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Simulation evaluation for on-demand bus system with electrical vehicles

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Abstract. In this paper, we focus on a new transport system called on-demand bus system which is introduced on a trial basis to local cities in Japan. In the system, share-ride buses transport customers door-to-door according to user's requests. A user can specify the position and time to get the bus in the service area, thus the on-demand bus is more flexible and profitable system compared to traditional transport systems (i.e., fixed route bus). Electrical vehicles are also attracting attention as a new transportation device in these years. The electric vehicles are environmentally friendly because they produce zero emissions and do not pollute the air. However, there is some issues to be solved for practical use of electrical vehicles, i.e., the price of charger and the mileage per charge. Therefore, we adopt an evolutionary approach to solve a path optimization problem for the on-demand bus with electrical vehicles. It is very important to reduce the amount of recharge time for effective operation of electrical vehicles. An evolutionary algorithm minimizes the traveling distance of vehicles by a mutation operation (i.e., the exchange of sub-routes of vehicles) in order to reduce the amount of recharge time. We will show some comparison experiments by computer simulation, and show the performance of our algorithm for the on-demand bus with electrical vehicles.

Keywords: On-demand bus system, electrical vehicles, evolutionary algorithm, battery charge

1. Introduction

The increasing of money-losing lines of bus business is a serious social problem in Japan. On the other hand, an on-demand bus system [1–3] is now attracting attention as a new transport facility. In the system, share-ride buses transport customers door-to-door according to user's requests. A user can specify the position and time to get the bus in the service area, thus the on-demand bus is more flexible and profitable system compared to traditional transport systems (i.e., fixed route bus). The on-demand bus has been introduced to some places in Japan, and contributes to the improvement of usability and profitability of bus businesses (e.g., On-Demand Bus for Nakamura-Machi, Japan). [1]

In these years, electrical vehicles are introduced to the on-demand bus on a trial basis. The electric vehicles are environmentally friendly because they produce zero emissions and do not pollute the air. However, there is some issues to be solved for practical use of electrical vehicles, i.e., the price of charger and the mileage per charge.

In order to operate electrical vehicles efficiently in the on-demand bus, it is necessary to develop a path planning algorithm which reduces the amount of recharge battery for electrical vehicles. There are some past works to solve the path planning problem for the on-demand bus. Uchimura et al. [2] proposed an optimization method which combines two algorithms: Node Insertion Algorithm (NIA) and Genetic Algorithm. The NIA is a simple scheduler to find initial solutions, and the GA optimizes the solutions by mutation and crossover operations. Noda et al. [3] evaluated the performance of the on-demand bus compared to the

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[1] http://www.kochi-seinan.co.jp/machif.html.

fixed route bus, and they adopted Sequential Insertion Algorithm (SIA), which is similar to the NIA, as path optimization algorithm. However, these works did not consider the electrical vehicles. Therefore, in this paper, we apply a path planning algorithm based on evolutionary approach to the on-demand bus with electrical vehicles. Paths of vehicles are optimized whenever a new demand is assigned to a vehicle by the algorithm. A set of paths is regarded as an individual, and it evolves by a mutation operation (i.e., the exchange of sub-routes) in an evolutionary process. Moreover, we show the simulation results to evaluate the performance of the on-demand bus with electrical vehicles, and we will compare our algorithm with the SIA.

The remainder of this paper is as follows: Section 2 defines a simulation model of the on-demand bus with electrical buses. Section 3 proposes a path optimization algorithm based on the evolutionary approach. Section 4 reports our experimental results. Finally, Section 5 describes conclusions and future works.

2. Formulation of on-demand bus problem

Our target problem (i.e., On-demand bus problem) is a variant of Vehicle Routing Problem (VRP) [4,5]. The VRP is a problem which finds the shortest paths for vehicles to pick up customers' demands, and the objective of the VRP is to minimize the sum of traveling distance. There are some variants of VRP, e.g., CVRP(Constrained VRP), VRPTW(VRP with Time Windows), and Dial-a-Ride. Our target problem is similar to the Dial-a-Ride. This section shows the simulation model of the on-demand bus with electrical vehicles on the basis of the VRP.

