A Passengers Matching Problem in Ridesharing Systems by Considering User Preference

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Abstract: Ridesharing system has been recognized as an efficient transport mode to solve the environment, energy, traffic congestion issues. In recent researches, user preference was revealed as an important factor to enhance the performance and reliability of ridesharing systems. With the development in ICT, internet-enabled devices and social network enable us to obtain real-time travel information and users’ personality. Therefore, user preference based on their personality is considered in this study. The aims of this study are to formulate a matching model between passengers by considering user preference and to investigate how user preference affects ridesharing system’s performance. The algorithm for solving stable roommates problem is modified for one-on-one passengers matching problem. The factors of user preference are personality and steadiness of user personality. The results of numerical experiments showed that steadiness of user personality affected to both individual and system success rate, while personality only affected to system success rate.

Keywords: Ridesharing System, Stable Roommates Problem, One-on-One Matching Problem, Taxi-Sharing, User Preference

1. INTRODUCTION

Ridesharing has been extensively introduced as an efficient transport mode to solve the environmental, energy and traffic congestion issues, however ridesharing has not yet been distinctly defined. Ridesharing is sometimes realized as carpooling which is a concept of sharing a private car to person who has similar travel route in order to share a travel cost. In fact, the definition of ridesharing is wider. Carpooling can be categorized as one type of ridesharing. Chan and Shaheen (2012) defined ridesharing as sharing a vehicle without
considering profit other than reducing travel cost or time such as carpooling, vanpooling, fam-pooling which means that taxi-sharing was not included in their definition. However, taxi-sharing (also known as cab-sharing) was considered as one type of ridesharing in Gidofalvi and Pedersen (2007) and Lin et al. (2012). Thus, ridesharing in this paper is given a definition as “a sharing of riding or driving vehicle to others who have similar travel route and time schedule including long term and short term commitment”. In other words, traditional carpooling, casual carpooling, vanpooling, fam-pooling, cab-sharing, lift-sharing (in United Kingdom), dynamic ridesharing (also known as real-time ridesharing) are all included in this definition of ridesharing. Ridesharing can be classified in many aspects such as profit and non-profit ridesharing, static and dynamic ridesharing.

As an era of development in information and communication technologies (ICT) such as smartphone and social network, these technologies have enhanced and changed the traditional ridesharing. The integration of ICT and ridesharing system is known as “smart ridesharing system”. Since internet-enabled devices such as smartphone or tablet provide the abilities to obtain real-time travel information and location, these advantages enable ridesharing system to perform matching on very short notice before making a trip (known as dynamic ridesharing system). With social network where people who have similar interests, communities, or even itineraries are gathered together; this advantage assists ridesharing system to provide more appropriate matches.

Subscribers in smart ridesharing system can be any type of users such as non-vehicle owners, private vehicle owners, or even public service vehicle owners (e.g., taxi owners). Subscribers are assumed to be connected by social network. The matching in smart ridesharing system can be divided into four different matching problems as shown in Figure 1. The first matching is between non-vehicle owners and private vehicle owner. The second matching is between non-vehicle owners themselves. This matching can make a trip by offline hiring public service vehicle or by online matching with private vehicle owner or public service vehicle owner, as the third and fourth matching, respectively. These four different matching problems concern in different issues. For instance, since matching between non-vehicle owners and private vehicle owners is a non-profit ridesharing, thus the concerned issue is sharing a ride without negative impact and private vehicle owner obtains some benefits such as authority to use HOV lanes. The matching between non-vehicle owners themselves concerns in cost saving. The matching between non-vehicle owner and public service vehicle owner has to concern the incentive for driver as well. Anyway, all users’ travel time schedule must be respected in every matching. Furthermore, smart ridesharing system also provides potential travel route, sharing fare, tentative time schedule, benefits from ridesharing.

The special characteristic of transport in Asian countries, which is the variety of public transport mode such as tuk-tuks and songtaews in Bangkok, jeepneys and tricycles in Manila
(Hayashi et al., 2004), advantages Asian countries in developing on-demand ridesharing since low capacity vehicles are more flexible to be assigned the route in order to serve all travelers’ demand. Even though varieties of ridesharing have been developed in Asian countries such as carpooling and vanpooling for work trips, bus and minibus sharing; but most of the projects are either long-term commitment ridesharing or fixed route ridesharing such as buspool for employees (Rudjanakanoknad, 2011), Park and Ride (P&R) project (Hai and Hiep, 2013). The successful projects of on-demand ridesharing with short-term commitment (one-time trip) have been rarely seen. Rudjanakanoknad (2011) gave several examples on ridesharing projects in Bangkok, Thailand. Friend in Car, a website for general public to find or share their ride, was one of the unsuccessful implementation examples. Although the reasons of unsuccessful implementation were not stated, but one possible reason was people did not feel comfortable and safe to share or have a ride with strangers. This situation can often be found especially in Asian countries. Therefore, this study is intended to provide some useful suggestions for those existing and new ridesharing projects.

