An Agent-based Distributed Approach for Bike Sharing Systems*

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Abstract. Shared bikes are wildly welcomed and becoming increasing popular in the world, as a result, quite a few bike sharing systems have been conducted to provide services for bike users. However, current bike sharing systems are not flexible and considerate enough for public bike users because of the fixed stations and not well emphasized about user's satisfactions. In this paper, an agent-based distributed approach for bike sharing systems is proposed, this approach aims at helping users obtain a needed shared bike successfully and efficiently. We pay more attention on user's preferences to improve the satisfaction to the target shared bike, meanwhile, trust and probability are considered to improve the efficiency and success rate. To the end, results from simulation studies demonstrate the effectiveness of our proposed method.

Keywords: Computer science · Agent· Trust· Optimization · Resource assignment · Bike sharing system · Preference.

1 Introduction

The first bike sharing system was launched in Amsterdam in 1965 [24, 20]. Since then, many cities have developed the bike sharing system for the purpose of providing an economical, convenient and environmentally way for the travelers. Until December 2017, more than 18880500 self-service public use bikes and pedelecs (electric assisted bicycles) have been put into use in 1525 cities. In addition, 417 cities are planning or under construction of utilizing shared bikes [9, 5]. The shared bikes play an increasing important role in our lives [14, 22].

Bike sharing can be simply defined as many shared bikes distributed in the city for multiple users. A bike user is able to get access to shared bikes when logs in the bike sharing system. So far, models include public bike share (PBS) can be classified into about eight categories according to their operating mechanisms (Resource: Models of bike share) [1]. We divide bike sharing models into two

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types, either station based using docks or non station based free-floating dockless. Self-service public bike sharing on street docking, smart bikes and geo-fencing are typical models that users have to rent and return shared bikes to fixed stations or within virtual geo-fencing. Free-floating systems allow the smart bikes to be dropped anywhere safety around the city [1]. In this paper, we focus on smart bike sharing system without restrictions of fixed locations. We consider a system to be more flexible and convenient for shared bike users. Accordingly, we propose an agent based distributed approach which makes contributions to general resource distribution systems. The remained of the paper is organized as follows, related works and proposed method are given in Section 2 and 3, respectively. In Section 4, a practical example is analyzed to show the working process and effectiveness of our proposed approach. Some conclusions and future works end the paper in the last section.

2 Related works

In the past decades, significant attention has been devoted to task assignment in distributed systems. In [11], Y. C. Jiang summarized the works on task allocations and load balances according to the characteristic differences between distributed systems, mainly about typical control, typical resource optimization, the methods of reaching reliability and so on [11]. In bike sharing systems, users need shared bikes to satisfy their requests, it can also be regarded as a task assignment problem.

Quite a few researchers have devoted themselves into public bikes. The existing literatures about this topic are numerous, most of their works focus on the following research points. Firstly, the related works mainly focus on the development history and advantages of shared bikes [22, 7]. Then, they pay much attention to concerning the policies and the satisfaction analysis for the cyclists [7, 15, 23]. Fishman, E. et al. [8] analyzed some factors that influence potential users for choosing shared bikes. In literature [2], a methodology is proposed to quantify user's perception and satisfaction about bike sharing, results show that safety and information are the two influential aspects that influence most.

Finally, relevant works are conducted considering the system designers and controllers. They mainly concentrate on the number and locations of the fixed bike stations, the number of shared bikes to put into service and the imbalance in bike distribution [12, 10, 4]. A good understanding of the operating mechanism is helpful for the system optimization exploitation. In a bike sharing system, the fixed station location is essential and it has been studied from the operational research point of view [12, 10, 4, 25]. Hu. et al. [10] proposed a mathematical location model of finding the optimal location to minimize the total fixed system cost for bike renting and the redistribution. In [25], a network flow model to estimate the flow of bikes within the network and the number of trips supported is proposed. In [4], a mathematical model to formulate public bike station distribution is conducted to minimize the total travel time and investment budget. To stress the unbalance distribution problem, the redistribution strategy is adopted [9, 16,

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26, 19]. In literature [16], vehicles are used to redistribute the bikes. Preisler et al.[19] built an incentive scheme that encourages users to pass nearby stations for selecting and returning bikes, thereby redistributing them in a self-organized fashion. In [26], Wong. et al. established an actual path distance optimization method for the shared bike redistribution.

