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Incorporative Relocation Team Planning and Staff Member Allocation in Electric Vehicle Sharing Systems

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Abstract

This paper presents a design and analyzes the performance of a relocation planner for electric vehicle sharing system, aiming at reducing management cost and enhancing service ratio by avoiding service degradation stemmed from stock imbalance. The proposed planner creates a set of relocation pairs, each of which consists of an overflow station and an underflow station for respective relocation teams. To simultaneously determine the team-by-team number of staff members and relocation pairs based on the genetic algorithm, each plan is encoded by an integer-valued vector composed of relocation pair and staff allocation parts. The relocation pair part translates individual station matching, complementarily combining overflow and underflow indices as well as including negative number separators. The staff part indicates the number of staff members for each team and thus how many identical pairs can be merged. Genetic operators are allowed only in the relocation pair part, while the fitness function gives precedence to a balanced plan. The performance measurement result, obtained by a prototype implementation, shows that our planner outperforms the reference scheme by up to 53.0 % for given parameter setting.

Keywords: *Electric vehicle sharing system, relocation schedule, multiple teams, genetic algorithm, relocation cost*

1. Introduction

[1]An electric vehicle, or EV in short, and a carsharing system are two most important entities in eco-friendly smart transportation [1]. EVs are powered by battery-stored energy, not burning fossil fuels as in gasoline-powered vehicles. Here, we can get electricity from many energy sources such as nuclear power, hydroelectric power, and diverse renewable energies. On the other hand, vehicle sharing systems can reduce the number of vehicles especially in downtown area, which is highly likely to suffer from lack of parking space. The drivers don't have to purchase their own cars, but rent and return a car just on necessary basis. Now, combining both advantages, EV sharing systems can achieve energy efficiency and greenhouse gas reduction. It can relieve the users of a burden of maintaining EVs, inevitably stemmed from long charging time and short driving range.

In carsharing, one-way rental is the most convenient way from the viewpoint of sharing users, as they are not required to return EVs to the same station they rented out

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[2]. However, uneven demand distribution, be it spatial or temporal, over different stations surely leads to stock imbalance, hence some stations have no EV to serve rent-out requests [3]. In this case, EVs must be relocated for better service ratio, under the coordination of a control system which definitely benefits from sophisticated information technologies. They can fully take advantage of ubiquitous connectivity provided by modern communication networks. For example, the PICAV system selects a return station for a flexible rent-out transaction based on the simulated annealing mechanism [4]. Next, Intellishare implements a user-oriented relocation mechanism with the combination of trip joining and trip splitting operations [5]. In addition, [6] proposes an explicit relocation scheme consisting of optimizer, trend filter, and simulation phases.

According to a specific relocation strategy, EVs in overflow stations must be moved to underflow stations. The coordinator triggers the relocation procedure either incrementally during operation hours [6] or in entire system scale during nonoperation hours, necessarily based on the future demand forecast [7]. The problem is to find a set of relocation pairs, each of which consists of one overflow station and one underflow station, to achieve the given performance goal. Considering that the relocation can be carried out by multiple teams having different number of staff members, how to make a relocation plan is quite a complex problem [8]. In this regard, this paper designs a relocation planner capable of harmoniously allocating staff members to each team and deciding relocation matching for each team. Based on the genetic algorithm, one of the most widely used suboptimal search techniques, our scheduler reduces the relocation distance and time, saving the management cost as well as improving the service ratio.

The rest of this paper is organized as follows: After issuing the problem in Section 1, Section 2 describes the system model and relation to our previous work. Section 3 explains how to encode a relocation schedule by an integer vector and subsequent genetic operators. Next, performance measurement results are demonstrated and discussed in Section 4. Finally, Section 5 summarizes and concludes this paper with a brief introduction of future work.

