Effect of Genetic Parameters in Tour Scheduling and Recommender Services for Electric Vehicles*

Junghoon Lee, Gyung-Leen Park, Hye-Jin Kim, Byung-Jun Lee, Seulbi Lee, and Dae-Yong Im

Dept. of Computer Science and Statistics,
Jeju National University, 690-756, Jeju Do, Republic of Korea
{jhlee,glpark,hjkim82,eothsk,gwregx,dlaeodyd123}@jejunu.ac.kr

Abstract. This paper assesses the performance of a tour scheduling and recommender service for electric vehicles, aiming at verifying its effectiveness and practicality as a real-life application. The tour service, targeting at electric vehicles suffering from short driving range, generates a time-efficient tour and charging schedule. It combines two computing models, one for user-specified essential tour spots as the traveling salesman problem and the other for service-recommended optional spots as the orienteering problem. As it is designed based on genetic algorithms, this paper intensively measures the effect of the population size and the number of iterations to waiting time, tour length, and the number of visitable spots included in the final schedule. The experiment result, obtained through a prototype implementations, shows that our scheme can stably find an efficient tour schedule having a converged fitness value both on average and overloaded set of user selection.

Keywords: Electric vehicle, tour scheduler, genetic algorithm, waiting time, visitable node.

1 Introduction

Not just for energy efficiency, but also for the reduction of greenhouse gas emissions, the market penetration of EVs (Electric Vehicles) is encouraged in modern and future transportation systems. Especially on tour places having a bunch of natural attractions, clean air is more important. In those places, EV rent-a-cars are considered to be a promising business model. However, it is well known that the driving range of EVs is too short and their batteries must be charged more often [1]. It takes about 6 ~ 7 hours to fully charge an EV with slow chargers, and a fully charged EV can drive at most 150 *km*. Moreover, terrain and climate effect can further reduce the driving range. As the daily driving distance of ordinary vehicles is less than this range, overnight charging is enough. However, EVs rented for a tour can possibly drive beyond this range, and they need to be charged during the tour, wasting the tour time.

---

* This work (Grants No. C0026912) was supported by Business for Cooperative R&D between Industry, Academy, and Research Institute funded by Korea Small and Medium Business Administration in 2012.

J.J. Park et al. (Eds.): GPC 2013, LNCS 7861, pp. 556–562, 2013.
© Springer-Verlag Berlin Heidelberg 2013

The constraint in the driving range is sure to affect the tour schedule. Even if tourists want to visit a famous tour spot, they can't go there provided that the distance between the spot and the last charging facility is longer than the driving range on the way to the spot. Moreover, waiting time during the tour will be different according to visiting sequences. As a result, for EV rent-a-cars, sophisticated tour scheduling is more important to deal with the driving range constraint. Just like other facilities and services in the smart grid, EV rent-a-cars can benefit from the intelligence of the computing algorithms. Hence, our previous work has developed a tour scheduling scheme which creates the visiting order capable of reducing the waiting time for EV charging for the given set of user-selected attractions [2]. It can further recommend additional tour spots having chargers to avoid time waste in a tour.

For the integration of such a service into the real-life product, it is necessary to evaluate and verify its performance and reliability. It includes many execution variables including the omission degree, charging facility probability, and stay time distribution. Basically, as this scheme is built on top of genetic algorithms, the performance behavior according to the genetic parameters is the first to be investigated. In this regard, this paper measures the performance of the EV tour scheduling and recommender system based on a prototype implementation. The performance metrics are consist of waiting time, tour length, and the number of visitable tour spots according to the population size and the number of iterations. With the performance data collected by the experiment, its practicality as a commercialized service will be assessed.

2 Background

For the given set of nodes, deciding a visiting order is a typical TSP (Traveling Salesman Problem), and there have been many researches and applications for them. However, this application belongs to non-polynomial complexity problems and has different cost functions. Sometimes, two or more goals may conflict. In the case of tour schedulers, each tour spot is associated with a profit, or degree of user satisfaction and it is not necessary to visit all spots. In addition, every time a tourist moves from one spot to another, travel cost is added. According to the survey of [3], one of the most efficient methods to solve such a problem is to define an object function which gives precedence to profit maximization, while taking the travel cost as a constraint. This problem type is called an orienteering problem, and a genetic algorithm has been designed for it [4]. In its encoding, a vertex will be removed by the omission probability and not every vertex will be included in each chromosome.