2.1. Customer model

A demand of a customer c_n is represented as Eq. (1). The pick-up and delivery positions of the user are p_n and d_n. In our simulation, the trend of demands is a uniform distribution (i.e., p_n and d_n are randomly selected from the field of on-demand bus). The main difference between the VRP and our target problem is that the time of demand occurrence is given in advance or not. In the VRP, all of demands are known, thus paths are optimized just one time in advance. However, in our target problem, demands continuously occur in chronological order, thus paths should be optimized periodically. Moreover, for simplicity, the time constraints (i.e., time windows) are not considered in our model, thus the service of on-demand bus is best-effort delivery.

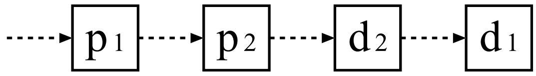

Fig. 1. An example of path.

$$c_n = (p_n, d_n) \tag{1}$$

2.2. Electrical bus model

An electrical bus b_i is represented as Eq. (2). The amount of remaining electrical battery is $battery_i (0 \leqslant battery_i \leqslant 100)$, the rate of electricity consumption is $consumption_i$, and the charging rate is $charge_i$. The electrical buses can charge their batteries at battery chargers which are located in the service area. If the battery runs out, the electrical vehicle becomes immovable on the spot. Nowadays, one of the technical difficulties in developing electrical buses has been to increase the mileage per charge. Moreover, chargers for the electrical buses are so expensive. Therefore, to keep the amount of battery high is a key issue to operate the electrical buses in the on-demand bus problem.

$$b_i = (battery_i, consumption_i, charge_i) \tag{2}$$

A path of an electrical bus b_i is the queue of pick-up and delivery positions. Whenever a new demand of a customer is assigned to the bus, its pick-up and delivery positions are inserted to the queue. The demands are satisfied continuously in the order of the queue, and a demand is removed from the queue when the demand is satisfied. Therefore, how to insert the pick-up and delivery positions into the queue is a main problem to improve the performance of the on-demand bus system. For simplicity, the constraint of road network is ignored (i.e., the bus moves between pick-up and delivery positions in a straight line). An example of a path is shown in Fig. 1. According to the path, the bus picks up customers c_1 and c_2, and then the bus drops off customers c_2 and c_1 in turn.

Figure 2 shows a flowchart of an electrical bus in each simulation cycle. First, the bus checks the amount of remaining battery. If the amount is less than threshold α, the bus goes to the nearest battery charger to charge its battery. Next, the bus checks the queue (i.e., path). If the queue contains one more pick-up and delivery positions, the bus goes to the position at the head of the queue. Otherwise, the bus goes to the nearest battery charger and waits for the next assignment of demands. This flowchart repeats during the operational time of the on-demand bus.

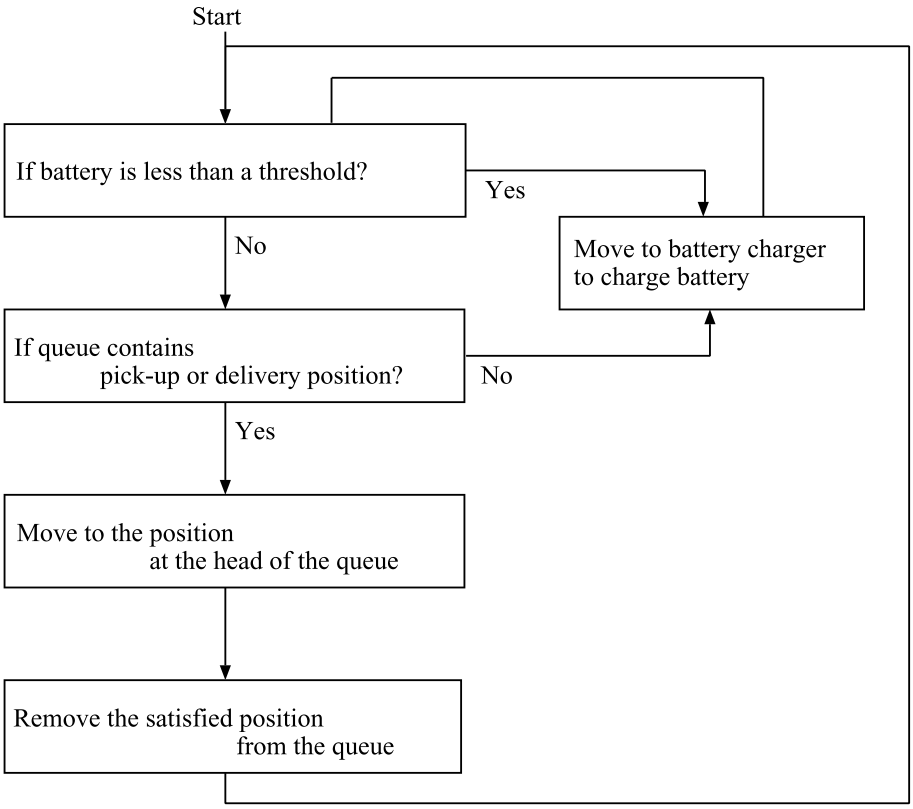

Fig. 2. Flowchart of electrical bus.