2. System Model

In a sharing station, let there be n stations, namely, $S = \{S_1, S_2, ..., S_n\}$. For the current and target distribution of EVs at a relocation time, the relocation vector, $R = \{R_1, R_2, ..., R_n\}$, can be calculated. Here, how to decide the target distribution and when to trigger the relocation procedure are another problems, and this paper just focused on the relocation procedure for the given target distribution. If R_i is positive, S_i is an overflow station, and as many EVs as R_i must be moved to an underflow station, say S_j, having negative R_j. Due to the high cost and uneasy maintenance of towing vehicles, it is a better option to make human staff relocate EVs. This strategy allows multiple relocations teams to move EVs in parallel. Here, a relocation team consisting of h staff members can move $h-1$ vehicles at the same time as follows: h staff members go to an overflow station together in a service vehicle. $h-1$ members drives respective EVs to the same underflow station, while 1 follows them in the service vehicle. Now, h staff members go to another overflow station. h is limited by the capacity of a service vehicle.

For a relocation procedure, the number of relocation teams and the number of total staff members are given in advance. Then, the coordinator decides how many staff members to allocate to each team and matches overflow and underflow stations, considering the team-by-team number of staff members and the number of mergeable operations. To solve this complex problem using genetic algorithms for reasonable response time, it is necessary to

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denote an allocation, or relocation schedule, by an integer vector. Our previous work has designed an encoding scheme for the allocation of relocation operations [9], so it is necessary to extend to include staff assignment for each team. Then, genetic operators such as selection, crossover, and mutation, are tailored to make populations, composed of a set of feasible schedules, evolve. Additionally, the cost function estimates the relocation distance by individually calculating the distance between each of two relocation pair elements.

3. Relocation Scheduler

Figure 1 illustrates our encoding scheme. It begins with two indices, one for overflow stations and the other for underflow stations [9]. Each index sequentially stores overflow/underflow stations, and an overflow station, S_i, will appear R_i times. In an encoded vector, each element represents a relocation pair consisting of an overflow station and an underflow station. If we just consider a single team case, the index in an encoded vector points to an overflow station while the value to an underflow station. In Figure 1, there are 5 stations from S_1 to S_5. S_1 and S_3 are overflow stations as R_1 and R_3 are 3 and 5, respectively. S_1 appears 3 times in the overflow index. In the figure, the value at the location 1 is 5 in the encoded vector. The element at the location 1 in the overflow index is S_1, while the element at the location of 5 in the underflow index is S_4. Likewise, 1 at the location of 2 in the encoded vector represents a relocation pair (S_1, S_2).

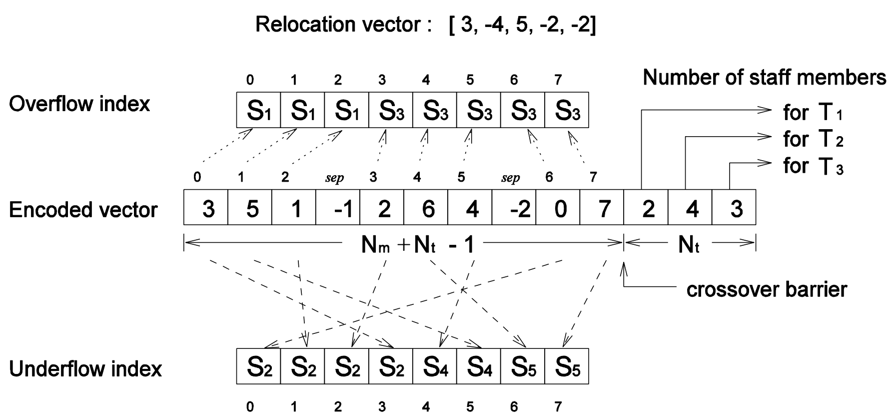

Figure 1. Main idea and encoding scheme

This encoding scheme will be extended for a multiple team schedule, where negative numbers are inserted to separate respective team schedules [10]. Basically, for N_t relocation teams, N_t-1 numbers are needed [11]. For example, Figure 1 contains 2 negative numbers for 3 teams. The relocation vectors for 3 teams from T_1 to T_3 are (3, 5, 1), (2, 6, 4), and (0, 7), respectively. The separators must be skipped in mapping an overflow station. This relocation plan corresponds to the relocation pair assignment of {(S_1, S_2), (S_1, S_4), (S_1, S_2)}, {(S_3, S_2), (S_3, S_5), (S_3, S_4)}, and {(S_3, S_2), (S_3, S_5)}, respectively. T_1 has two (S_1, S_2) pairs. If T_1 has 3 staff members, these two can be processed at the same time, reducing the relocation distance. Identical pairs can be merged depending on the number of staff members in the team. Hence, N_t elements are added to the encoded vector, making the total vector length N_m+N_t−1+N_t, where N_m is the number of EVs to move. Above integration is the main difference from our previous work [10].

