Vehicle Allocation Algorithm Improving User Satisfaction in Ride-Sharing

Yuta Wakazono, Shigemi Ishida, and Yoh Shiraishi

Abstract Ride-sharing services have attracted attention as a new public transportation service. Previous studies on ride-sharing services focused on a vehicle allocation algorithm maximizing the number of accepted requests while minimizing vehicle travel distance. To make ride-sharing services sustainable, maximization of user satisfaction is important. Users have different satisfaction aspects. We therefore propose a vehicle allocation algorithm that can handle the individual user satisfaction preference. The key idea is to switch the cost function used in the optimization of vehicle allocation based on an individual user satisfaction preference. In this paper, we assume that there are users whose satisfaction preference consists of quick arrival and economy. We define convenience, economy, and balance cost functions based on user satisfaction preferences of quick arrival and economy. Combining the cost functions with the existing successive best insertion (SBI) vehicle allocation algorithm, we allocate vehicles to requests while maximizing user satisfaction. We show the improvement of user satisfaction compared to the existing vehicle allocation algorithm by up to 11% in simulation experiments a dataset of taxi trips on Manhattan Island in New York City.

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1 Introduction

Recent advances in information systems and wireless communication technologies have led to practical ride-sharing services. In ride-sharing service, a ride-sharing system schedules the route of vehicles to allow users to share a ride providing low-cost door-to-door transportation. Ride-sharing services are one of the promising candidates for future transportation services [1].

To realize practical ride-sharing services, pioneering work studied the feasibility of ride-sharing services and optimization of vehicle routing as well as allocation [2, 3]. Noda et al. and Ma et al. showed the advantages of ride-sharing services compared to public vehicle-transportation systems such as buses and taxis.

Allocation optimization in dynamic situations where requests are sequentially generated is difficult because of a considerable amount of computation. In ride-sharing services, vehicles are allocated by a heuristic algorithm due to the difficulty in allocation optimization. The literature has reported the optimization of ride-sharing services based on estimated demands/requests, efficient vehicle routing as well as allocation, and various pricing strategies [4–9]. Sustainability is an important aspect to encourage users to continue to use a ride-sharing service as a public transportation service. However, the sustainability of ride-sharing services has not been well studied.

To realize sustainable ride-sharing services, maximization of user satisfaction is an important aspect. This paper therefore proposes a vehicle allocation algorithm considering the satisfaction of users. Our key idea is simple: we optimize vehicle allocation with the cost function considering user satisfaction preference. User satisfaction depends on an individual user's situation. We assume that a ride-sharing sharing system asks users to explicitly declare their requirements such as *quick arrival* and *the lowest cost*.

As a first step of the ride-sharing service considering user satisfaction, this paper presents a vehicle allocation algorithm maximizing a user satisfaction metric. The vehicle allocation algorithm is an extended version of the existing heuristic vehicle allocation algorithm named successive best insertion (SBI) [2]. The SBI is a semi-optimal vehicle allocation algorithm operating in realtime with limited computational resources. The optimization of the SBI is based on a cost function. We define new cost functions considering user satisfaction preference and use the SBI to allocate vehicles maximizing user satisfaction. We switch cost functions based on user satisfaction preference because individual users have different satisfaction preferences. In this paper, we define cost functions based on the user requirements of *quick arrival* and *the lowest cost*, which correspond to the user satisfaction preference of convenience and economy, respectively.

To confirm the effectiveness of our vehicle allocation algorithm, we conducted simulation experiments with requests extracted from a dataset of taxi trips on Manhattan Island in New York City. The experimental results reveal that our vehicle allocation algorithm successfully improved user satisfaction. Specifically, our main contributions are twofold:

- We present the design of a vehicle allocation algorithm with the consideration of user satisfaction preference. We use the existing SBI algorithm with newly defined cost functions to allocate vehicles maximizing user satisfaction.
- We show the improvement of user satisfaction compared to an existing vehicle allocation algorithm by up to 11% in simulation experiments using a dataset of taxi trips on Manhattan Island in New York City.

The remainder of the paper is organized as follows. Section 2 looks through related work on ride-sharing systems. We present our vehicle allocation algorithm in Sect. 3, followed by simulation evaluations in Sect. 4. Section 5 concludes the paper.

2 Related Work

Vehicle allocation in a ride-sharing services with sequentially generated requests is one of the Dial-a-Ride Problems (DARPs) [10]. We assume a dynamic situation where requests are sequentially generated. References [11,12] pointed out that optimization in dynamic situations is more difficult than in static situations where requests are reserved in advance. To solve a DARP in real time, quasi-optimization is a practical approach. For this reason, algorithms that optimize in about polynomial time are widely used in actual ride-sharing services [13–15].

In the field of ride-sharing, pioneering work demonstrated the effectiveness of ride-sharing services compared to fixed-route buses while keeping the travel distance low [2, 3]. Based on the pioneering work, ride-sharing optimization is studied. Previous studies have investigated the optimization of vehicle routing [4, 5], vehicle allocation [6], vehicle location [7], and rational pricing [8, 9]. However, user satisfaction with ride-sharing services has not been well studied.

