and waiting in the policy generated by the algorithm versus having each driver take the shortest path available to them. The different arrival probabilities indicate the probability of a vehicle arriving at each time step. For arrival probabilities between 0.05 and 0.1 the algorithm substantially lowered the amount of delays. When the arrival probability was 0.025 there were no delays at all (and thus the greedy policy was optimal). When the arrival probability was greater than 0.1 there were too many cars so all of the vehicles had to wait until the end of the day before a battery was ready, and so the algorithm was ineffective.

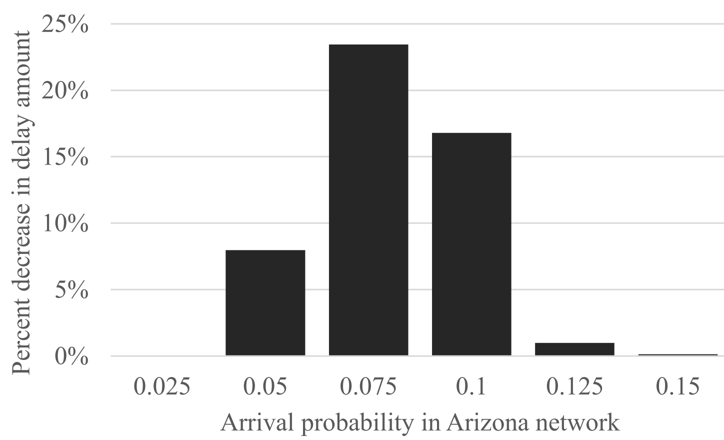

Figure 1: a comparison of the algorithm vs. the greedy policy runs on different random networks

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REFERENCES

[1] J. Bakker, “Contesting range anxiety: The role of electric vehicle charging infrastructure in the transportation transition,” Eindhoven University of Technology, 2011.

[2] N. Shemer, “Better Place Unveils Battery-Swap Network,” *Jerusalem Post*, Feb-2012.

[3] J. Motavalli, “Tesla fast-tracks battery swapping while fighting a legislative attack,” *New York Times*, 2013. [Online]. Available: http://wheels.blogs.nytimes.com/2013/06/21/tesla-fast-tracks-battery-swapping-while-fighting-a-legislative-attack/.

[4] W. B. Powell, *Approximate Dynamic Programming: Solving the Curses of Dimensionality*, 2nd ed. Hoboken, NJ: John Wiley & Sons, Inc., 2011.

[5] C. Upchurch, M. Kuby, and S. Lim, “A model for location of capacitated alternative-fuel stations,” *Geogr. Anal.*, vol. 41, no. 1, pp. 85–106, 2009.