For a complete relocation plan, we can estimate the relocation distance for each team. Basically, each team has 2 staff members and additional members can be assigned. Even though relocation pairs for T_2 and T_3 have no identical pairs in Figure 1, they unnecessarily have 4 and 3 staff members, that is, 3 and 2 EVs can be moved simultaneously. On the contrary, T_1 has just two staff members, so all relocation pairs must be processed one by one [10]. The cost function estimates the relocation distance for each team, considering such mergeable pairs. Maximum of them will be the final cost for a relocation plan. The selection procedure sorts chromosomes according to the cost, to give better chromosomes more chances to mate for the creation of next generation. The crossover operator swaps substrings from two parents. However, the last N_t should not be swapped, as the number of total staff members must be kept constant. The crossover barrier indicates this bound. After crossover, duplicated genes must be replaced by disappearing ones.

4. Experiment Result

This section measures the performance of our relocation scheme via a prototype implementation using Microsoft Visual Studio. This genetic scheduler version takes the Roulette wheel selection, random population initialization, and two-point crossover. For better population diversity, identical chromosomes are not allowed to coexist in the population. In addition, the inter-station distance exponentially distributes with the average of 3 *km*. The number of overflow stations is equal to that of underflow stations. Whether a station is an overflow or underflow station is selected randomly. The performance metric is relocation distance, while performance parameters consist of population size, the number of teams, the number of total staff members, the number of moves, and the number of stations, respectively. The default parameter values are listed in Table 1. For each parameter setting, 20 sets are generated and their results are averaged.

Table 1. Default parameter values

Parameters	Values
Population size	64
The number of stations	15
The number of teams	3
The number of extra staff members	2
The number of EVs to move	30
The number of EVs in the system	100

The first experiment traces the relocation distance, or relocation cost, along the evolutionary iterations, and the result is shown in Figure 2. It shows 3 curves, where e means the number of extra staff members. Basically, each team is assigned 2 staff members to be able to move at least 1 EV ($e=0$). For the case of $e=1$, a member is assigned to one of 3 teams. The team schedule having mergeable pairs can better benefit from more staff members. The case of $e=0$ converges in the much earlier stage of genetic iterations, as its scheduling complexity is not so high, compared with other cases. The case of $e=2$ keeps improving the relocation cost until 550 iterations. This case definitely shows better relocation distance compared with the cases of $e=0$ and $e=1$ by 40.2 % and 8.4 %, respectively. For more complex conditions, computational

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intelligence achieves better optimization. Above result indicates that our scheduler can make an efficient relocation plan within a reasonable time bound.