2.3. *Objective*

In general, transport systems including on-demand bus are multi-objective problems (e.g., fuel bill, fare, fleet, travel time, and so on). Furthermore, there is a trade-off relation among the objectives. For example, in order to minimize travel time, so many buses are needed, but it is wasteful. In this model, we adopt the objective of VRP as our target objective, i.e., to minimize traveling distance as small number of buses as possible. For the mileage per charge is low, and the electrical chargers are expensive as mentioned above.

3. Path optimization by evolutionary approach for electrical vehicles

The VRP is one of the NP-hard problems like Traveling Salesman Problem (TSP). For this reason, most approaches to the problem depend on meta heuristic algorithms to produce approximate solutions of the VRP and its variants: tabu search [6,7], ant colony optimization (ACO) [8], simulated annealing (SA) [9], genetic

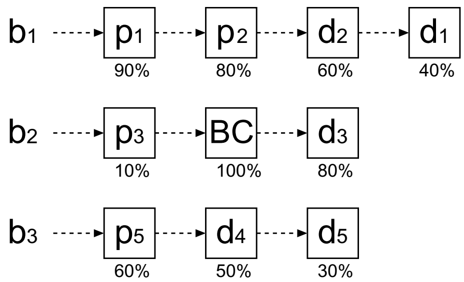

Fig. 3. Representation for solution.

algorithm (GA) [10,11], and so on. Moreover, there are some representations for an solution (i.e., an individual in evolutionary process), e.g., Path Representation (PR) [12], Genetic Vehicle Representation (GVR) [13–18], and so on. We adopt the GVR as a solution for our target problem.

3.1. *Representation for solution*

The representation for a solution we adopted is called Genetic Vehicle Representation (GVR). The GVR is a set of paths for buses shown in Fig. 3. The main