User satisfaction in ride-sharing services has primarily been defined in terms of arrival time [16, 17]. In these studies, the time difference between estimated and actual arrival due to the ride-sharing is considered to affect user satisfaction. User satisfaction, however, is difficult to model only using the arrival time. Ref. [18] reported that user satisfaction in ride-sharing services is dependent not only on the arrival time, but also on many aspects including convenience and safety. There is a study defining user satisfaction based on both arrival time and fare [19]. Although these studies defined user satisfaction, no optimization was performed to maximize user satisfaction.

Levinger et al. proposed a vehicle allocation algorithm based on user satisfaction [20]. However, the proposed vehicle allocation algorithm assumes static requests from a single origin. In practical ride-sharing services, requests are sequentially generated by users with various origins and destinations. Beirigo et al. proposed the vehicle allocation algorithm that prioritizes and responds to requests according to the usage style selected by users [21]. There are three levels of usage styles: Business (1st), Standard (2nd), and Low-cost (3rd). Business (1st), which has the highest priority, is served by occupied vehicles and not shared rides, in exchange for a higher fee. Standard (2nd) and Low-cost (3rd) services are available at a lower cost than the Business (1st) services by sharing their rides. However, only three categories of usage patterns are set, making it difficult to respond to the various desires of users.

3 Vehicle Allocation Based on User Satisfaction

3.1 Use Case

In this paper, we assume the use case below.

1. A user requests a ride at any time to a ride-sharing management system. The request consists of the origin point, destination point, arrival deadline, and the number of passengers.
2. The ride-sharing management system allocates a vehicle to the request. A request acceptance signal including estimated boarding and arrival time is sent to the user. On allocation failure, a request rejection signal is sent to the user. A typical allocation failure occurs when the estimated arrival time exceeds the arrival deadline.
3. When the user receives an acceptance signal, the user boards the allocated vehicle at the origin point specified by the user. Immediately after the vehicle arrives at the destination point, the user gets off.
4. The allocated vehicle might carry another user on the way to the origin and destination points specified by the user. Therefore, the actual boarding and arrival time might be different from the estimated boarding and arrival time. Note that the requested information never changes during a ride.
5. The ride-sharing management system calculates the fare for the ride based on the ride time and an arrival delay from the estimated arrival time, which is charged to the user.
6. Users send feedback after using the ride-sharing service. In the feedback, the user explicitly selects from three options: “desire to spend cheaply”, “desire to travel faster” or “satisfied with the service”.

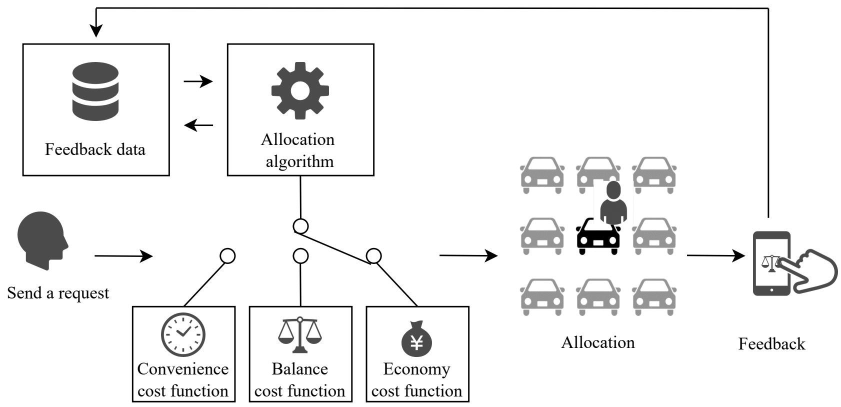

Fig. 1: Overview of vehicle allocation algorithm

3.2 Overview of Vehicle Allocation

Figure 1 illustrates the overview of our vehicle allocation algorithm. Our key idea is to switch multiple cost functions based on an individual user satisfaction preference in a vehicle allocation optimization process. In this algorithm, we find the vehicle with minimum additional cost and allocate the request. The additional cost of each vehicle is calculated using the cost functions selected based on user satisfaction preference.

A user satisfaction preference is represented by a combination of convenience weight W_{C} and economy weight W_{E}, where $W_{\mathrm{C}}+W_{\mathrm{E}} = 1$. We assume that a user satisfaction preference dynamically changes. We therefore update the weights for each user based on feedback after the service use. In this paper, the ratio of W_{C} and W_{E} is assumed to be unchanged from the pre-defined ratio.

In this paper, we define three cost functions: convenience, economy, and balance cost functions. In the vehicle allocation process, we calculate the cost of vehicle allocation for each vehicle using the cost function depending on the weights of a new request. When $W_{\mathrm{C}} > W_{\mathrm{E}}$, we use the convenience cost function in the cost calculation. When $W_{\mathrm{C}} < W_{\mathrm{E}}$, the economy cost function is used. The balance cost function is used when $W_{\mathrm{C}} = W_{\mathrm{E}}$. Note that we always use the convenience cost function for vehicles with no request because the economy and balance cost functions incur a huge delay when there is no request other than a new request.

We do not limit the vehicle allocation optimization algorithm. In this paper, we use the successive best insertion (SBI) algorithm [2].

The following subsections describe the basics of the SBI algorithm, followed by the definition of the cost functions.