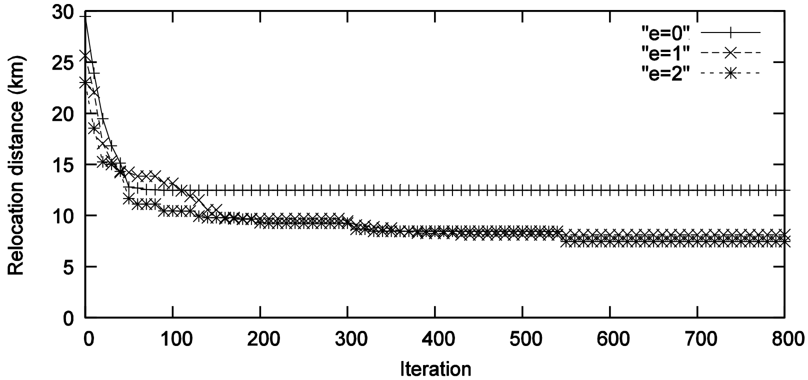

Figure 2. Relocation distance according to the iteration

Subsequent experiments compare the performance of the proposed scheme with the random scheduling scheme which generates feasible plans during the approximately same amount of the execution time of our scheme and selects the best one. Actually, there is no similar planning mechanism for EV relocation, this scheme can give us a reference for the performance assessment. First, Figure 3 plots the effect of the number of teams to the relocation distance when the number of teams changes from 1 to 5. For one team, there is no influence from the staff allocation as all staff members are included in a single team. The difference results solely from relocation matching efficiency, and our scheme outperforms by 45.3 %. Both schemes benefit from the increased number of staff members and the performance gap reaches 49.0 %, when the number of teams is 5. Hence, our scheme can better take advantage of available staff members.

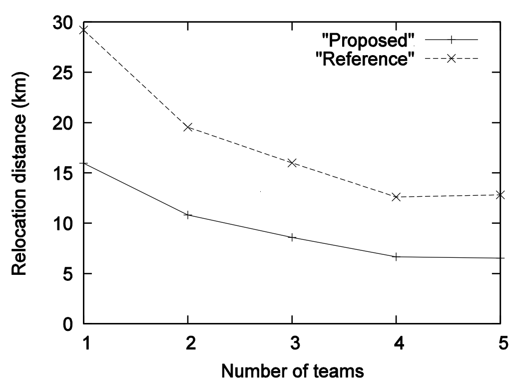

Figure 3. Effect of the number of teams

Next experiment measures the effect of the number of staff members to relocation distance to find out the efficiency of assigning members to each team. Here, after basically assigning 2 members for each team out of total staff, remaining ones, called extra staff members, are subject to staff allocation. As shown in Figure 4, both schemes largely improve the relocation distance according to the increase in the number of staff members. However, our scheme outperforms by at least 42.1 % for the range of 0 to 7 extra staff members. Moreover, its performance behavior changes quite stably, indicating that the search space visited by our scheme includes sufficiently reasonable quality solutions, even not the best one. From the point of 2 members, an addition of members hardly contributes to the reduction of relocation efficiency. That is, our scheme can find this point much earlier, saving the cost of hiring service staff members as well as improving the system efficiency.

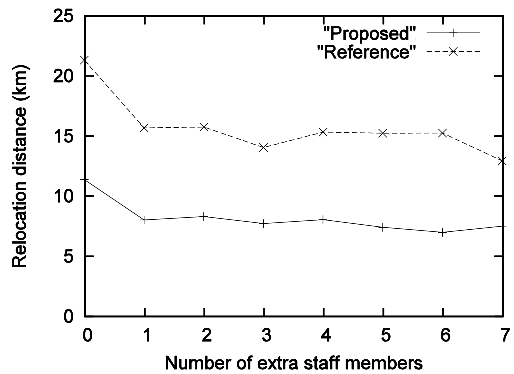

Figure 4. Effect of the number of staff members

Figure 5 plots the effect of the number of EVs to move to relocation distance. With more EVs to move, the search space will get larger and the effect of wrong search scope will be severe. The experiment changes the number of moves from 10 to 40. For the case of just 10 moves, there is almost no difference between two schemes. However, according to the increase in the number of moves, the efficiency of our scheme becomes clearer. Particularly, for the interval from 20 to 35 moves, the relocation distance of our scheme rarely increases, resulting from the efficient combination of relocation matching and staff assignment. During this interval, many relocation pairs are merged. The performance gap begins from 8.1 % and reaches 53.0 % when the number of moves is 35. This result finds out that our scheme can efficiently cope with the complexity stemmed from the increased number of EVs to move. It must be mentioned that the execution time of genetic algorithms is not affected by the number of EVs but just by the number of iterations.