The major aim of this paper is to formulate a matching model between those non-vehicle owners in smart ridesharing system. As user personal preference has been revealed as one of the important factors in ridesharing system, our matching model was performed based on ridesharing preference which involved personal preference and travel cost saving. Personal preference in this context refers to the preference on personality attributes which are considered when sharing private space to others such as smoking, personality, interest. For instance, non-smoking people may prefer having a ride with non-smoking people.
to smoking people. Our model allows users to evaluate other users based on their own personal preference. By considering ridesharing preference, user ridesharing preference list can be generated for each user. The matching algorithm was performed based on this ridesharing preference list. Actually, a mobile application for finding taxi rideshare partners has already appeared in ridesharing market such as ainoriya.net. The ainoriya.net provides a matching service while travelers are waiting at the taxi stand. This service implicitly includes user preference and user’s social relations by associating with Facebook ID, providing profile and common friends information, and allowing users to set conditions for desired partner. Unfortunately, this service provider has no intention to analyze the mechanism of this matching. Thus, it is necessary to study on the characteristics and mechanism of this matching process in order to develop a better ridesharing system. In order to understand basic characteristics of the model, numerical analysis was performed. The performance of this model was evaluated by success rate of matching. With this matching model, users can be assigned their match based on their preference.

The remainder of the paper is structured as follows. In section 2, literature review on ridesharing is provided. The model’s assumptions and concept of our matching model are explained in section 3. Then, the numerical experiments are constructed in section 4. The conclusion of this study and future work are provided in the last section.

2. BACKGROUND

In this decade, related studies have been majorly focused on the improvement of the potential and efficiency in ridesharing to minimize the total travel cost or time and increase the success rate. The optimization of static taxi-sharing concept was proposed in Lin et al. (2012). The matching between non-vehicle owners (passengers) and public service vehicle owner (taxi driver), the fourth matching problem in Figure 1, was considered in their study. The vehicle routing problem was used to maximize passenger satisfaction and minimize operation cost. In their paper, passenger satisfaction referred to passenger’s travel time which included direct travel time (without congestion), waiting time, and extra riding which may occur from operation characteristic. Passenger information such as origin/destination, desired departure/arrival time and total demand were assumed to be known in prior. This research revealed and emphasized that taxi-sharing is one of the effective ways to solve the environmental, traffic congestion, energy issues.

Even though the importance and effectiveness in ridesharing have been emphasized in numerous researches, together with researches on enhancing the potential of ridesharing; the employment of ridesharing has not been widely adopted. Even in U.S., one of the most suitable environments for ridesharing and large number of projects and policies have been
developed, hasn’t obtained a satisfying statistical record in ridesharing share among the other transport modes. According to the Commuting in America 2013 report (AASHTO Census Transportation Planning Products Program, 2014), mode share of private vehicle commuting in U.S. represented that carpooling share had been declining from 19.7% in 1980 to 9.7% in 2010.

There are several researches mentioned on challenges to enhance ridesharing and convince more subscribers. “Stranger Danger” was stated as one of the challenging issues to be solved besides power mismatch and the need for mutual dependency, reliability of service, schedule flexibility and consistency of expectations (Amey et al., 2011). According to their survey, only 3-10% of ridesharing was occurred between unknown passenger, while the rest of ridesharing was occurred between family members, co-workers and neighbors. HOV-3 or greater occupancy requirements policy was suggested to be one of the solutions for Stranger Danger in casual carpooling (Oliphant, 2008). However, in order to solve the stranger danger issue, it is necessary to consider participations’ feeling and attitude in sharing a ride or their private space with others. Matching them with acquaintance or based on their preference are remarkable alternatives. Social networking has recently been considered in several researches and ridesharing communities such as Zimride community, Kleiner et al. (2011), Graziotin (2010), Yousaf et al. (2014) to increase reliability and success rate of matching.

In an aspect of user preference, the stable marriage problem is well-known matching problem based on user preference (Gale and Shapley, 1962). The stable marriage problem is to match all men and women together with as high preference as possible under the assumption of all information is known. Wang (2013) integrated the stable marriage problem to the first matching problem in Figure 1. Preference in his assumption referred to the travel cost saving where higher saving implied to higher preference. Unfortunately, even though considering in cost saving is very important and two-side matching is very reasonable method, but a problem in terms of safety and comfort is still existed, and the intention in increasing number of subscriber cannot be achieved. Kleiner et al. (2011) included user preference together with social distance as variables in their auction model for ridematching. Personal preference similarity (i.e., age, gender, smoking, pet restriction and music) was formulated in Yousaf et al. (2014) to provide the matching pair as close to the user preference as possible. As revealed in recent researches, user preference has been receiving high attention to be considered in matching model.

Since two-side matching is very reasonable method to consider user preference, thus two-side matching algorithm was adopted in our model. With an intention to increase the performance and reliability of the ridesharing systems in terms of safety and comfort, both user personal preference and travel cost saving were considered in our matching model. According to the literature review, the first and fourth matching problems in Figure 1 have already been studied, while the second matching problem hasn’t been well studied. Thus, this
matching model was developed under the assumption of matching problem between those non-vehicle owners or passengers. The matching model developed in this paper is a static matching for understanding the basic characteristics of the passenger matching problem. The dynamic version of the model will be presented in the near future.