These approaches are helpful for the proper functioning of bike sharing systems. However, operating bike sharing systems and redistributing strategies cost plenty money [13], so we would like to consider a system without fixed stations and the redistribute strategy will no longer be needed.

3 Proposed method

The agent concept is quite important in both artificial intelligent and mainstream computer science, it can be defined to denote a hardware or commonly the software-based computer system that holds the properties of autonomy, social ability, reactivity and pro-activeness [27, 17]. In this part, we present an agent-based distributed approach for bike sharing system. In the system, all agents work together to rent or return shared bikes efficiently and freely.

When a user needs to travel by shared bikes, she attempts to send requests to all the bike agents in the system. After she receives the responses from bike agents, evaluations of the shared bikes are conducted according to her preferences and the responses. Simultaneously, the reliability of the responses is calculated by its own experiences and the other agents' information. Meanwhile, the probability of getting the shared bike can be obtained. These three factors work together to improve the satisfaction for users. The proposed agent based distributed approach is detailed discussed as follows, some explanations about the common variables are listed in Table 1, their specific meanings are also discussed in the text.

Table 1. Some commonly used variables and explanations

m :Numbers of users	i : the ith user
n : Numbers of shared bikes	j : the jth shared bike
p : Numbers of influential aspects	k : the kth influential aspect
q : Numbers of sub-factors of kth aspect	l : the lth sub-factor of kth aspect
$e_{i,j,k}$: $User_i$'s requests on j on kth aspect	$r_{j,i,k}$: Bike j' responses to i about k
pf_{ij} : Preference evaluations of i to j	M_{ij} : Trust evaluation of i to j
p_{ij} : Probability for i to get j	E_{ij} : The final assessment of i to j

3.1 User's preferences—Shared-bike evaluations

Choosing a shared bike according to the user's preferences should completely depend on the user's own judgements. In fact, considering the user's preferences

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is essential, for example, a shared bike user prefers to have a bike with basket if she has brought a heavy goods. For the economic saving users, they would like to choose cheaper bikes, similarly, the deposit-payed shared bikes are always their only choices.

Evaluating the shared bikes according to a user's preferences is a multi-attribute decision making problem. In the bike sharing system, we assume that

- 1: There are m users which can be represented as $Users = \{User_1, User_2 ... User_i ... User_m\}$.
- 2: n shared bikes exist in the system, denoted as $Bikes = \{Bike_1, Bike_2 ... Bike_j ... Bike_n\}$.
- 3: p mainly influential aspects of evaluating the bikes denoted as $Aspects = \{Aspect_1, Aspect_2 ... Aspect_k ... Aspect_p\}$.
- 4: For each influential aspect, q sub-factors are considered, for aspect k, we have $Subfactors = \{Subf_{k1}, Subf_{k2} ... Subf_{kl} ... Subf_{kq}\}$.

When a bike user needs a shared bike at time t, she firstly needs to give her own requirements about the sub-factors of some influential aspects, they can be represented as

$$e_{i,j,k} = (e_{i,j,k,1}, e_{i,j,k,2} ... e_{i,j,k,l} ... e_{i,j,k,q}), \tag{1}$$

where $e(i, j, k, l)$ represents the evaluation result given by $User_i$ to $Bike_j$ about the main influential $Aspect_k$, l shows the influential sub-factor. For example, when $User_i$ demands a shared bike, she believes that bike type is one of the influential aspects, three sub-factors, $V'LILLE$, $Mobike$ and OfO are considered. For $User_i$, $V'Lille$ and $Mobike$ can be chosen while she prefers $V'Lille$ much, as a result, she gives her requirements as $e_{i,j,1} = (0.8, 0.2, 0)$. Similarly, all the other factors can be judged in the same way.

Then the user advocates her requests to the shared bike agents and bikes immediately reply with boolean values $True$ or $False$. Their responses can be represented by

$$r_{j,i,k} = (Boolean(k1), ...Boolean(kl), ...Boolean(kq)). \tag{2}$$

For example, when considering the shared bike types, $Bike_j$ belongs to "OfO", so its response can be $r_{j,i,1} = (0, 0, 1)$ when evaluating bike types.