Algorithm 1: Successive Best Insertion (SBI)

Data: List Z of vehicles, list L_ζ of origins O_i and destinations D_j corresponding to requests assigned to vehicle ζ, origin O_n and destination D_n of new request, *deadline* of arrival time

Result: $v \Leftarrow$ vehicle with minimum cost, $L \Leftarrow$ new origin/destination list including O_n and D_n

1 all $cost[\,] = \infty$;
2 **for** ζ *in* Z **do**
3   all $routes[\,]$ = empty list;
4   $l = sizeof(L_\zeta)$;
5   **for** k *in* $\binom{l+2}{2}$ **do**
6     $routes[k] = L_\zeta$ with inserted O_n and D_n;
7   all $cost\_r[\,] = \infty$;
8   **for** *route in routes*[ ] **do**
9     $cost\_r[route] = cost\_func(route)$;
10   **if** $time(D_n) > deadline$ **then**
11       $cost\_r[route] = \infty$;
12   $L'_\zeta = \arg\min_{route} cost\_r[route]$;
13   $cost[\zeta] = cost\_r[L'_\zeta]$;
14 $v = \arg\min_\zeta cost[\zeta]$;
15 $L = L'_v$;

3.3 Successive Best Insertion (SBI) Algorithm

The SBI is a vehicle allocation algorithm for ride-sharing services [2], which calculates semi-optimal vehicle allocation with limited computational resources.

Algorithm 1 summarizes the process of the SBI algorithm. In Algo. 1, $cost\_func(route)$ is the cost function over the given *route*, $time(D)$ is the estimated time of arrival at destination D, and $\binom{x}{y}$ represents a binomial coefficient. The SBI is a two-step optimization process. In the first step, the minimum cost caused by the new request is calculated for each vehicle. L_ζ is a list of origins/destinations of vehicle ζ. We insert origin O_n and destination D_n of a new request to each position of L_ζ and create a list *routes*[ ] of new route candidates on lines 5–6. The number of the new route candidates is calculated by a binomial coefficient $\binom{l+2}{l}$, where l is the number of origins/destinations assigned to vehicle ζ. We change index number k within a range from 1 to $\binom{l+2}{l}$ to store each route candidate in *routes*[ ]. On lines 8–11, a cost for each route candidate is calculated. The cost of vehicle ζ is then calculated by finding the route candidate with a minimum cost on lines 12–13. In the second step, find the vehicle with the minimum cost and allocate the vehicle to the new request on lines 14–15.

3.4 Cost Functions

We define convenience, economy, and balance cost functions based on each of user's satisfaction preferences of convenience and economy. In ride-sharing services, a fare discount is applied when users allow shared rides, when shared rides occur, and when delays occur. The economy in this study is represented by reduced fares. We therefore define a new cost function to allocate vehicles prioritizing non-economic users, which promotes shared rides to users with preferences of economy. The convenience cost function C_C is defined with an estimated arrival time of a new request and arrival delay of the requests assigned to a vehicle, which is incurred by the new request. Let R be a set of requests assigned to a vehicle. Note that a new request is not included in R. The convenience cost function C_C is defined as:

$$C_{\mathrm{C}} = t_{\mathrm{EA}} - t_{\mathrm{EEA}} + \sum_{r \in R} W_{\mathrm{C,r}} \delta(r), \tag{1}$$

where t_{EA} is the absolute time of estimated arrival. We insert the origin and destination of the new request into each position of the vehicle's origin/destination list and calculate t_{EA} for each origin/destination set. t_{EEA} is the absolute time of estimated earliest arrival when a vehicle picks up a user immediately after the user's request and travels to the destination on the shortest route. We calculate t_{EEA} by adding the shortest travel time to the time that the user requests a ride. $\delta(r)$ is the delay incurred by the new request to request r, which is one of the requests already assigned to the vehicle. For each request r in R, we calculate the estimated arrival time for r when we insert the new request and subtract the new arrival time from the estimated arrival time without the new request, deriving $\delta(r)$.

The term $\sum_{r \in R} W_{\mathrm{C,r}} \delta(r)$ in formula (1) is the sum of delays weighted by the convenience weight $W_{\mathrm{C,r}}$. The sum is calculated over all the requests assigned to a vehicle. We can take user satisfaction preferences into account for the requests already assigned to a vehicle. When the user satisfaction preference ratio is $W_{\mathrm{C}} : W_{\mathrm{E}} = 1.0 : 0.0$, as an extreme example, the delay time incurred by the request is 100% included in the cost. When the user satisfaction preference ratio is $W_{\mathrm{C}} : W_{\mathrm{E}} = 0.0 : 1.0$, the delay time is excluded from the cost calculation. In short, a greater economy weight W_E incurs arrival delays.

For economy-oriented users, we define an economy cost function. The economy cost function C_{E} is defined as:

$$C_{\mathrm{E}} = t_{\mathrm{D}} - t_{\mathrm{EA}} + \sum_{r \in R} W_{\mathrm{C,r}} \delta(r), \tag{2}$$

where t_{D} is the arrival deadline for the new request. The economy cost function aims to deliver users a ride as cheaply as possible arriving before the arrival deadline. We therefore designed the economy cost function to be small when the time length of the shared ride is long.