3. MODEL DEVELOPMENT

With the development of ICT, ridesharing system has been enabled to obtain real-time travel information by internet-enabled devices. Moreover, users can evaluate others through social network. In our developed model, users refer to those passengers with internet-enabled devices and social network account. Thus, travel information (e.g., origin, destination) and users’ personality can be obtained as inputs for our model. By performing the matching algorithm, users will either obtain their most available preferred travel partner as an output if they are successfully matched, or be notified to travel alone if they are not successfully matched with anyone. Furthermore, sharing travel cost for each user is also provided.

3.1 Model Assumptions

In order to understand the model characteristics, this model was developed under the simple assumptions, but simultaneously maintained the ability to reflect real world problem as follows.

1) All travelers have same departure time with same origin but different destinations.
2) Travelers have two choices of transport mode, riding taxi alone or sharing a taxi.
3) Taxi supplies are always sufficient.
4) Travel time is given and fixed as there is no traffic congestion.
This kind of situation in the first assumption is often seen at any airport where arrival passengers seek for a taxi to city center, as shown in Figure 2. The same departure time in the first assumption was set to allow matching to be performed, and travelers can immediately depart when the matching is finished. Same origin but different destination situation implies to the situation of all travelers are waiting at the same place (e.g., taxi rank) for a ride to different destinations (e.g., home, work place). Matching can be performed on this group of travelers while they are waiting for a ride. As all travelers are able to check travel times and personalities of others by using their smart devices, they know travel and personal information in prior. The second assumption reduces the complexity of the model by considering only taxi as a transport mode. Moreover, in the airport situation, travelers generally have baggage with them, thus using public transport such as train may not be so convenient for this group of travelers. This reason also leads to the second assumption where travelers prefer to take a taxi for their convenience. Since riding taxi alone is costly, another choice of transport mode becomes sharing a taxi with others who have similar itinerary. Thus, the travel cost for sharing a taxi can be shared by travel partner. For instance, two users are sharing a ride with same origin and same destination, the individual travel cost can be reduced by 50%. The third assumption in sufficient taxi supplies is set to enable travelers to immediately depart once their matching pair is completed. The last assumption is set to assume that there is no traffic congestion; hence direct travel time and cost are constant through the matching algorithm.

3.2 One-on-One Matching Algorithm

The stable roommates problem (Irving, 1985) was modified for one-on-one passengers matching problem in ridesharing system. The objective of stable roommates problem is to find a stable matching where every users are matched with their most available preferred partner based on their preference list. The stable solution provides exact n/2 pairs of successful matches. Since this paper focuses on one-on-one matching problem between passengers (non-vehicle owners) themselves which means that there is only one set of passengers, this one-on-one passengers matching problem is identical to the stable roommates problem. In addition to this, we described ‘riding taxi alone’ as a type of pairing. Thus, the algorithm for solving stable roommates problem was modified by involving user himself in his preference list as a choice of traveling alone which can be explained as follows.

According to the second assumption, riding taxi alone is another choice of transport mode, user $i$ is then included in his own preference list. Those users who are ranked after user $i$ in user $i$’s preference list imply that user $i$ prefers riding alone instead of sharing a ride with those users. In each user preference list, all users including preference list owner are ranked by ridesharing utility $u_{ij}$, which denotes the ridesharing utility of user $i$ to user $j$. 
indicating on how much user $i$ would like to share a taxi with user $j$. The ridesharing utility calculation is explained in the next section. The higher in ridesharing utility means a more preferable partner. Thus, user $j$ whose $u_{ij}$ is the highest among others in user $i$’s preference list is ranked the first in user $i$’s preference list. On the other hand, user $j$ whose $u_{ij}$ is the lowest among others in user $i$’s preference list is ranked the last in user $i$’s preference list. With this preference list, matching algorithm can result in three different ways, matching pair $(i,i)$, matching pair $(i,j)$, or unstable matching. Stable matching pair $(i,i)$ implies that user $i$ will travel alone. Stable matching pair $(i,j)$ implies that user $i$ will share a ride with user $j$. Those users who cannot be matched in stable matching will travel alone. The unstable matching can occur when there are one or more blocking pairs. The blocking pair implies to a pair of users who prefer each other than their actual partner. In other words, users in unstable matching can still find a more preferable partner. The detailed algorithm (in pseudo code) is provided in Appendix.

The algorithm for solving the stable roommates problem always provides a stable solution if it exists, where no user prefers others than his actual partner, if there is no blocking pair; otherwise those blocking pairs are unmatched. Even though these qualitative characteristics can be easily described, but the numerical analysis is required in order to describe quantitative characteristics such as success rate, tendency.