Our previous work has designed a tour scheduling and recommender service for EVs to enrich EV rent-a-car business by computational intelligence [2]. For the set of user-selected tour places, it finds the visiting order and where to charge the EV, considering the inter-spot distance as well as tracing battery remaining. However, if a tourist wants to visit a series of spots far away from each other, he or she must stop by a charging station and wait for his or her EV to be charged. Instead, our service recommends additional spots in which the tourist can take another tour activity while the EV is being charged, even though they are not selected at first. In this design, genetic operations are tailored to create a tour plan consisting of essential selected and optional recommended places by means of combining legacy traveling salesman problem and orienteering problem solvers. Its encoding scheme represents a visiting order by a fixed-length integer-valued vector, while the fitness function estimates time waste for a tour route.

3 Service Scenario

For EV-based tours, the renters select the set of tourist attractions they want to visit and the tour planner or recommender helps them to decide the visiting order [5]. It has the time and space complexity of $O(n!)$, where n is the number of attractions. So, computerized selection will be better than human calculation. Genetic algorithms investigate just a part of the whole search tree to meet the time constraint [3]. That is, the schedule must be created within user-tolerable response time. If a tour spot has a charging facility, the EV can be charged during the renters take a tour. Battery remaining increases in proportion to the stay time at the place [6]. On the contrary, when no charging facility is available, the EV gains no battery charging. This makes the visiting sequence more critical to waiting time.

Waiting time can be serious enough to make travelers feel severely inconvenient, if they cannot do anything while their EVs are being charged. Instead, they can avoid this waste, if they visit a place where both tour activities and charging facilities are available, even though the places are not selected at first. The list of recommendable spots is available in tour information services and can be retrieved through spatial queries. While all the places selected by the tourists must be included in the final tour plan, the recommendable places don't always have to be included. After all, the route planner for the EV-based tour is a combination of the legacy TSP solver for the user-selected places and the orienteering problem solver for recommendable places. The planner pursues the reduction of waiting time and the enhancement of tourists' satisfaction. It can be quantified by the number of visitiable places or the sum of satisfaction degrees for visitable spots.

For a genetic algorithm-based design, each schedule is encoded to an integer-valued vector. Its length coincides with the total number of both user-selected and service-recommended spots. In this fixed size vector, some of recommended spots are omitted and marked by -1. Next, the fitness function calculates the cost for a schedule. As this service focuses on the waiting time for EV charging, it is necessary to follow the sequence to find out where and how much charging is required, considering the stay time usually available in tour statistics. Finally, the genetic operators are run generation by generation. In the mean time, after crossover operations, some essential entries appear more than once while others become absent. Hence, the duplicated entries are replaced by disappearing ones. On the contrary, for optional spots, duplicated entries are replaced by other optional ones.

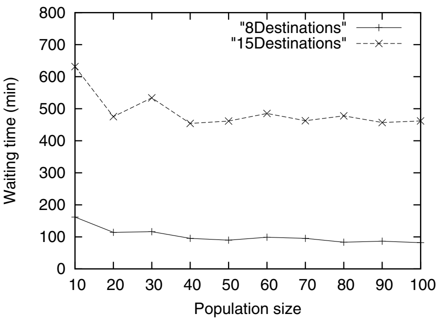
4 Experiment Result

Before the experiment on the genetic parameters, the scheduler-specific parameters need to be chosen, mainly considering the target tour environment. In our experiment, each tour spot is located randomly in the map. The inter-spot distance exponentially distributes with the average of 20 *km*. For two destinations *A* and *B*, the distance from *A* to *B* is different from that from *B* to *A*. They are not symmetric, but the difference is less than 5 %. Next, stay time also distributes exponentially with the average of 20 *minutes*. But, its lower and upper bounds are 20 *minutes* and 3 *hours*, respectively. The probability that a tour spot has a charger is set to 0.8 and the omission degree is to 0.8. Finally, an EV is assumed to start a day trip with it battery charged enough to go 90 *km*, considering overnight charging. The experiment generates 20 parameter sets for each parameter setting, and averages the results.