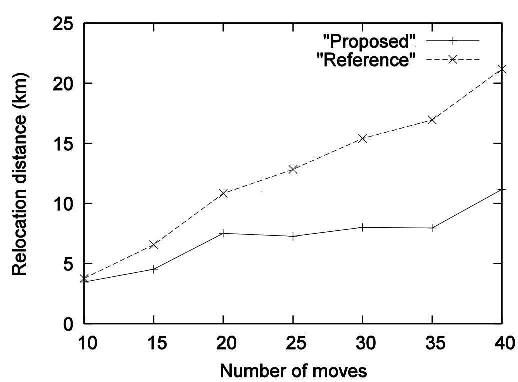

Figure 5. Effect of the number of moves

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Finally, Figure 6 shows the relocation distance according to the number of stations. With more stations, there are more options in selecting overflow and underflow stations for a relocation pair. Hence, it is possible to find a pair having a shorter distance. The experiment changes the number of stations from 10 to 20. The reference scheme does not show reduction in the relocation distance regardless of this advantage. The relocation distance ranges from 15.5 to 18.2 *km*. As contrast, our scheme significantly and consistently improves the relocation distance according to the increase in the number of stations. The performance gap begins from 15.5 % and reaches 54.5 % when there are 20 stations. However, this improvement will be dependent also on the locations of sharing stations and the current distribution of EVs. Hence, it is necessary to further investigate the effect of geographic factors and demand patterns of EV sharing systems.

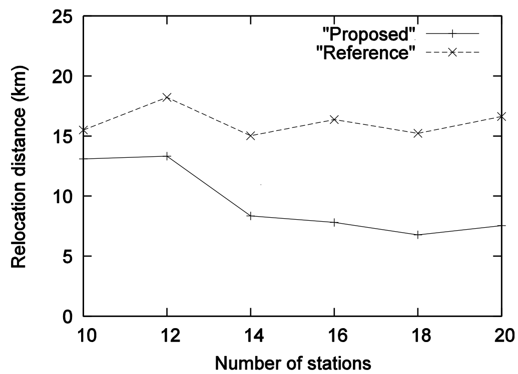

Figure 6. Effect of the number of stations

5. Concluding remarks

Not just for its eco-friendliness, EV sharing is a promising business model capable of coping with EVs' high price and uneasy maintenance. One-way rental systems inevitably suffer from stock imbalance due to spatially and temporally different demand patterns. For the given number of relocation teams and the number of total staff members, how to allocate staff members to each team, how to match overflow and underflow stations, and how to assign relocation pairs to each team are quite complex problems. This paper has designed a relocation planner to systematically make a relocation schedule based on genetic algorithms. For encoding a feasible plan, a chromosome is consist of two parts, one for relocation pairs and the other for staff allocation. Each relocation pair is represented by an integer associated with overflow and underflow indices as well as including negative number separators. The genetic operators can work just in the first part.

The performance of the proposed scheme has been extensively measured by means of a prototype implementation. Most importantly, our scheme can find a relocation plan even when the number of moves increases, efficiently allocating staff members to those teams having many mergeable pairs. It outperforms the reference scheme by up to 53.0 % in terms of the relocation distance, when the number of EVs to relocate is 40 in our experiment environment. Moreover, the proposed scheme finds the point from which additional staff members are not necessary, saving the employment cost as well as achieving system efficiency. Those results indicates that our scheme stably calculates a reasonable quality schedule even if the problem complexity gets worse by the increased number of EVs to move and the number of stations.

As future work, we are planning to develop a city-wide telematics system which coordinates all EV entities including taxis, rent-a-cars, sharing vehicles, and the like [12]. Based on real-time tracking of each vehicle object as well as continuous monitoring of charging facilities, this system intelligently coordinates charging activities between heterogeneous objects having different charging demand dynamics, aiming at achieving respective vehicle type-specific goals. From the global viewpoint, the relocation scheme developed in this paper is not restricted to shared vehicles. The taxi system can take advantage of the vehicle relocation mechanism to enhance the service ratio by making empty taxis wait at a specific location which is expected to have high demand density. Such a systematic design will enrich the smart grid services, further obtaining sophisticated orchestration of activities in different domains such as renewable energy and power generation [13].

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