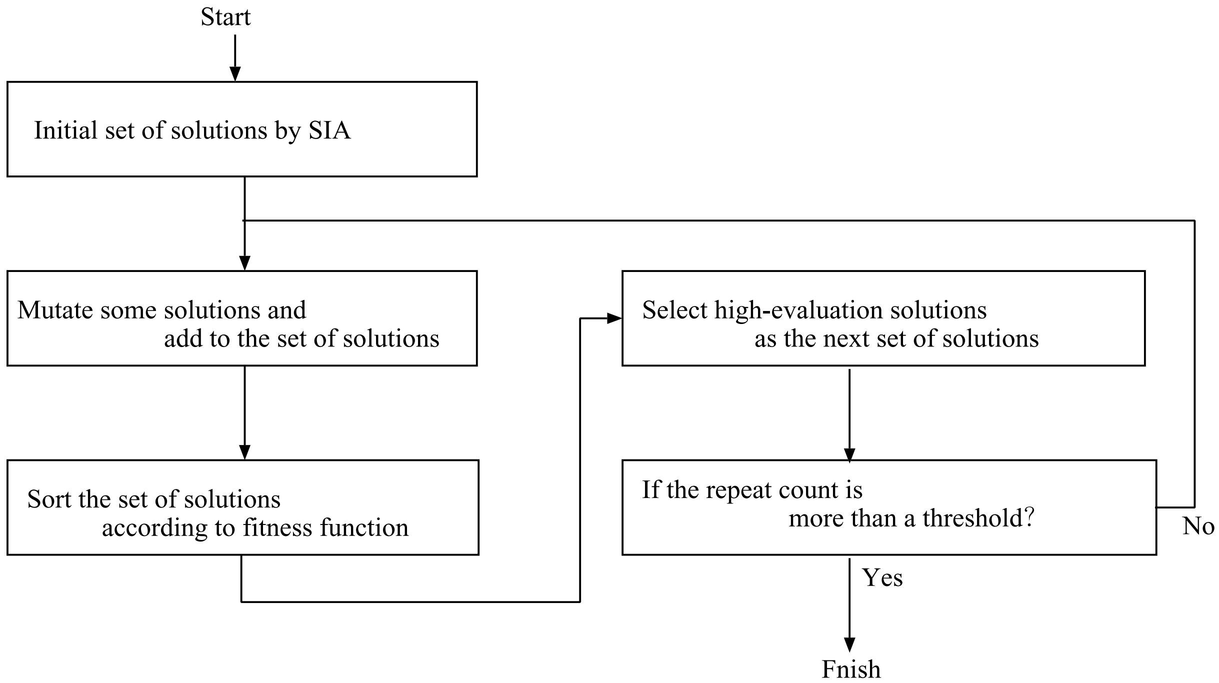

Fig. 4. Flowchart of optimization process.

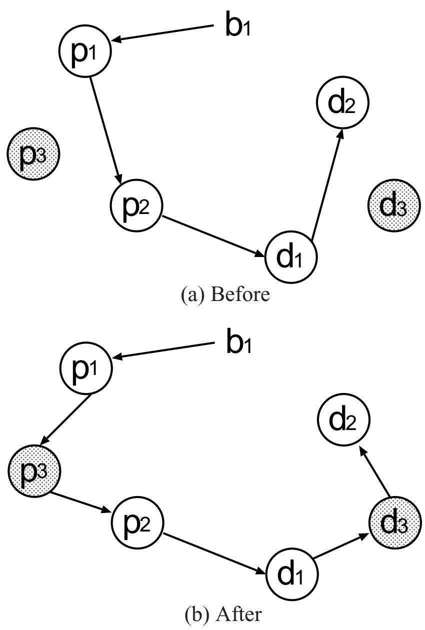

Fig. 5. Assignment by SIA.

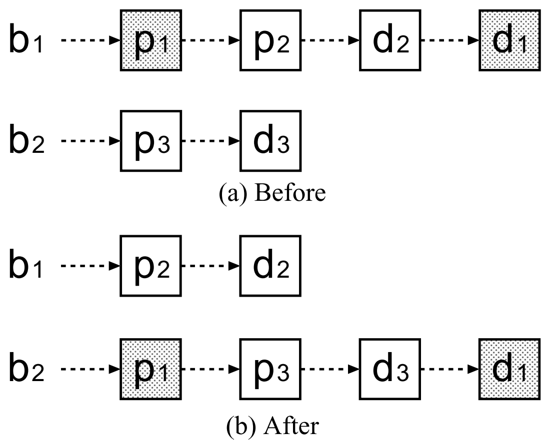

Fig. 6. Mutation operation.

feature of the GVR is that a route is distinct from each other (Path Representation (PR) combines plural paths together into one path). In the case of CVRP, the constraint of capacity should be considered, thus a depot position is inserted to the path when the amount of burden is more than the capacity (the amount of burden clears at the depot). On the other hand, in our target problem, the constraint of battery should be considered, thus a battery charger position is inserted to the path when the amount of buttery is less than the threshold α. Moreover, if the queue (path) is empty, the bus goes to the nearest battery charger to keep battery high. In the example, there are three paths for b_1, b_2, and b_3. The amount of battery b_2 is less than the threshold at p_3, the battery charger position is inserted to between p_3 and d_3.

3.2. Flow of optimization process

Figure 4 shows a flowchart of an optimization process by an evolutionary approach. The optimization process starts when a new demand of a customer is assigned to a bus. An initial assignment is based on Sequential Insertion Algorithm (SIA) [3], and it used as an initial set of solutions for evolutionary process. Next, some solutions are randomly selected from the set of solutions, and the selected solutions evolve by a mutation operation. The evolved solutions are reinserted to the set of solutions. Then, the solutions in the set are ranked by a fitness function. The fitness function we used is the sum of distances of the paths. The high-evaluation solutions are selected and used as the next set of solutions (i.e., elite strategy). The optimization process is repeated until the maximum repeat count β. Finally, the highest evaluation solution in the set of solutions is used as paths for electrical buses.

3.3. Sequential insertion algorithm (SIA)

The detail of SIA is explained as below. When a new demand of a customer occurs, its pick-up and delivery positions must be assigned to a bus. The SIA finds the best insertion positions (i.e., the increased amount of distances is minimized) in the paths for the pick-up and delivery positions by full search subject to the condition that the order of the paths before the insertion is never changed. The SIA cannot find the optimum paths because the original paths are fixed. However, the SIA is very useful as the initial solution for evolutionary process because its computational cost is not expensive. For example, in Fig. 5, there is a path for bus b_1. A new demand (p_3 and d_3) is incrementally inserted to the path, but the order of the original path (i.e., p_1-p_2-d_1-d_2) is fixed.