For users who want a balanced response between convenience and economy, we define a balance cost function. The balance cost function C_{B} is defined as:

$$C_{\mathrm{B}} = \left| \frac{1}{2}(t_{\mathrm{D}} + t_{\mathrm{EEA}}) - t_{\mathrm{EA}} \right| + \sum_{r \in R} W_{\mathrm{C,r}} \delta(r). \tag{3}$$

The balance cost function aims to balance arrival time and fare. By equalizing the weights of convenience and economy, $\sum_{r \in R} W_{\mathrm{Cr}} \delta(r)$, i.e., the sum of the delay on requests assigned to a vehicle, is likely to be minimized. Compared to the convenience cost function C_C, the impact of the term $\sum_{r \in R} W_{\mathrm{Cr}} \delta(r)$ is small in C_B. The balance cost function therefore minimizes the sum of the delay while prioritizing the minimum delays for convenience-oriented users.

4 Evaluation

To confirm the effectiveness of the proposed method, we conducted simulation experiments. We first evaluated economy user satisfaction against the user satisfaction preference weights. We also evaluated the impact of fare parameters on economy user satisfaction. User satisfaction with different weight distributions was evaluated because the number of users with specific user satisfaction preference weights affects the mean user satisfaction.

4.1 Experiment Environment

We used the Simulation of Urban Mobility (SUMO) simulator. The SUMO is an open-source road traffic simulator, which is equipped with the Traffic Control Interface (TraCI) allowing us to integrate external programs to control vehicle behavior [22]. We implemented a vehicle allocation algorithm in Python, which was integrated into the SUMO via the TraCI.

Figure 2 shows a road network used in the simulation. The road network is a part of Manhattan Island and covers an area of approximately 20km^2, which was constructed using OpenStreetMap[1]. The numbers of nodes and edges, i.e., roads and intersections, are 20454 and 11133, respectively.

Requests were generated based on the taxi trip open data[2]. We randomly extracted requests from 09:00 am to 10:00 am on weekdays in May 2019. The number of extracted requests was determined as the mean daily num-

[1] `https://www.openstreetmap.org/`

[2] `https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page/`

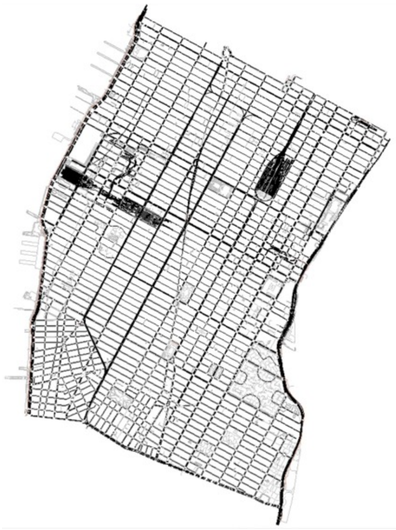

Fig. 2: Road network

ber of requests from 09:00 am to 10:00 am on weekdays in May 2019. The request data contains boarding and arriving time, boarding and arriving locations, and the number of passengers. The boarding and arriving locations are recorded as an area ID[3], which is uniquely given to each of the divided areas in Manhattan. In our experiment, we randomly chose edges in the boarding and arriving areas, respectively, as boarding and arriving edges.

Table 1 shows simulation parameters. A vehicle can carry up to 4 persons in addition to a driver. The simulation started at time $t = 0$ and stopped at $t = 10000$ seconds. Requests were generated between $t = 400$ and $t = 4000$ second.

Table 1: Simulation parameters

Parameter	Value
# of requests	4456
# of person / request	1
# of vehicles	800, 1000, 1200
Seating capacity	4
Vehicle speed V [km/h]	30

To avoid impossible request generation, the arrival deadline t_{D} for each request was determined as:

[3] `https://data.cityofnewyork.us/Transportation/NYC-Taxi-Zones/d3c5-ddgc/`

$$t_{\mathrm{D}} = t_{\mathrm{O}} + m\frac{d}{V} + T_{\mathrm{P}}, \tag{4}$$

where t_{O} is the time when the request occurs, d is the distance between origin and destination points of the request, m is a margin coefficient, and T_{P} is a constant value corresponding to the mean time required for pick-up. The margin coefficient m is a simulation parameter for calculating the rational deadline.

In this experiment, T_{P} and m were set to 600 seconds and 1.5, respectively. Each vehicle was put at a random point at $t = 0$ second. An empty vehicle kept the current position until a new request was assigned.

To demonstrate relative performance, we compared the user satisfaction of the following two methods.

(P) Proposed: The proposed method presented in Sect. 3. Cost functions are switched based on the users' preference.

(O) Original: The original SBI, which minimizes the number of request rejections. The SBI uses the cost function C_{O} defined as:

$$C_{\mathrm{O}} = t_{\mathrm{EA}} - t_{\mathrm{EEA}} + \sum_{r \in R} \delta(r), \tag{5}$$

which is designed to minimize the arrival delay caused by new requests.