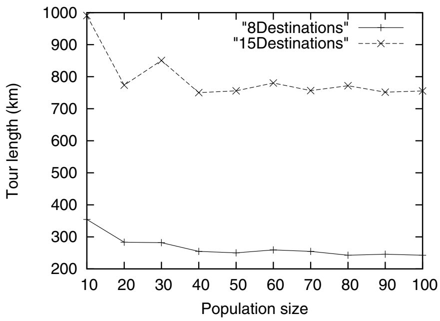
In genetic algorithms, the population size affects the diversity of chromosomes. However, if it is large, execution time will also increase. For applications having a constraint in the maximum response time, a large population does not always find a better solution, as the number of iterations can be limited. Particularly, each genetic loop sorts or at least partitions chromosomes in the population, so its time complexity can be approximated to be O($p \log p$), where p is the population size, or the number of chromosomes. Next, with more iterations, we can expect to get better solutions. However, in most cases, the genetic loop converges to a reasonable solution very quickly in the early stage of the whole generations. Thus, the fitness value remains unchanged in the subsequent iterations. After all, it is important to find an efficient parameter selection capable of obtaining an acceptable schedule within the given time bound.

Each experiment is conducted for the cases of 8 and 15 destinations, respectively. The first accounts for the most common tour pattern and the second for the overloaded condition, in which genetic algorithms can possibly fail to converge to an acceptable schedule. Hence, they can check the practicality and the stability of our tour scheduling and recommender service, respectively. Here, the number of recommended destinations is set to 15. Hence, the tour scheduler takes either 23 or 30 destinations in total. It cannot be calculated with exhaustive search methods and genetic algorithms can investigate only the part of the whole search space. Actually, recommended spots are supposed to be retrieved from the spatial database. However, as the charging facility map is not available yet, our experiments locate them randomly. As a result, in spite of the increase in the number of recommended destinations, waiting time does not always get better, as they can be located far away from the feasible routes.

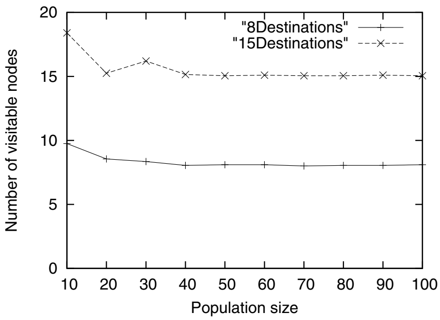
The first experiment measures the effect of population size to waiting time, tour length, and the number of visitable destinations, respectively, and the results are shown in Figure 1. In this experiment, we change the population size from 10 to 100. As the fitness function mainly calculates the waiting time for each schedule, a large population can reduce waiting time by the improved diversity. In the case of 8 destinations, the waiting time is 161.7 *minutes* when the population size is 10 and gets improved to 82.55 *minutes* when the population size is 100. It corresponds to 42.9 % reduction as shown in Figure 1(a). In the case of 15 destinations, we can see 26.9 % improvement. Even if waiting time is reduced thanks to the increase in the population size, it hardly gets better after the population size of 50. Further increase in the population size just leads to the extension of execution time.



(a) Waiting time change



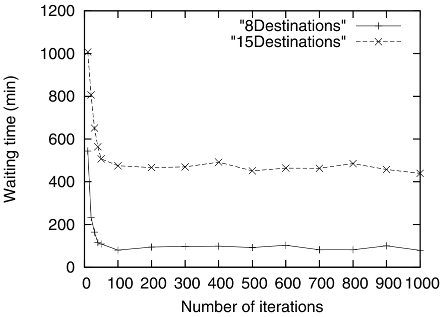
(b) Tour length change



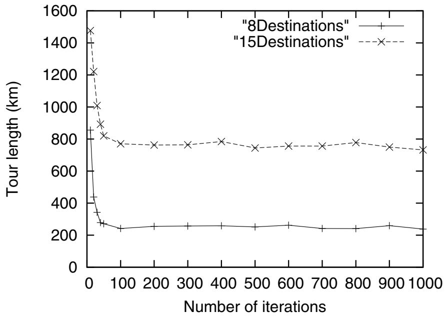
(c) Change in the number of visitable nodes