### 3.3 Ridesharing utility

Ridesharing utility is a subjective measure of individual ridesharing preference. Ridesharing preference involves two aspects which are travel cost saving and personal preference. The later indicates how much a traveler prefers the personality of a person with whom he/she shares a taxi. Since users’ destination is different, sharing travel cost with different users can be different. Furthermore, each user has a unique personality, personal preference is also different. Therefore, ridesharing utility of each user to others is unique. Ridesharing utility of user $i$ to user $j$ can be formulated as shown in equation (1). Given $S = \{1, 2, 3, ..., N\}$ is a set of $N$ travelers in one specific time period with travel distance, $D = \{d_1, d_2, d_3, ..., d_n\}$.

$$u_{ij} = x_{ij} - \alpha d_{ij} \quad \text{for } i \in S, j \in S$$

$$d_{ij} = \begin{cases} d_i & \text{for } i \in S, j \in S, i = j \\ (d_i - d_j) + \left(\frac{d_j}{2}\right) & \text{for } i \in S, j \in S, i \neq j, d_i > d_j \\ \frac{d_i}{2} & \text{for } i \in S, j \in S, i \neq j, d_i \leq d_j \end{cases}$$

where,

- $u_{ij}$: ridesharing utility of user $i$ to user $j$,
- $x_{ij}$: personal utility of user $i$ to user $j$,
- $d_{ij}$: sharing travel distance of user $i$ if sharing a ride with user $j$. 

\( \alpha \) : utility for traveling 1 unit of distance.

In equation (1), ridesharing utility matrix is asymmetric where \( u_{ij} \) is not equal to \( u_{ji} \) since the component \( x_{ij} \) is only dependent on user \( i \), but user \( j \), and the component \( d_{ij} \) is not equal to \( d_{ji} \) unless \( d_i \) is equal to \( d_j \). Ridesharing utility \( u_{ij} \) can be increased when sharing travel distance \( d_{ij} \) is reduced or personal utility \( x_{ij} \) is increased. In the fields of economics, measuring utility, which is a measurement of an individual preference over something, has been widely studied (McFadden, 1974). Thus, personal utility \( x_{ij} \) can be obtained through some appropriate methods such as formulating a utility function from social networking attributes for choosing ridesharing partner. Since travel cost varies directly with travel distance, sharing travel cost can be described by sharing travel distance which can be calculated as shown in equation (2). For \( i = j \), this means user \( i \) riding alone, thus user \( i \) has to absorb the whole travel cost from his travel distance \( d_i \). For \( i \neq j \), this means user \( i \) sharing a ride with user \( j \), however the sharing travel cost depends on whose destination is farther. For \( d_i > d_j \), only travel cost of common travel path is shared, and only user \( i \) has to absorb the travel cost occurred by extra travel path. For \( d_i \leq d_j \), the whole travel cost is shared by user \( j \).

Once the ridesharing utility is given, the stable matching of travelers can be calculated by applying modified stable roommates matching algorithm mentioned in section 3.3. As a result, some of the travelers will be matched and share the taxi, and rest of them will travel alone.

4. NUMERICAL EXPERIMENT

In order to understand the quantitative characteristics of our matching model, such as success rate, tendency; the numerical experiment was constructed. The effect of the personal preference to the matching result was investigated in this section.

4.1 Experimental Design

Since our matching algorithm is performed based on ridesharing utility which consists of personal utility and sharing travel distance, thus the inputs of matching algorithm are personal information, i.e., personality which is represented by \( \mu_i \) and \( \sigma_i^2 \), and travel distance \( d_i \), as shown in Figure 3. The parameters of personality are used to generate a random number for personal utility. The parameters \( \mu_i \) and \( \sigma_i^2 \) were differently given among the experiments as illustrated in Figure 3 (a), (b), and (c) for the first, second, and third experiment, respectively. Individual travel distance \( d_i \) was given as a random number from normal distribution. The
detailed explanation of these inputs is further described in this section. The output of matching algorithm is a matching between user \( i \) and user \( j \). The performance of this model is evaluated in terms of individual success rate and system success rate.

As previously mentioned, these ridesharing situations are often seen at the airport, thus given this airport case as an example for the numerical experiment. An airport is generally located far from the residential area. The central of residential area has high density of housing. The density is decreasing along the radial extension. Thus, distance from the airport to the residence of each user is a random number from truncated normal distribution where users’ travel distance is always greater than zero. This can be represented as follows:

\[
d_i \sim N(\mu_d, \sigma_d^2).
\]  
(3)

Every user must travel from the origin (airport) to the destination (residence). The parameters of this distance distribution, \( \mu_d \) and \( \sigma_d^2 \), imply to distance from the airport to the central of residential area, and a dispersion of residential area, respectively.