3.4. Mutation operation

In [15], effective mutation and crossover operations for GVR are proposed by Tavares et al. On the other hand, in this paper, we adopt very simple mutation operation for simplicity. The detail of mutation operation is explained as below. In an evolutionary process, some solutions evolve by the mutation operation. The mutation operation randomly selects a demand from a path in the solution. If both pick-up and delivery for the demand are not satisfied, a pair of pick-up and delivery positions is randomly moved to other positions in the path (but delivery position must be inserted to the rear of pick-up position). If pick-up for the demand is only satisfied, delivery position is randomly moved to other positions in the same path. An example of mutation operation is illustrated in Fig. 6. There are two paths for b_1 and b_2. A pair of p_1 and d_1 is selected from b_1, and the pair is inserted to b_2.

Table 1
Parameter setting

Parameter	Value
unit distance	600 m
unit time	36 seconds
service area	50×50
operational hour	1200
running speed	1
electricity consumption	0.6
battery charge	1 or 0.5
number of buses	5
number of battery chargers	10
demand occurrence	1%–10%
threshold for charge	20%
size of solutions for one cycle	20
size of mutated solutions	30
maximum repeat count	30

4. Experiments

We implemented a simulation program for on-demand bus shown in Fig. 7 by Artisoc[2] which is a multi-agent simulator. We performed experiments by using the simulation program to evaluate our proposal algorithm for on-demand bus with electrical buses. In this section, we report our experimental results.

4.1. Experimental setting

Here, we show the parameter setting for our simulation experiments. In my simulation program, unit distance is 600 m, and unit time is 36 seconds. We assume large-scale on-demand bus service, thus the service area is 50 squared (30 km), and the operational hour is 1200 steps (12 hours). The running speed of electrical buses is 1 per unit time (60 km/h). The rate of electricity consumption is 0.6 per unit time (i.e., a electrical bus can travel about 100 km). The rate of battery charging is 1 per unit time (i.e., rapid charge) or 0.5 per unit time (i.e., regular charge). It takes 1 hour

[2] http://mas.kke.co.jp/.

