Distance-Based Heuristic in Selecting a DC Charging Station for Electric Vehicles*

Junghoon Lee and Gyung-Leen Park

Dept. of Computer Science and Statistics,
Jeju National University, Republic of Korea
{jhlee,glpark}@jejunu.ac.kr

Abstract. This paper proposes a suboptimal tour-and-charging scheduler for electric vehicles which need to select a DC charging station on their single day trips. As a variant of the traveling salesman problem, the tour scheduler finds a visiting order for a given set of destinations and one of any charging stations. To reduce the search space stemmed from a larger number of candidate stations, our distance-based heuristic finds first the nearest destination from each charging station, and calculates the distance between them. Then, m' out of the whole m candidates will be filtered according to the distance. The reduced number of candidates, namely, m', combined with constraint processing on the waiting time, significantly cuts down the execution time for tour schedule generation. The performance measurement result obtained from a prototype implementation reveals that the proposed scheme just brings at most 4.1 % increase in tour length and its accuracy is at least 0.4 with 5 picks, for the given parameter selection.

Keywords: Electric vehicles, tour scheduler, DC charging, TSP variant, distance-based heuristic.

1 Introduction

EVs (Electric Vehicles) are powered by battery-stored electricity [1]. It makes even the transport system be a part of the power network, as their batteries are mainly charged by the energy provided from the grid. EV-based transport will be highly eco-friendly as EVs create no air pollution, while electricity can be produced even from renewable sources such as wind and sunlight [2]. Here, their wide penetration must be preceded by the construction of charging infrastructure, particularly because their driving range is quite short and charging time is much longer than gasoline-powered vehicles. In the early stage charging infrastructure, AC chargers, by which it takes about 6 hours to fully charge an EV battery, are dominating, as they are cheap and pose less burden on the grid

* This research was financially supported by the Ministry of Knowledge Economy (MKE), Korea Institute for Advancement of Technology (KIAT) through the Inter-ER Cooperation Projects.

M.N. Murty et al. (Eds.): MIWAI 2014, LNAI 8875, pp. 47–56, 2014.

[3]. However, their long charging time inherently prevents users from readily purchasing EVs.

Gradually, DC chargers are more preferred as they can reduce charging time to 30 minutes [4]. They are quite expensive and may bring a sharp increase in the energy consumption to the grid, especially when many EVs are plugged-in to the grid at the same time [5]. Moreover, fast charging 2 or more times a day may shorten the battery life. However, the convenience brought by the reduced charging time outweighs such problems. In addition, as the daily driving distance is usually covered by overnight AC charging, EVs need to be charged at most once with a DC charger during the daytime. Now, EVs driving beyond the driving range are required to consider where to charge. It is desirable for them to decide the driving route and charging station before they start a trip, possibly making a reservation of a charger. This problem becomes complex when an EV visits multiple destinations like in rent-a-car tours, and the computation time gets longer beyond the tolerable bound.

For the given set of DC chargers, how to select one can be considered a variant of the well-known TSP (Traveling Salesman Problem), which is known to be one of the most time-intensive applications [6]. Basically, it decides the visiting order for n fixed destinations, and many researchers have developed excellent algorithms. However, in our problem, $(n + 1)$-th destination is not given and there are m candidates. Intuitively, it is necessary to add each candidate to the destination set and run the TSP solver one by one to find the best solution. Hence, the time complexity reaches $O(m \times (n + 1)!)$. Here, if we exclude those chargers having little possibility to be selected, we can cut down the response time. Moreover, we can further improve the computation speed by investigating only a set of promising m' (not m) chargers. According to our observation for the problem, a DC charger near a destination is highly likely to reduce the total tour distance and time.

In this regard, this paper designs a distance-based heuristic in selecting a DC charger to make a tour-and-charging schedule for a given set of destinations. A classic computer algorithm is customized to this problem and integrated into our smart grid framework. The information server manages all necessary status records, tracks the current location of each EV, and finally provides the requested operation result to the mobile terminals. Importantly, many artificial intelligence techniques enrich the EV information service [7]. Here, the system design is targeting at a real-life road network and the geographic distribution of chargers and tour spots on Jeju city, Republic of Korea.