Once we obtain the individual personal utility for ridesharing partners through any appropriate method, the distribution of individual personal utility is expected to be normal distribution. Each user has individual parameters for their personal utility distribution, i.e., \( \mu_i \) and \( \sigma_i^2 \). In this numerical experiment, the personal utility of user \( i \) to user \( j \), \( x_{ij} \), is given as a random number from normal distribution as follows:

\[
x_{ij} \sim N(\mu_i, \sigma_i^2).
\]  
(4)
Personal utility of traveling alone \((x_{ii})\) is set equal to zero for all users, implying that user \(i\) prefers sharing a ride with user \(j\) than traveling alone if \(x_{ij}\) is greater than zero. Hence, mean of the personal utility distribution \((\mu_i)\) can imply that user \(i\) whose mean is greater than zero mostly evaluates the others as sharing a ride with them is better than traveling alone. In other words, this user has friendly personality in term of ridesharing because he mostly prefers sharing a ride with others than traveling alone. In term of variance of personal utility distribution \((\sigma_i^2)\), it represents the steadiness of user personality where variance equal to zero implies that user \(i\) personality is stable to any user \(j\). For instance, user whose mean and variance of his personal utility distribution are 50 and 0, respectively, equally evaluates any user at 50, meaning that his friendliness in term of ridesharing is stable to any user \(j\).

In the numerical experiment, the performance of ridesharing system is evaluated in terms of average system success rate \((SSR)\) and individual success rate \((ISR)\) as shown in equations (5) and (6), respectively.

\[
SSR = \sum_{r=1}^{R} \left[ \frac{\sum_{i=1, i\neq j}^{N} \left( m_{ij}^{(r)} \right)}{N} \right] / R \quad \text{for } i \in S, j \in S, i \neq j \quad (5)
\]

\[
ISR(l) = \sum_{r=1}^{R} \left[ \frac{\bar{m}_l^{(r)}(l)}{R} \right] / R \quad \text{for } i \in S, j \in S, i \neq j \quad (6)
\]

\[
m_{ij}^{(r)} = \begin{cases} 
1 & \text{if user } i \text{ matches with user } j \text{ in run } r \\
0 & \text{otherwise} 
\end{cases} \quad \text{for } i \in S, j \in S \quad (7)
\]

\[
m^{(r)}(l) = \left\{ m_{ij}^{(r)} \mid l - 1 < \mu_i^{(r)} \leq l \right\} \quad \text{for } i \in S, j \in S, i \neq j \quad (8)
\]

\[
\bar{m}^{(r)}(l) = \frac{\sum_{m \in m^{(r)}(l)} m}{|m^{(r)}(l)|} \quad (9)
\]

where,

- \(SSR\) : average system success rate,
- \(ISR(l)\) : individual success rate of user \(i\) whose \(\mu_i^{(r)}\) is between \((l-1, l]\),
- \(m_{ij}^{(r)}\) : dummy variable representing user \(i\) is matched to user \(j\) in run \(r\),
- \(m^{(r)}(l)\) : set of \(m_{ij}^{(r)}\) of users whose \(\mu_i^{(r)}\) is between \((l-1, l]\) in run \(r\),
- \(\bar{m}^{(r)}(l)\) : mean of \(m^{(r)}(l)\),
- \(l\) : level of friendliness personality,
- \(R\) : total number of runs,
- \(N\) : total number of users,

The average system success rate \((SSR)\) in equation (5) is the average of percentage of number of users who are successfully matched with another user among the total number of users. The individual success rate in equation (6) is an average percentage of successful matches between users whose \(\mu_i^{(r)}\) between \((l-1, l]\) and another user \(j\) among the total
number of runs. Equations (7) and (8) represent how to obtain dummy variable representing user \( i \) is matched to user \( j \) for SSR and ISR, respectively. The mean of dummy variable \( m(r)(I) \) for ISR can be obtained by equation (9).

Equations (10)-(12) must be satisfied for an arbitrary matching. Equations (10) and (11) are constraints to confirm that user \( i \) and \( j \) only matches with one another or himself. Equation (12) is a constraint to confirm that if user \( i \) is matched with user \( j \), user \( j \) is also matched with user \( i \) as well. The algorithm described in section 3.2 and Appendix satisfies these conditions.

\[
\sum_{j=1}^{N} m_{ij}^{(r)} = 1 \quad \text{for } i \in S, j \in S \quad (10)
\]

\[
\sum_{i=1}^{N} m_{ij}^{(r)} = 1 \quad \text{for } i \in S, j \in S \quad (11)
\]

\[
m_{ij}^{(r)} = m_{ji}^{(r)} \quad \text{for } i \in S, j \in S \quad (12)
\]

4.2 Experiment Results

To study on the effect of user preference to the model performance, parameters and the rest input variables besides personality and steadiness of user personality were given the same through the experiments as follows. The utility of traveling 1 unit of distance (\( \alpha \)) was given equal to 1. Each group of users contained 100 users (\( N = 100 \)). Travel distance was given as a random number from truncated normal distribution with parameters \( \mu_d = 100 \) and \( \sigma_d = 16.67 \) throughout the experiment.

4.2.1 Experiment on different groups of same personality users

To understand the effect of the personal preference to the matching algorithm, we firstly performed the matching algorithm 100 times for different group of users. The mean of the normal distribution on personal utility, \( \mu_i \), was given the same for all users to represent the personality of each group. Each group was assigned \( \mu_i \) as an integer number between \([-100, 100]\). We performed the test with different \( \sigma_i \) which are 0, 10 and 20 to represent the steadiness of user personality. The group with \( \mu_i = 0 \) and \( \sigma_i = 0 \) implies that user personal preference doesn’t affect to the ridesharing preference. The SSR of this test is illustrated in Figure 4, while the standard deviation is illustrated in Figure 5. The matching was performed 100 times for the same user groups.