4.2 User Satisfaction Metric

To validate the effectiveness of our proposed vehicle allocation, we evaluated user satisfaction using a user satisfaction metric. A user satisfaction preference is dependent on users. We define a user satisfaction metric S as:

$$S = W_{\mathrm{C}} S_{\mathrm{C}} + W_{\mathrm{E}} S_{\mathrm{E}}, \tag{6}$$

where S_{C} and S_{E} are convenience user satisfaction and economy user satisfaction metrics, respectively. The user satisfaction metric S takes a value between 0 and 1; a higher value indicates higher user satisfaction. As described in Sect. 3.2, W_{C} and W_{E} are given by the user. S_{C} and S_{E} are defined as follows.

Convenience user satisfaction metric S_{C} : For convenience-oriented users, we use the convenience user satisfaction metric S_{C} defined as the ratio of the actual remaining time to the estimated remaining time until the arrival deadline:

$$S_{\mathrm{C}} = \frac{t_{\mathrm{D}} - t_{\mathrm{A}}}{t_{\mathrm{D}} - t_{\mathrm{EA}}}, \tag{7}$$

where t_{A} is the actual drop-off time. S_{C} takes a value between 0 and 1 because actual arrival is never before the estimated arrival and never after the deadline.

Economy user satisfaction metric S_{E} : For economy-oriented users, we use the economy user satisfaction metric S_{E} defined as the ratio of discounted fare to the original fare:

$$S_{\mathrm{E}} = \max\left\{0, 1 - \frac{F_{\mathrm{B}} + dF_{\mathrm{U}} - (t_{\mathrm{A}} - t_{\mathrm{O}})F_{\mathrm{D}}}{F_{\mathrm{B}} + dF_{\mathrm{U}}}\right\}, \tag{8}$$

where F_{B} is a fixed base fare, F_{U} is the fare per unit distance, and F_{D} is the fare discount per unit time delay. We emphasize that F_B, F_U, and F_D have different dimensions: F_B has the dimension of currency, while the dimensions of F_U and F_D are currency per distance and currency per time, respectively.

S_{E} takes a value between 0 and 1. Formula (8) is based on the evaluation formula used in the Japanese ride-sharing service named Smart Access Vehicle Service (SAVS) [13]. Formula (8) consists of terms corresponding to a maximum fare and a rebate charge. The maximum fare is calculated from the sum of F_{U} and F_{B} multiplied by d, where d is the distance between the origin and destination of a request. The rebate charge is calculated by multiplying time required for arrival, which is calculated by subtracting t_{O} from t_{A}, multiplied by F_{D}. The later the arrival time t_{A} becomes due to sharing or traffic congestion, the lower the fare becomes.

For example, if F_{D} is increased relative to F_{U}, a small delay can significantly increase user satisfaction. However, if F_{D} is excessively large compared to F_{U}, it becomes difficult to make it profitable. In this formula, the value of user satisfaction varies greatly depending on the value of F_{U} and F_{D}. In this experiment, we set $F_{\mathrm{B}} = 300$ JPY, $F_{\mathrm{U}} = 0.4$ JPY$/m$, and $F_{\mathrm{D}} = 0.4$ JPY$/s$, referring to Ref. [23].

4.3 User Satisfaction against the User Satisfaction Preference Weights

Figure 3 shows the mean user satisfaction. The horizontal and vertical axes indicate the number of vehicles and user satisfaction, respectively. We can fairly compare user satisfaction because all requests were accepted by both methods. Figure 3 shows that the proposed method has higher user satisfaction than the original method for all cases of the number of vehicles. We can confirm that the smaller the number of vehicles, the higher user satisfaction with the proposed method. When the number of vehicles is 800, user satisfaction is improved by 11% compared to the original method.

Figures 4 and 5 show the user satisfaction as a function of the user satisfaction preference weight. Figures 4 and 5 indicate the following:

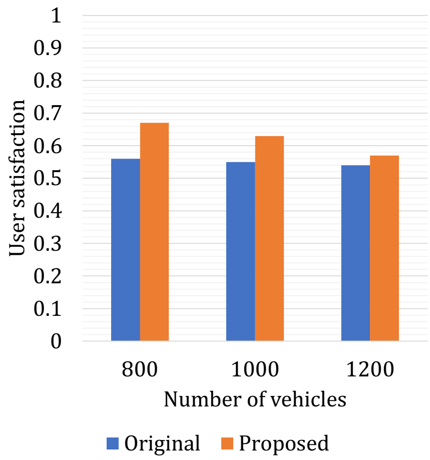

Fig. 3: Mean user satisfaction

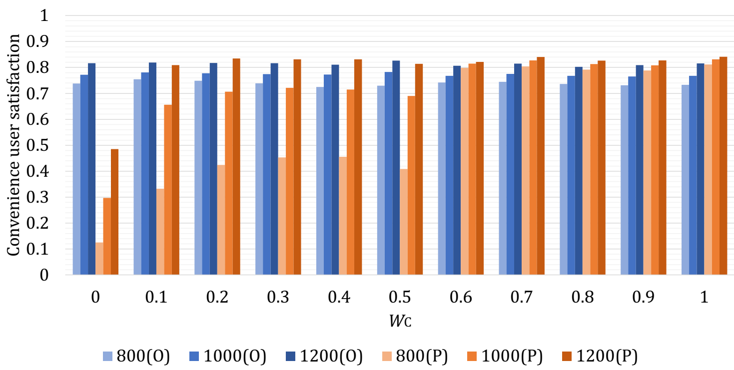

Fig. 4: Mean convenience user satisfaction by weight. For each vehicle number of 800, 1000, and 1200. (O) and (P) in the legend represent the original and proposed methods.