2 Related Work

Especially for the fleet management, EV planning is more important for better availability and service ratio. [8] designs an information service architecture for both prior and en-route planning. It focuses on economic itinerary planning based on the retrieval of real-time charging station information. It is built upon location and SoC (State of Charge) tracking for EVs as well as status monitoring for charging stations and road conditions. The global server estimates the battery consumption along the route using previous trip reports and searches the nearest charging station from its local database, when the battery shortage is foreseen. Here, the authors develop a battery consumption model consisting of not only the force factor for an EV to move at a given speed but also the necessary amount of power to overcome the resistance force. Out of several routes recommended by the server, a driver can choose and load the best itinerary to his or her smart phone, which also collects the trip records and reports to the server when returning to the company.

For charging-combined routing, it is necessary to search and reserve a charging station on the way to a destination. [9] presents a routing mechanism in which a broker selects the best charging station for the driver to reserve. The broker considers resource availability, location convenience, price signal change, and others, contacting with various information sources. For the reservation service, each charging station supports the coordination among multiple charging requests over the time slots for both predictable operations and peak-load reduction. In addition, City Trip Planner can create personalized tour routes, providing its service in major cities [10]. For a given set of user-selected tour spots, it maximizes the sum of scores gained by visiting the spot. It automatically inserts tour spots not chosen by users but thought to be preferred. We think that the local search heuristic taken by this approach is worth being considered also for EV tour services.

Not just restricted to charging and tour planning, EVs can bring more profits to EV owners and grids of different levels [11]. Basically, an efficient charging schedule can significantly reduce the fueling cost, considering day-ahead energy prices. The Danish Edison project investigates various EV application areas including a design of EV aggregators operating under the control of mathematical prediction models of driving patterns and charging demand [12]. Those models identify the available charging interval, pursuing cost optimization. In addition, DC charging allows EVs to be charged quickly, namely, within tens of minutes, and even sell electricity back to the grid on peak intervals based on the V2G (Vehicle-to-Grid) technologies [13]. Interestingly, integrating more renewable energies is an attractive advantage of EV charging infrastructure. In [14], the control agent tries to capture as much energy available from renewable sources as possible, maintaining power output as stable as possible. It stores surplus energy to the second-life batteries for better energy efficiency.

Our research team has been developing a tour-and-charging scheduler for EVs which want to visit multiple destinations, considering various options and requirements specified by EV rent-a-car users. The first step of this service design is to trace the SoC change along the tour route [15]. Our team is also refining a battery consumption model for the major roads in Jeju City. The designed scheduler does not only reduce the tour length but also avoids the waiting time, making the tour time overlap EV charging as much as possible. Moreover, a set of system-recommended tour spots facilitating chargers and hosting other activities can eliminate the waiting time. Instead of waiting for batteries to be charged, the tourist can take other actions like dining. In the service implementation, we take both the exhaustive search for accuracy and the genetic algorithm for responsiveness. In addition, one of our previous work has designed a DC charger selection scheme based on the sequential distance from the starting point [16].

3 DC Charging Station Selection

In the target city, namely, Jeju City, Republic of Korea, 21 DC chargers are currently installed. DC chargers evenly distribute over the whole island area and the number of DC chargers keeps increasing. To decide a TSP path, it is necessary to know the cost of every destination pair. Our service allows tourists to select the tour spots only from this fixed set for manageable computation time. This restriction makes it possible to precalculate all inter-destination distances by conventional point-to-point shortest path algorithms such as Dijkstra or A*, regardless of their execution time. The north region has the largest population and many facilities such as the international airport and hotels, making many tours start from here. The in-town chargers are mainly used by local residents during day and night time.

In Jeju City, having the perimeter of 250 km and a variety of tourist attractions, the statistics tell that the daily tour length usually falls into the range of 100 to 150 km. Hence, one charging is essential during the trip, but it may extend the tour length and time. Straightforwardly, given a set of user-selected n destinations, every DC charger is added to the tour set and the one making the tour length smallest will survive the competition. With the exhaustive search, the tour scheduler investigates all feasible schedules. Here, the first level of the search tree has m subtrees, each of which has $n!$ leaves, making the depth of the tree $(n+1)$. Lke other optimization technologies, reaching a leaf node, a complete schedule is built and its cost is evaluated according to the given criteria. If its tour length is less than the current best and it does not violate the constraint, this schedule will replace the current best.