According to the result in Figure 4, performing matching algorithm among those users who are very unfriendly personality (very low \( \mu_i \)) resulted in very low success rate. The SSR for the group with \( \mu_i = -100 \) reaches 0 for all \( \sigma_i \). However, SSR is higher when \( \sigma_i \) is increased for the groups that \( \mu_i \) is lower than \(-20\). The results of the groups with \( \mu_i \) greater
than −20 are not significantly different for each $\sigma_i$. The groups with $\mu_i$ greater than −20 and $\sigma_i$ equal to 0 provided the average percentage of success rate at 100% with standard deviation equal to 0 as shown in Figure 5. While $\sigma_i$ equals to 10 and 20 resulted around 95% with standard deviation around 6.1 and 6.6, respectively. The difference in values of $\sigma_i$ resulted in different descending point of the graph. The larger in $\sigma_i$, the descending point of $SSR_i$ is extended to a lower $\mu_i$ group. In addition for $\sigma_i$ equals to 10 and 20, standard deviation (Figure 5) at the beginning of descent of SSR tends to be smaller than high SSR region and increased during the middle of descent. Then, standard deviation will finally be decreasing for lower $\mu_i$.

4.2.2 Experiment on different groups of variety personality users

In real world situation, there is always a combination of variety users, both friendly and unfriendly personality users. Therefore, we firstly performed a matching algorithm 10,000 times for a group of 100 users consists of 50 friendly personality users which are represented by fixed $\mu_i$ at 100, and 50 unfriendly personality users which are represented by fixed $\mu_i$ at −100, and $\sigma_i$ given at 10 for both types of users. The ISR for friendly personality users is 93.32% with standard deviation of 8.92, while the ISR for unfriendly personality users is 0.0046% with standard deviation of 0.09. We continued testing the same experiment by given 50 friendly personality users represented by 50, while 50 unfriendly personality users represented by −50; this resulted in ISR for friendly personality users at 95.76% with standard deviation of 5.27, while ISR for unfriendly personality users at 82.72% with standard deviation of 6.21.

Then, we tested our model with a group which consists of users with different personality. Given each user had different personality in a group assigning by a random
number from normal distribution, \( \mu_i^{(r)} \sim N(\mu, \sigma^2) \) where \( \mu \) was given at \(-10, 0, 10\) and \( \sigma \) was fixed at 33. The different group had different normal distribution. The matching algorithm was performed 10,000 times for each group. From this experiment, the type of users who has a tendency to obtain high ISR can be investigated. The ISR for individual user is illustrated in Figure 6.

By fixing \( \sigma_i \) the same for all users at 10, ISR for individual user was not affected by the different mixture of users in a group. Those friendly personality users still obtained high success rate at around 95\% for performing on a group with majority of unfriendly users. In the same way, those unfriendly personality users still obtained low ISR even performing on a group with majority of friendly users. The result of those users whose \( l \) equal to \(-100, -50, 50 \) and 100 in Figure 6 conformed to the previous result in the first paragraph of this subsection. However, groups with different mixture of users affected to SSR as shown in Figure 7. The group with \( \mu \) equal to \(-10, 0 \) and 10 provided SSR at 89.95\%, 90.11\% and 93.41\%, respectively. In other words, the group with a mixture of friendly personality users provided higher in SSR.

4.2.3 Experiment on a group of variety personality users but different preference degree

Since \( \sigma_i \) was a factor that impacts to success rate in our first experiment, thus the difference in \( \sigma_i \) was tested on a group of variety personality users. A group with normal distribution \( \mu_i^{(r)} \sim N(0, 1089) \) was tested with different \( \sigma_i \); 0, 10 and 20. The result shown in Figure 8 implies that a higher in \( \sigma_i \) could increase an ISR for those unfriendly personality users. However, besides \( \sigma_i \) equal to 0, ISR remained about the same for those friendly personality users. For \( \sigma_i \) equal to 0, ISR was even better at above 99\% for friendly personality users.

In term of SSR, assigning \( \sigma_i \) as an integer between 0 to 20 for a group of variety users
provided the SSR as shown in Figure 9. Besides $\sigma_i$ equal to 0, SSR was higher when $\sigma_i$ was increased. The lowest SSR at 83.86% was resulted from $\sigma_i$ equal to 1. Even though the increasing in $\sigma_i$ provided higher in SSR, but standard deviation was slightly increased as well. The result of $\sigma_i$ equal to 0 differed from the model’s tendency with high SSR at 92.70% and low standard deviation at 1.23 (Figure 9) due to the certainty in ISR at above 99% among those friendly users as shown in Figure 8. However, SSR at 92.70% from $\sigma_i$ equal to 0 could be exceeded by higher of $\sigma_i$. For instance, $\sigma_i$ equal to 40 provided SSR at 93.56%, but the standard deviation is quite higher than $\sigma_i$ equal to 0 at 5.83.