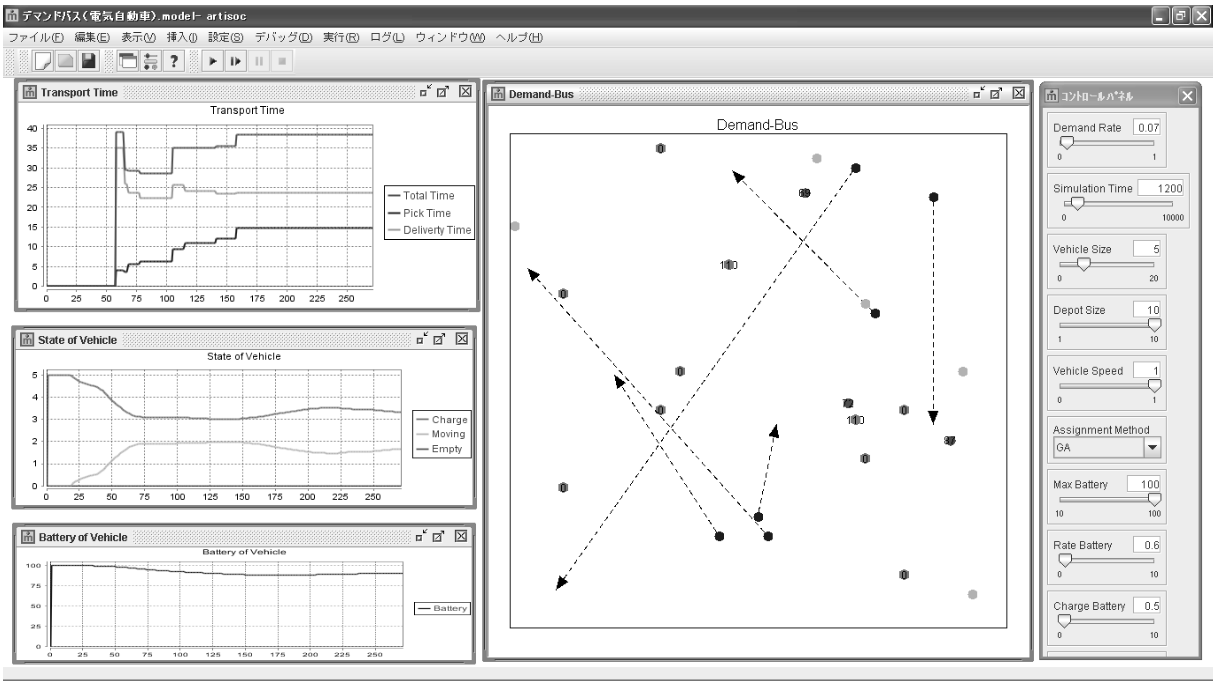

Fig. 7. Screen shot of simulation program.

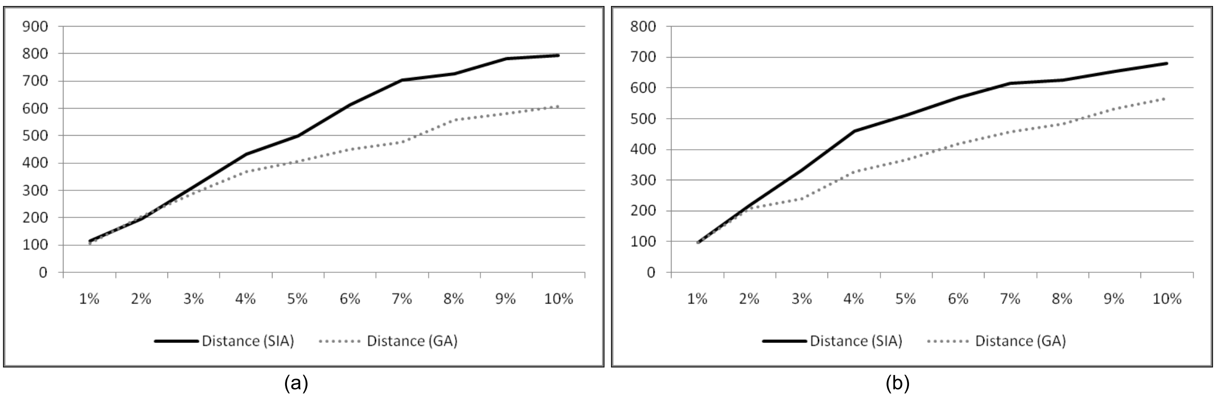

Fig. 8. Distance Colors are visible in the online version of this paper (DOI 10.3233/IDT-2010-0092).

to recharge an electrical bus with rapid charge, 2 hours with regular charge. The setting of parameters related to the electrical buses are based on the information by Hokuriku Electric Power Company.[3] The number of buses is set to 5, the number of battery chargers is set to 10, and the rate of demand occurrence is changed from 1% (1 demand per 60 minute) to 10% (1 demand per 6 minute) per unit time. We compare our path optimization algorithm with SIA in the case of rapid and regular charges. The parameter setting is summarized in the Table 1.

4.2. Experimental results

4.2.1. Distance

Figure 8 shows a result of traveling distance. The result indicates that our algorithm can reduce the traveling distance compared with SIA although the number of satisfied demands is the same, and we found that our algorithm is more effective in the case that demands occur more frequently. This is because the number of

[3]http://www.rikuden.co.jp/.