If a schedule makes passengers to wait somewhere on the route to charge the battery with slow chargers, they cannot accept it. To remove such a schedule, the search procedure estimates the SoC change along the route [17]. The Soc decreases according to the distance the EV has taken. If SoC drops below 0 somewhere on the sequence specified in the schedule, the schedule will be automatically discarded without further evaluation. In the process of the search space traversal during which each node is expanded one by one, a subsequence from the root, namely, the subpath from the starting point to the currently expanding node, can be already larger than the current best. Then, it is necessary to stop the expansion immediately by pruning the branch. In the tour schedule, the number of selected tour spots, namely, n, is usually less than 10 in most tour cities, and the tour schedule can be generated within a tolerable bound even with an average-performance PC. In spite of much achievable improvement in response time, a large m can make the execution time too much.

Our main idea lies in achieving an acceptable response time even if m gets larger according to the installation of more DC chargers. The responsiveness comes with a small accuracy loss as the scheduling procedure investigates just m' out of m chargers. m' is a tunable parameter and the number of chargers to investigate. The problem definition and the main idea are both illustrated in Figure 1, where D_1, D_2, D_3, and D_4 are destinations an EV wants to visit and tour length will be decided by the visiting order. We assume that the EV starts from and returns to D_1. There are 5 DC charging stations from C_1 to C_5 and the EV needs to be charged once during the tour and thus it must additionally visit one of them. In addition, the pure tour length decided by a TSP solver for $\{D_1, D_2, D_3, D_4\}$ is defined as TSP length. It must be distinguished from the travel distance which includes the addition of some C_i.

A preprocessing procedure has calculated the battery consumption and the distance for each pair of two destinations and also for each pair of a destination and a charging station. By a legacy TSP solver, we can traverse the search space and find an optimal schedule for n destinations based on the inter-destination cost matrix. Hence, the problem is reduced to finding C_k which minimizes the tour length of a schedule for $\{D_1, D_2, .., D_n, C_k\}$ without making its waiting time nonzero. Basically, the TSP sovler can be invoked m times, namely, for $\{D_1, D_2, .., D_n, C_1\}$, $\{D_1, D_2, .., D_n, C_2\}$, ..., $\{D_1, D_2, .., D_n, C_m\}$ to find the optimal schedule. However, if m is large, the execution time is extended too much, as the TSP solver basically belongs to the $O(n!)$ problem category. If we can find a reasonable quality solution with m' candidates ($m' \ll m$), the search space will be significantly cut down, and $\frac{m'}{m}$ is the speedup ratio.

Our heuristic of selecting m' candidates can be better explained with the example of Figure 1. An addition of a charging station to the tour inevitably increases the tour length and time. However, if a station on the tour route is selected, the tour distance is hardly affected. We cannot know which link (pair of two destinations) will be included in the final schedule until the time-intensive TSP solver completes the schedule. On the contrary, if a station near any destination is selected, it is highly likely not to increase the tour length. Hence, in Figure 1, for each charging station, it is necessary to find the closest