4.3. DISCUSSION

According to the result in section 4.2, we can conclude that performing on any group of users does not affect to the ISR for individual users. Those friendly personality users always obtain high ISR, while unfriendly personality users always obtain a lower ISR as described in subsection 4.2.2. This characteristic occurs because friendly personality user is likely to prefer the others who are trying to match with him/her; in contrast, even though there are users trying to match with unfriendly personality user, but unfriendly personality user is likely to prefer himself/herself better than others. However, ISR of unfriendly personality users can be improved by increasing value of $\sigma_i$ as shown in subsection 4.2.3. In other words, the high steadiness of user personality resulted in low success rate, while the low steadiness of user personality can increase ISR due to the low steadiness of user personality gives unfriendly users a chance to prefer some users, while unfriendly users with high steadiness of user personality always do not prefer the others. Therefore, ISR only depends on his personality and personal preference.
In term of SSR, performing matching algorithm on a group of variety users with majority of friendly personality users provides higher SSR as shown in Figure 5, because they are more likely to prefer each other. Besides that, SSR can also be increased by low steadiness of personal preference (large $\sigma_i$) because unfriendly users have more chance to prefer the others as previously mentioned. However, the most steadiness of personal preference at $\sigma_i = 0$ has a unique characteristic of the result by providing high SSR in contrast with the model’s tendency which is a higher steadiness of personal preference provides a lower in SSR because the certainty of ISR for the majority at above 95% can compensate the unsuccessful match for the minority (very unfriendly users).

In addition, since the characteristic of algorithm for solving the stable roommates problem is an $O(n^2)$ algorithm, number of users should be taken into consideration. The very large group of users requires long computation time. Therefore, to implement this algorithm, when to perform the matching algorithm must be clearly defined. For instance, matching algorithm is set to perform every 10 users or every 10 minutes.

5. CONCLUSION

In this paper, we formulated a matching model between those non-vehicle owners in smart ridesharing system. As user personal preference has been revealed as one of the important factors in ridesharing system, we modified an algorithm used for solving a stable roommates problem for a passengers matching problem by considering user preference in ridesharing system. The factors of user personal preference are personality and steadiness of user personality. Due to the existing ridesharing systems, the matching is mostly performed based on dial-a-ride problem without considering user preference which may lead to the undesired matches in real world. It means that the offered ridesharing partner from the system will not be successful in practice if the partner doesn’t satisfy user preference. Our model is necessary to discuss the effects of considering user preference for matching.

The performance of this model was evaluated by the individual success rate and system success rate of matching based on numerical experiments. The steadiness of user personality affected to both individual success rate and system success rate, while personality only affected to system success rate. With high individual success rate for majority of users, users have high chance to be successfully matched with their preferred travel partner. The comfort issue on sharing private space to strangers is expected to be improved by this matching model since users are matched with their preferred partner based on their preference. Moreover, integrating our model with ICT, the efficient matching application with ability to obtain travel and personal information can be developed on smart devices such as smartphone. The traditional ridematching (e.g., verbal matching, hand-matching) or the poor matching
applications (e.g., random matching) can be replaced by this matching application in order to increase the system performance and convenience of using the matching system.

For those existing ridesharing projects, the idea of considering user preference can be adopted in their matching model to increase the performance of ridesharing system, since this paper revealed that considering user preference still provides the acceptable system success rate. Furthermore, since Asian countries have an advantage on variety of public transport such as tuk-tuks and jeepneys, there are the opportunities to develop on-demand ridesharing with short term commitment project by using the existing resources. This matching model can be applied to those on-demand ridesharing projects or developing for a new project at a new site by using the existing resources. Therefore, the adoption of ridesharing system can be increased.

As steadiness of user personality is revealed as an important factor of this model, this factor should be carefully measured in numerical number. Even though we assumed the user personal preference to other users as a random number of normal distribution, but the study on measurement of personal preference is still required in order to implement for a real world problem. Moreover, steadiness of user personality is different among people in real world situation. Thus, matching algorithm on users with different personality and steadiness of user personality will be further studied.

Even though our matching model is suitable for some real world situations such as an airport case, but in order to cover more real world situations which users stochastically appear with many-to-many OD patterns and different departure time, our future work will be considering on developing this passengers matching model for a dynamic ridesharing system. Thus, ridematching can be performed at any time.

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REFERENCES


APPENDIX

The detailed matching algorithm of this study is provided in pseudo code as shown in Tables 1-3. In matching algorithm, proposal is assumed to be a request from user \( i \) to user \( j \) to share a ride with. The behavior of user \( i \) proposes user \( j \) can be written as \( P_j = i \) where \( P_j \) denotes the proposal set of user \( j \). In case, the proposal satisfies user \( j \), then user \( j \) holds the proposal from user \( i \), otherwise user \( j \) rejects the proposal from user \( i \). Removing user \( i \) from user \( j \)'s preference list implies that user \( i \) is no longer available for user \( j \) to choose as a ridesharing partner, since users will only choose their ridesharing partner based on their preference list.