- The proposed method tends to have a higher convenience user satisfaction for users who placed more importance on convenience, and a lower convenience user satisfaction for users who did not place importance on convenience. In particular, there is a significant decrease in convenience user satisfaction for users who do not value convenience for the parameters with 800 and 1000 vehicles.
- The proposed method shows a drop in convenience user satisfaction only when the number of vehicles is 1200 and the weight of convenience is 0.1. Because there were sufficient vehicles in response to requests, the algorithm incurred not so many shared rides.

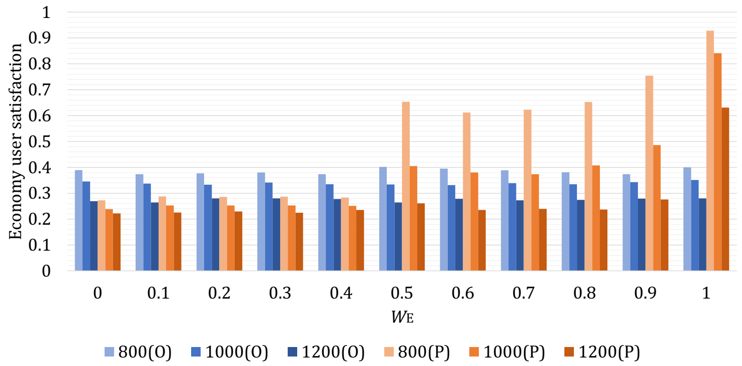

Fig. 5: Mean economy user satisfaction by weight. For each vehicle number of 800, 1000, and 1200. (O) and (P) in the legend represent the original and proposed methods.

Fig. 6: Economy user satisfaction for each parameter of the original method. F_U is the fare per unit distance, and F_D is the fare discount per unit time delay.

- Economy user satisfaction is higher for the proposed method when the weight of the economy is 0.5 or higher.
- The proposed method has the highest economy user satisfaction when the number of vehicles is 800. Because the supply of vehicles in response to requests is lower than that of the other number of vehicles, the algorithm incurred many shared rides, which resulted in lower fares.

Fig. 7: Economy user satisfaction for each parameter of the proposed method. F_{U} is the fare per unit distance, and F_{D} is the fare discount per unit delay time.

4.4 Economy User Satisfaction against Different Fare Parameters

Next, we conducted further analysis of the economy user satisfaction. In Sect. 4.3, the economy user satisfaction was evaluated only with the parameters of $F_{\mathrm{B}} = 300$ JPY, $F_{\mathrm{U}} = 0.4$ JPY$/m$, and $F_{\mathrm{D}} = 0.4$ JPY$/s$. The parameters F_{U} and F_{D} have a significant impact on the economy user satisfaction. Therefore, we analyzed the change in the economy user satisfaction when the parameters F_{U} and F_{D} were changed.

Figures 6 and 7 show the economy user satisfaction of the original and proposed methods when F_{U} and F_{D} are changed from 0.1 to 1.0. The horizontal and vertical axes indicate parameters F_{D} and F_{U}, respectively. Figures 6 and 7 indicate the following:

- Both methods show higher values of economy user satisfaction when F_{D} is large compared to F_{U}. Economy user satisfaction is higher when F_{D} is large compared to F_{U}. This is natural because a small delay significantly reduces the fare.
- When F_{D} is large compared to F_{U}, the original method tends to have higher economy user satisfaction, while the proposed method has higher economy user satisfaction when F_{D} is small compared to F_{U}. However, the configurations such that F_{D} is large compared to F_{U} are impractical in terms of profitability because the fare discount is too large.

4.5 User Satisfaction against Different Weight Distribution

To validate the effectiveness of the proposed method, we conducted an experiment with requests for the distribution of various user satisfaction preferences. In Sect. 4.3 experiment, the distribution of user satisfaction preference weights is determined randomly. However, the actual distribution of user satisfaction preference weights is likely to be diverse. The diversity of the distribution may vary based on a variety of factors, including hours of operation, the population of the service area, the distribution of users' annual income, and the distribution of user age groups.

In our experiment, we assumed six patterns of the distribution of user satisfaction preference weights. Figure 8 shows the distribution of the weights used in our experiment. The horizontal and vertical axes indicate the convenience weights and the number of generated requests, respectively. The weight distribution shown in Fig. 8(a) is the one used in the aforementioned experiment. Other experimental conditions are the same as described in Sect. 4.1. In this experiment, the parameter for the number of vehicles was set to 1000.

Figure 9 shows the mean user satisfaction for the six weight distribution patterns. The horizontal and vertical axes indicate the distribution of requests and user satisfaction, respectively. Figure 9 indicates the following:

- For all patterns of the user satisfaction preference weight distributions, user satisfaction of the proposed method is higher than that of the original method.
- User satisfaction is higher for distributions with more convenience-oriented users. From the results in Sect. 4.4, user satisfaction tended to be higher for convenience user satisfaction than for economy user satisfaction. It is natural that user satisfaction is higher for distributions with more convenience-oriented users.
- The larger the number of economy-oriented users is, the greater the difference in user satisfaction between the original and proposed methods.