Fig. 1. Effect of population size

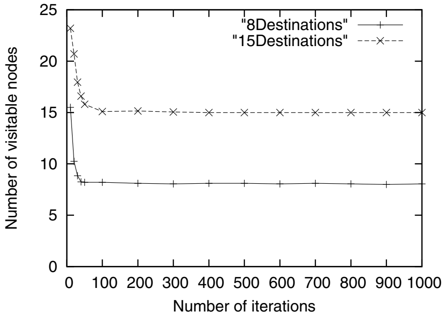
Tour length is closely related to waiting time, so they show a similar pattern. If tour length increases, the tourists are likely to charge their EV for longer time. The increase in the population size from 10 to 100 results in the reduction of tour length by 31.6 % in the case of 8 destinations and 23.7 % in the case of 15 destinations, respectively, as shown in Figure 1(b). On the contrary, the number of visitable spots decreases according to the increase of the population size. Actually, the reduction in waiting time tends to remove non-essential destinations in the tour schedule. A recommended destination can contribute to the reduction of waiting time when it is located between two stations unreachably far away from each other with average battery remaining. Hence the number of visitable spots is reduced from 9.75 to 8.1 with the improvement in the efficiency of the tour schedule, as shown in Figure 1(c).



(a) Waiting time change



(b) Tour length change



(c) Change in the number of visitable nodes

Fig. 2. Effect of the number of iterations

The next experiment measures the effect of the number of iterations to waiting time, tour length, and the number of visitable destinations, respectively, and the results are shown in Figure 2. In this experiment, we change the number of iterations from 10 to 1,000. Genetic iterations improve the fitness of the solution generation by generation. Our main concern lies in how many iterations are usually needed to get the converged result. In the case of 8 destinations, waiting time is 544 *minutes* at first and cut down to 78.7 *minutes* with 1,000 iterations, showing 85.6 % improvement, as shown in Figure 2(a). In addition, in the case of 15 destinations, waiting time is reduced from 1,007 *minutes* to 439 *minutes*, showing 56.4 % improvement. As the experiment generates the destination set randomly, each set has a different optimal schedule. Hence, even with more iterations, waiting time may increase as respective fitness values are averaged.

As in the case of the experiment on population size, tour length shows a similar pattern as waiting time. It is shown in Figure 2(b). Tour is length is less sensitive to the number of iterations, compared with waiting time, as the reduction is 72.1% in the case of 8 destinations and 50.4 % in the case of 15 destinations, respectively. In addition, just like waiting time, tour length reaches a stable value within 100 iterations in most cases, and then rarely changes. Finally, as for the number of visitable spots, it is reduced according to the enhancement of waiting time. Particularly, in the case of

15 destinations, no recommended spot survives in the final tour schedule after 500 iterations. This result indicates that the locations of recommended spots are important and accurate spatial information is essential to this service. Additionally, in the case of 8 destinations, the number of visitable spots is cut down from 15.5 to 8.05.

5 Conclusions

Due to their eco-friendliness, EVs are encouraged in many tour cities which have many natural attractions, not just for personal ownership but also car sharing and rent-a-car services. However, the short driving range of EVs is the main obstacle and inconvenience factor in EV rent-a-car services. In this paper, we have assessed the performance of a tour scheduling and recommender system, focusing on the effect of genetic algorithm-specific parameters such as the population size and the number of iterations to waiting time, tour length, and the number of visitable tour spots included in the final schedule. Combining the traveling salesman problem and the orienteering problem, this service generates a visiting sequence for user-specified essential and service-recommended optional tour spots. The measurement result shows that our scheme can stably find an efficient tour schedule having a converged fitness value both on average and overloaded set of user selection. Moreover, waiting time can be managed below 1 *hour* for the given tour scenarios.

References

1. Bessler, S., Grønbæk, J.: Routing EV users towards an Optimal Charging Plan. In: International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium (2012)
2. Lee, J., Park, G.: A Tour Recommendation Service for Electric Vehicles Based on a Hybrid Orienteering Model. Submitted to ACM SAC (2013)
3. Giardini, G., Kalmar-Nagy, T.: Genetic Algorithm for Combinational Path Planning: The Subtour Problem. Mathematical Problems in Engineering (February 2011)
4. Tasgetiren, M., Smith, A.: A Genetic Algorithm for the Orienteering Problem. In: Proc. Congress on Evolutionary Computing. pp. 1190–1195 (2000)
5. Ferreira, J., Pereira, P., Filipe, P., Afonso, J.: Recommender System for Drivers of Electric Vehicles. In: Proc. International Conference on Electronic Computer Technology, pp. 244–248 (2011)
6. Lee, J., Kim, H.-J., Park, G.-L.: Integration of Battery Charging to Tour Schedule Generation for an EV-Based Rent-a-Car Business. In: Tan, Y., Shi, Y., Ji, Z. (eds.) ICSI 2012, Part II. LNCS, vol. 7332, pp. 399–406. Springer, Heidelberg (2012)