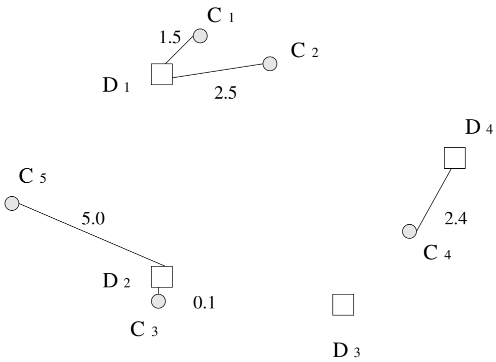


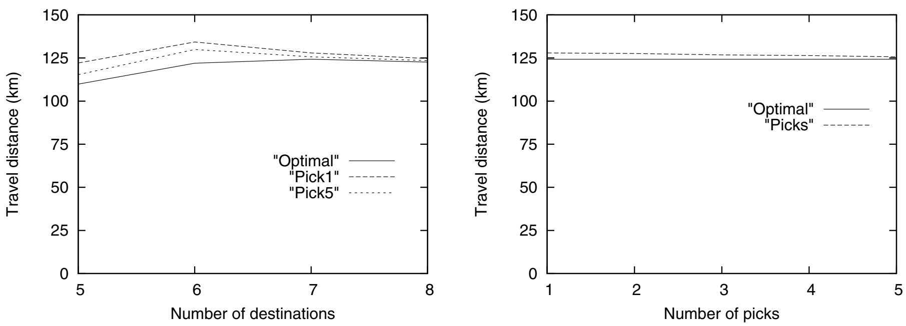
Fig. 1. Distance-based heuristic

destination. Here, C_1 and C_2 are commonly closest to D_1. As the cost matrix from a station to every destination is also given, this step just finds the D_i having the smallest distance. Now, excluding the start point, which is the first and last destination of a sequence and thus charging near this point may make the waiting time nonzero, we can find the charging station having the smallest distance. In this figure, C_3 has 0.1 and will be chosen to the m' candidates first. If m' is 2, C_4 will be selected.

4 Performance Measurement

This section first implements a prototype of the proposed tour scheduler and evaluates its performance. An optimal scheduler, which investigates all feasible schedules, namely, $m{=}m'$, is also developed for performance comparison. For simplicity, we assume that there is no queuing delay to focus on the pure effect of DC charger selection, as it can be easily integrated with a charging schedule. When multiple charging requests concentrate on the same time slot, the queuing time must be considered. In selecting m' candidates, those stations already reserved on the estimated arrival time of the EV should be avoided. Main performance metrics include tour length and accuracy. The accuracy means the probability that a scheduler finds the optimal sequence. For 40 destinations, the distance for each pair of them is calculated in priori. (n-1) destinations are randomly picked in addition to the airport, the start point. If a schedule is found for a given set of destinations, it will be regarded as a feasible one. For each parameter setting, 10 sets are generated and the results are averaged.

The first experiment measures the travel distance according to the number of destinations and also the number of picks, while the results are plotted in Figure 2. As shown in Figure 2(a), the experiment changes the number of destinations from 5 to 8. Here, the destination sets having the TSP length of 100.0 to 120.0 km are chosen. For 9 or more destinations, it is hard to find a destination set whose TSP length falls in this range. Figure 2(a) shows 3 curves. As expected,



(a) Effect of the number of destinations (b) Effect of the number of picks

Fig. 2. Effect of the number of picks

the optimal scheme has the smallest travel distance on the whole range. The Pick$n$ curve corresponds to the case m' is n. The performance gap is largest on 5 destinations and gets smaller according to the increase in the number of destinations. With 8 destinations, Pick5 and Pick1 are just 0.7 % and 1.6 % longer than the optimal result, respectively. This behavior can be explained by the observation that with more destinations, the scheduler is more likely to find candidates closer to destinations.

Next, Figure 2(b) shows a deeper investigation result on the effect of the number of picks. Here, the number of destinations is fixed to 7 and the TSP length is made to range from 100.0 to 120.0 km as in the previous experiment. The travel distance of the optimal schedule outperforms others and with more candidates we can expect a better travel distance. In this parameter setting, even with just 1 pick, which corresponds to $\frac{1}{21}$ of the legacy computation time, the travel distance is just 1.6 % longer than the optimal schedule. Furthermore, the gap linearly decreases each time a candidate is added. This result indicates that Pick5 almost always finds the optimal schedule for 10 sets just with the $\frac{5}{21}$ of the execution time.