These results show that the proposed method can improve user satisfaction in various situations.

5 Conclusion

In this paper, we proposed a ride-sharing service employing a vehicle allocation algorithm using three cost functions to improve user satisfaction. The cost function used in the vehicle allocation is switched based on the individual user satisfaction preference. We conducted simulation experiments and demonstrated the performance of the proposed switching vehicle allocation algorithm improved user satisfaction by up to 11% while maintaining vehicle allocation performance.

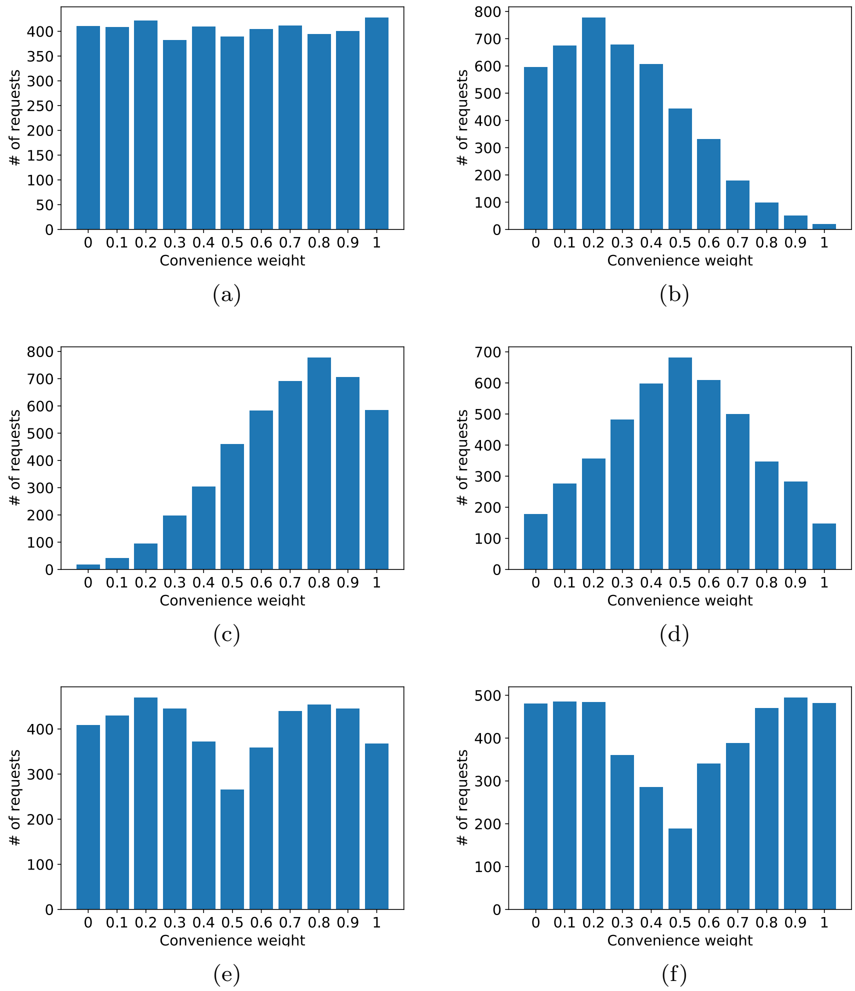

Fig. 8: Six patterns of the distribution of user satisfaction preference weights. The weight distribution represents the distribution of users' requests corresponding to each weight.

In this paper, we assumed that user satisfaction preference is represented by a combination of convenience and economy. However, user satisfaction can also be considered from preferences other than convenience and economy. For example, ride comfort and the outside view can be also considered to become a factor of user satisfaction. In our future work, we plan to design a new cost function to support other user satisfaction preferences.

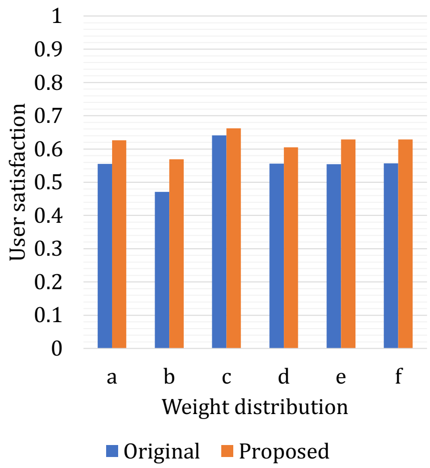

Fig. 9: Mean user satisfaction for each weight distribution (number of vehicles = 1000)