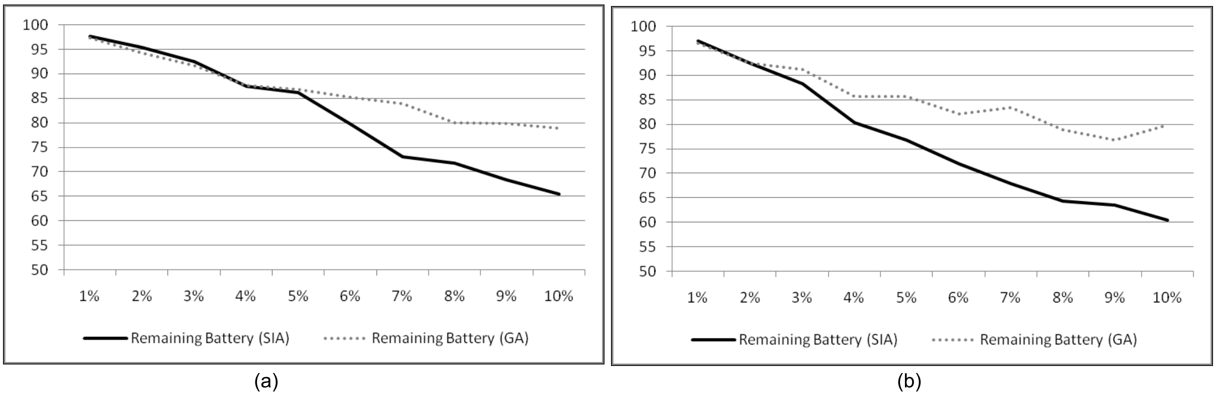

Fig. 9. Remaining battery Colors are visible in the online version of this paper (DOI 10.3233/IDT-2010-0092).

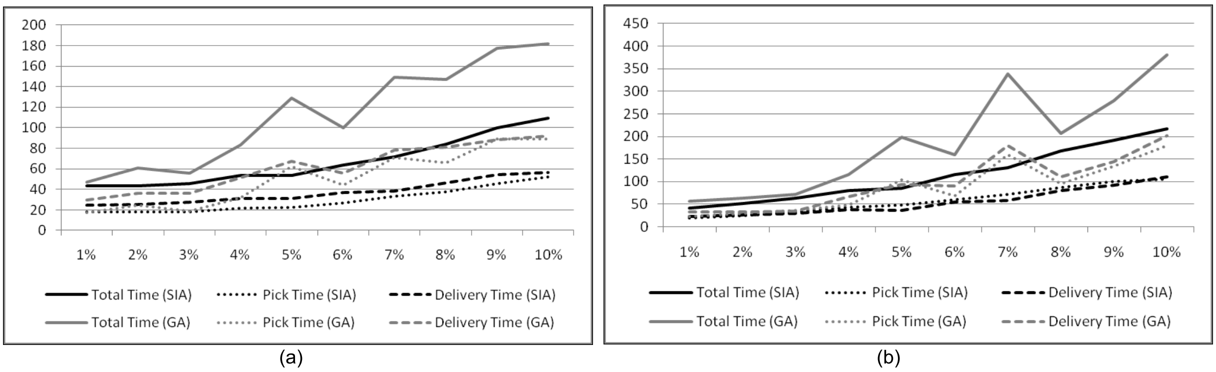

Fig. 10. Transport time Colors are visible in the online version of this paper (DOI 10.3233/IDT-2010-0092).

assigned demands to one bus increases with the demand occurrence, and our algorithm can find better solution in the large search space compared with SIA. Moreover, we found that the distance of regular charging is less than rapid charging. The reason is that the free time of buses is long in the case of rapid charging, and the buses return to the battery charger to keep their batteries high when they are free. Therefore, the traveling distance to battery charger is also long in the case of rapid charging.

4.2.2. Remaining battery

Figure 9 shows a result of remaining battery. The result indicates that our algorithm can keep battery high compared with SIA. In our algorithm, the fitness function is to minimize the total traveling distance, but it also reduces the amount of battery consumption as a result. Moreover, the rapid charging can keep battery high than regular charging, but there is a little difference between them for our algorithm.

4.2.3. Transport time

Figure 10 shows a result of transport time for customers. The pick time is the time from occurrence to pick-up, the delivery time is the time from pick-up to delivery (arrival), and the total time is the sum of them. The result indicates that our algorithm is inferior to SIA. This is because our problem model does not consider time constraints. In addition, the objective of the model (the fitness function) is to minimize traveling distance only. Thus, the number of running buses is few in the case of our algorithm to minimize their traveling distance, and this trend causes to increase transport time for customers. Therefore, the introduction of the time constraints is future work for practical use.

5. Conclusions

In this paper, we focused on the on-demand bus which is more flexible transport method compared wtih traditional bus systems. It is necessary to consider the battery charging schedule so as to introduce electrical vehicles to the on-demand bus. Therefore, we adopted a path optimization algorithm based on evolutionary approach to minimize traveling distance. Consequently, our algorithm can reduce the traveling distance and keep remaining battery high compared with Sequential Insertion Algorithm (SIA). However, our simulation model did not consider time constraints of customers, thus our algorithm is inferior to the SIA on transport time for customers. Therefore, we must consider the time constraints and improve the algorithm and its fitness function for the on-demand bus problem.

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