The second experiment measures the effect of the TSP length to the travel distance. It must be mentioned again that the difference between them comes from the addition of a charging station to the entire tour schedule. Figure 3 shows the travel distance according to the TSP length. Here, for each 10 km interval in the TSP length, for example, from 100.0 to 110.0 km and from 130.0 to 140.0 km, 10 destination sets are selected. The number of destinations is fixed to 7. In Figure 3, the Pick1 graph goes quite higher than the others, especially when the TSP length is over 120.0 km. It reaches 19.3 % for the range of 130.0 to 140.0 km. In selecting a DC charger, Pick1 simply considers the distance from any one of the destinations. If a DC charger close to the start (or last) destination in the sequence is selected, it can lead to the nonzero waiting time. On the contrary, when m' is 5, this effect can be almost completely masked out. As shown in the figure, Pick5 generates a schedule at most 4.1 % longer than the optimal scheme.

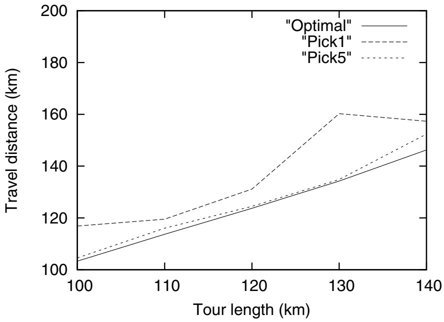
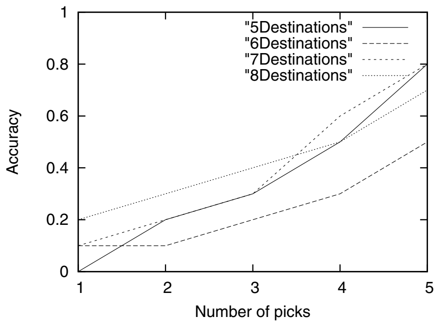
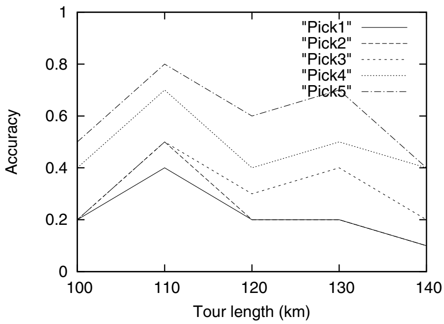


Fig. 3. Effect of the TSP length

The final experiment measures the accuracy according to the number of picks and also the number of destinations, the results being shown in Figure 4. Figure 4(a) plots the measured accuracy according to the number of picks from 1 to 5. In all experiments, the TSP length is made to range from 100.0 to 120.0 km. Each curve corresponds to the respective number of destinations. For all curves, the increase in the number of picks essentially improves the accuracy. With 5 picks, the accuracy is at least 0.5, reaching 0.8 for the cases of 5 and 7 destinations. Even in the case the scheduler fails to find an optimal schedule, its quality is comparable to it. This result indicates that our scheme can find a near optimal schedule with much less and even tunable response time compared with the optimal schedule which may take too much time when there are many charging stations.



(a) Effect of the number of picks



(b) Effect of the TSP length

Fig. 4. Accuracy analysis

In addition, Figure 4(b) plots the accuracy according to the TSP length. Here, the number of destinations is fixed to 7. This figure includes 5 curves, each of which is associated with each number of picks. Unlike Figure 4(a), Figure 4(b) doesn't seem to be linearly dependent on the TSP length. The destination set specific features, such as tour spot distribution, have more effect on the accuracy. The accuracy tends to deteriorate according to the increase in the TSP length, but this effect is not so vivid. However, during the interval from 110.0 to 130.0 km, we can find the accuracy remains at least 0.6 with 5 picks and this result confirms again that it is possible to obtain a reasonable quality schedule for the whole range of TSP length, with much less response time, compared with the optimal scheme.

5 Conclusions

Modern grids are getting smarter with the integration of computational intelligence supported by information technologies. EVs, still facing an obstacle of long charging time and short driving range towards their wide penetration, can also benefit from intelligent tour planning. For EV rent-a-cars which visit multiple destinations and need to be charged once a day, an efficient selection of a charging station along with a tour schedule can reduce the tour length and save energy. However, we must cope with the time complexity according to the increase in the number of available chargers following the expansion of charging infrastructure. This paper achieves this goal by constraint processing and the reduction of the number of candidate stations from m to m', where m is the number of all stations in the area and m' is that in the selected subset. The subset is built by a heuristic which selects m' candidates based on the distance from each station to any of given destinations.