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References

1. N. Yaraghi and S. Ravi, "The current and future state of the sharing economy," *Brookings India IMPACT*, no. 032017, Mar. 2017.
2. I. Noda, M. Ohta, K. Shinoda *et al.*, "Evaluation of usability of dial-a-ride systems by social simulation," in *Multi-Agent-Based Simulation III (MABS2003)*, LNCS, pp. 167–181, Jul. 2003,
3. S. Ma, Y. Zheng, and O. Wolfson, "Real-time city-scale taxi ridesharing," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 7, pp. 1782–1795, Jul. 2015.
4. Q. Lin, L. Deng, J. Sun *et al.*, "Optimal demand-aware ride-sharing routing," in *IEEE INFOCOM*, pp. 2699–2707, Apr. 2018.
5. J. Alonso-Mora, A. Wallar, and D. Rus, "Predictive routing for autonomous mobility-on-demand systems with ride-sharing," in *IEEE/RSJ Int. Conf. Intell. Robots Systems (IROS)*, pp. 3583–3590, Sep. 2017
6. F. Miao, S. Han, S. Lin *et al.*, "Taxi dispatch with real-time sensing data in metropolitan areas: A receding horizon control approach," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 463–478, Apr. 2016.
7. R. Iglesias, F. Rossi, K. Wang *et al.*, "Data-driven model predictive control of autonomous mobility-on-demand systems," in *2018 IEEE Int. Conf. Robotics Automation (ICRA)*, pp. 6019–6025, May. 2018.
8. M. Asghari and C. Shahabi, "An on-line truthful and individually rational pricing mechanism for ride-sharing," in *ACM SIGSPATIAL*, pp. 1–10, Nov. 2017.
9. M. Asghari and C. Shahabi, "ADAPT-pricing: A dynamic and predictive technique for pricing to maximize revenue in ridesharing platforms," in *ACM SIGSPATIAL*, pp. 189–198, Nov. 2018.

10. J.-F. Cordeau and G. Laporte, "The dial-a-ride problem: Models and algorithms," *Ann Oper Res*, vol. 153, no. 1, pp. 29–46, Sep. 2007.
11. N. Agatz, A. Erera, M. Savelsbergh *et al.*, "Optimization for dynamic ride-sharing: a review," *European Journal of Operational Research*, vol. 223, no. 2, pp. 295–303, 2012.
12. M. Furuhata, M. Dessouky, F. Ordóñez *et al.*, "Ridesharing: the state-of-the-art and future directions," *Transportation Research Part B: Methodological*, vol. 57, pp. 28–46, 2013.
13. H. Nakashima, S. Sano, K. Hirata *et al.*, "One cycle of smart access vehicle service development," in *Serviceology for Designing the Future. ICServ 2014*, pp. 247–262, Sep. 2016.
14. J. Bischoff, M. Maciejewski, and K. Nagel, "City-wide shared taxis: a simulation study in Berlin," in *Proc. 2017 IEEE ITSC*, pp. 275–280, 2017.
15. S. Iwata and K. Suzuki, "Two way allocation methods in SAVS for large depopulated area," in *Asia Pacific Symp. Intell. Evol. Syst. (IES2019)*, pp. 33–45, Dec. 2019.
16. Y. Lin, W. Li, F. Qiu *et al.*, "Research on optimization of vehicle routing problem for ride-sharing taxi," *Procedia - Social and Behavioral Sciences*, vol. 43, pp. 494–502, May. 2012.
17. J. Yang, J. Li, Y. Chen *et al.*, "Multi-objective distribution model and algorithm for online shopping express logistics," *Journal of Computers*, vol. 8, no. 10, pp. 2558–2564, Oct. 2013.
18. M. Jahan, "Factors affecting customer satisfaction of the ride-sharing industry in bangladesh," *Business Ethics and Leadership*, vol. 3, no. 4, pp. 74–80, Dec. 2019.
19. B. Atasoy, T. Ikeda, X. Song *et al.*, "The concept and impact analysis of a flexible mobility on demand system," *Transportation Research Part C: Emerging Technologies*, vol. 56, pp. 373–392, Jul. 2015.
20. C. Levinger, N. Hazon, and A. Azaria, "Human satisfaction as the ultimate goal in ridesharing," *Future Generation Computer Systems*, vol. 112, pp. 176–184, Nov. 2020.
21. B. A. Beirigo, R. R. Negenborn, J. Alonso-Mora *et al.*, "A business class for autonomous mobility-on-demand: modeling service quality contracts in dynamic ridesharing systems," *Transportation Research Part C: Emerging Technologies*, vol. 136, p. 103520, Mar. 2022.
22. P. A. Lopez, M. Behrisch, L. Bieker-Walz *et al.*, "Microscopic traffic simulation using SUMO," in *Proc. 2018 IEEE ITSC*, pp. 2575–2582, Nov. 2018.
23. I. Noda, "Case Study of Price System Design for Taxi Sharing by Co-Evolutional Process between Service Corporations and Users," in *IPSJ*, vol. 2020-ICS-198, no. 16, pp. 1–7, Feb. 2020. (in Japanese)

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Acronyms

SBI	Successive Best Insertion
DARP	Dial-a-ride problem
SUMO	Simulation of Urban Mobility
TraCI	Traffic Control Interface
SAVS	Smart Access Vehicle Service

Glossary

Ride-sharing service A ride-sharing system schedules the route of vehicles to allow users to share a ride providing low-cost door-to-door transportation.

User satisfaction A satisfaction with the service received by users of ride-sharing services.

User satisfaction preference A user satisfaction preference is represented by a combination of convenience weight W_{C} and economy weight W_{E}, where $W_{\mathrm{C}} + W_{\mathrm{E}} = 1$. The ratio of W_{C} and W_{E} is assumed to be unchanged from the pre-defined ratio.

Dial-a-ride Problem The Dial-a-Ride Problem consists planning of vehicle routes and schedules for multiple users who specify the origin and destination points of the request.