Table 1: Matching Algorithm for Matching Round \((r)\)

\[
S \leftarrow \text{a set of all users;}
\]
\[
\text{Pref}(i) \text{ is a set of preference list of user } i \text{ for } \forall i \in S;
\]
\[
\text{Phase1} \leftarrow S;
\]
\[
\text{Call Phase}_1;
\]
\[
\text{WHILE } \sum_{i=1}^{N} \sum_{j=1}^{N} m_{ij}^{(r)} < |S| \rightarrow \sum_{i=1}^{N} |\text{Pref}(i)| = 1 \text{ for } \forall i \in \text{Phase1}
\]
\[
\text{Call Phase}_2;
\]
\[
\text{ENDWHILE}
\]
\[
\text{Return } m_{ij}^{(r)};
\]

Table 2: Phase 1 in Matching Algorithm for Matching Round \((r)\)

\text{SUBPROCEDURE Phase}_1; \text{Propose} \leftarrow \text{Phase1};
\text{i } \leftarrow \text{an arbitrary user in Propose};
\text{REPEAT}
\text{j } \leftarrow \text{the first user in } \text{Pref}(i);
\text{A_set } \leftarrow \text{a set of users who ranked after } i \text{ in } \text{Pref}(j);
\text{IF } |P_j| = \emptyset \rightarrow \text{THEN } \text{if no one proposes to } j
\text{P}_j \leftarrow \{i\}; \text{ // i proposes to } j, \text{ and } j \text{ holds proposal from } i
\text{ELSE}
\text{k } \leftarrow \text{P}_j; \text{ // set } k \text{ to a user who proposes to } j
\text{P}_j \leftarrow \text{P}_j - \{k\} + \{i\}; \text{ // } j \text{ rejects proposal from } k \text{ and holds proposal from } i
\text{Propose } \leftarrow \text{Propose } + \{k\}; \text{ // add } k \text{ to Propose}
\text{ENDIF}
\text{Pref}(h) \leftarrow \text{Pref}(h) - \{j\} \text{ for } \forall h \in \text{A_set; // remove } j \text{ from Pref}(h) \text{ for } \forall h \in \text{A_set}
\text{Pref}(j) \leftarrow \text{Pref}(j) - \text{A_set; // remove all users in A_set from Pref}(j)
\text{Propose } \leftarrow \text{Propose } - \{i\}; \text{ // remove } i \text{ from Propose_set}
\text{i } \leftarrow \text{an arbitrary user in Propose_set;}
\text{UNTIL } |P_j| = 1 \text{ for } \forall i \in \text{Phase1}
\text{Phase2_set1 } \leftarrow \emptyset; \text{ // set Phase2_set1 to an empty set}
\text{FOR } i \in \text{Phase1}
\text{IF } |\text{Pref}(i)| = 1 \rightarrow \text{THEN } \text{Pref}(i) \text{obtains only 1 user}
\text{j } \leftarrow \text{Pref}(i); \text{ // set } j \text{ to an only user in Pref}(i)
\text{ENDFOR}
\begin{verbatim}
m_{ij}^{(r)} = 1; // user i matches with user j
ELSE
    Phase2_set1 ← Phase2_set1 + \{i\}; // add i to Phase2_set1
ENDIF
ENDDO
END

Table 3: Phase 2 in Matching Algorithm for Matching Round (r)

SUBPROCEDURE Phase_2;
i ← an arbitrary user in Phase2_set1;
B_set ← \emptyset; // set B_set to an empty set
B_set ← \{i\}; // add i to B_set
k ← 0; // set k equal to 0 as an initial value
WHILE TRUE
    j ← the second user in Pref(i);
i ← the last user in Pref(j);
    IF i ∈ B_set THEN
        k ← i;
        BREAK;
    ELSE
        END
    END
END

k_index ← an index of k in B_set;
Reduction_set ← \emptyset;
Reduction_set ← \{B_set \_idx_j \mid \forall idx \geq k\_index\};
// set Reduction_set to a set of users from k to the last user in B_set
FOR i ∈ Reduction_set
    j ← the first user in Pref(i);
    Pref(j) ← Pref(j) − \{i\}; // remove user i from Pref(j)
    Pref(i) ← Pref(i) − \{j\}; // remove user j from Pref(i)
ENDFOR
Phase2_set2 ← \emptyset; // set Phase2_set2 to an empty set
FOR i ∈ Phase2_set1
    IF |Pref(i)| = 1 THEN // Pref(i) obtains only 1 user
        j ← Pref(i); // set j to an only user in Pref(i)
        m_{ij}^{(r)} = 1; // user i matches with user j
    ELSE
        Phase2_set2 ← Phase2_set2 + \{i\}; // add i to Phase2_set2
    ENDIF
ENDFOR
IF |Phase2_set2| > 0 THEN
    Phase1_set ← Phase2_set2; // set Phase1_set to Phase2_set2
    Call Phase_1;
ELSE
    ENDIF
END
\end{verbatim}