The performance measurement result, conducted on the real-life environment of the target city, shows that with 5 candidates, the tour length is prolonged just by 0.7 % and finds the optimal schedule with the probability of 0.8, with the speedup of $\frac{5}{21}$. Next, for the given TSP length range, the proposed scheme just brings at most 4.1 % of distance overhead, compared with the optimal scheme. As future work, we are planning to combine with the spatial query processing system to cope with the increase in the number of DC chargers. By filtering out those chargers far away from selected destinations, we can further reduce the size of m.

References

1. Timpner, J., Wolf, L.: Design and evaluation of charging station scheduling strategies for electric vehicles. IEEE Transactions on Intelligent Transportation Systems 15(2), 579–588 (2014)
2. Mischinger, S., Hennings, W., Strunz, K.: Integration of surplus wind energy by controlled charging of electric vehicles. In: 3rd IEEE PES Innovative Smart Grid Technologies Europe (2012)
3. Botsford, C., Szczepanek, A.: Fast charging vs. slow charging: Pros and cons for the new age of electric vehicles. In: International Battery Hybrid Fuel Cell Electric Vehicle Symposium (2009)
4. Veneri, O., Capasso, C., Ferraro, L., Pizzo, A.: Performance analysis on a power architecture for EV ultra-fast charging stations. In: International Conference on Clean Electrical Power, pp. 183–188 (2013)
5. Vedova, M., Palma, E., Facchinetti, T.: Electric load as real-time tasks: An application of real-time physical systems. In: International Wireless Communications and Mobile Computing Conference, pp. 1117–1123 (2011)
6. Shim, V., Tan, K., Tan, K.: A hybrid estimation of distribution algorithm for solving the multi-objective multiple traveling salesman problem. In: IEEE World Congress on Computational Intelligence (2012)
7. Ramchrun, S., Vytelingum, R., Rogers, A., Jennings, N.: Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence. Communications of the ACM 55(4), 86–97 (2012)
8. Mehar, S., Remy, G.: EV-planning: Electric vehicle itinerary planning. In: International Conference on Smart Communications in Network Technologies (2013)
9. Bessler, S., Grønbæk, J.: Routing EV users towards an optimal charging plan. In: International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium (2012)

10. Vansteenwegen, P., Souffriau, W., Berghe, G., Oudheusden, D.: The City trip planner: An expert system for tourists. Expert Systems with Applications 38, 6540–6546 (2011)
11. Andrandt, A., Andersen, P., Pedersen, A., You, A., Poulsen, B., O'Cornel, N., Østergaard, J.: Prediction and optimization methods for electric vehicle charging schedules in the Edison project. IEEE Transactions on Smart Grid, 111–119 (2011)
12. Ortega-Vazquez, M., Bouffard, F., Silva, V.: Electric vehicle aggregator/system operator coordination for charging scheduling and services procurement. IEEE Transactions on Power Systems 28(2), 1806–1815 (2013)
13. Kisacikoglu, M., Ozpineci, B., Tolbert, L.: EV/PHEV bidirectional charger assessment for V2G reactive power operation. IEEE Transactions on Power Electronics 28(12), 5717–5727 (2013)
14. Hamidi, A., Weber, L., Nasiri, A.: EV charging station integrating renewable energy and second-life battery. In: International Conference on Renewable Energy Research and Applications, pp. 1217–1221 (2013)
15. Lee, J., Park, G.: A tour recommendation service for electric vehicles based on a hybrid orienteering model. In: ACM Symposium on Applied Computing, pp. 1652–1654 (2013)
16. Lee, J., Park, G.: DC charger selection scheme for electric vehicle-based tours visiting multiple destinations. In: ACM Research in Applied Computation Symposium (to appear, 2014)
17. Lee, J., Park, G.-L.: Design of a multi-day tour-and-charging scheduler for electric vehicles. In: Ramanna, S., Lingras, P., Sombattheera, C., Krishna, A. (eds.) MIWAI 2013. LNCS, vol. 8271, pp. 108–118. Springer, Heidelberg (2013)