Obviously, not all the influential aspects are of equal importance, so we need to know their actual weights. Many methods can be used for the calculation of weights, such as principal component analysis, analytic hierarchy process (AHP), entropy method and coefficient of variation method [29]. Coefficient of variation method is a simple but efficient method which bases on the resolution information contained in the evaluation index. The coefficient of variation is defined as the ratio of the standard deviation σ to the mean $\overline{\mu}$. The bigger the coefficient of variation is, the greater the weight is assigned.

We suppose that q sub-factors effect on influential $Aspect_k$, let $\overline{\mu_k}$ be the average value of all the index of sub-factors, σ_k be the standard deviation of the index $Sub_{i,j,k}$, then the coefficient of variation of this index is $Coff(i, j, k) =$

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$\frac{\sigma_k}{\mu_k}$. After that we normalize all the coefficients of variation and the weights of $Aspect_k$ can be obtained by

$$W_{i,j,k} = \frac{Coff(i,j,k)}{\sum_{k=1}^{P}(Coff(i,j,k))}. \tag{3}$$

When all the sub-factors are discussed, then final preference evaluations of $User_i$ to $Bike_j$ can be concluded as

$$preference(i,j) = pf_{ij} = \sum_{k=1}^{p}\{W_{i,j,k}(e_{i,j,k} \cdot r_{j,i,k})\}. \tag{4}$$

In the bike sharing system, at time t, all m users and n free bikes have been evaluated according to user's own preferences. The evaluation results of available bikes at time t can be denoted as

$$Preference(User(i), Bike(j))(t) = \begin{bmatrix} & Bike(1) & ... & Bike(j) & ... & Bike(n) \\ User(1) & pf_{11}(t) & ... & pf_{1j}(t) & ... & pf_{1n}(t) \\ ... & & ... & ...... & & \\ User(i) & pf_{i1}(t) & ... & pf_{ij}(t) & ... & pf_{in}(t) \\ ... & & ... & ... & ... & \\ User(m) & pf_{m1}(t) & ... & pf_{mj}(t) & ... & pf_{mn}(t) \end{bmatrix}. \tag{5}$$

At different time, whenever there is a new request message, a new preference matrix is generated. Users would like to choose a bike with higher evaluation values. However, agents might response with unreliable information, meanwhile, the well-evaluated bikes might be pursued by other users. Therefore, trust and probability to get the target bike are formulated.

3.2 Trust evaluation

Trust can be regarded as the expectation given by all members of a society, they believe that the existing natural or moral social orders persist, just as we believe that the sun rises from the east and fall to the west [28, 18, 30]. Han Yu et al. summarized that the proposed methods to evaluate the agents' trust can be divided into four main categories [28], they are direct trust evaluation models, indirect/reputation-based trust evaluation models, socio-cognitive trust evaluation models and organization trust evaluation models. The mostly frequently used are direct trust evaluation models which depend on the direct interaction experience. The indirect/reputations-based trust evaluation models rely on the recommendation results from a third comity in the same system. These two trust evaluation models are easy to be accessed and efficient in distributed systems. As a result, these main trust evaluation models have been considered simultaneously. Dempster-Shafer theory of evidence is used for the representation of semantic assessment and weighted Dempster's combination rule is adopted for the combination of different information.

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3.2.1 Dempster-Shafer theory of evidence Dempster-Shafer theory of evidence also known as evidence theory which was proposed by Dempster and Shafer [6, 21]. This theory is efficient in uncertainty representation, Dempster's combination rule has the ability to combine different basic probability assignments (BPA). In this paper, evidence theory is adopted to represent the trust and reputation, then Dempster's combination rule is used for the fusion of these two aspects. Some details about evidence theory are introduced as follows.

Definition 1 (The frame of discernment). *The frame of discernment U, consisted of N mutually exclusive and collectively exhaustive elements, can be defined as $U = (e_1, ...e_h...e_N)$, satisfying $\cap e_h = \emptyset$.*

Definition 2 (Basic probability assignment). *The power set of U represented by 2^U, any elements belong to 2^U is said to be propositions, the basic probability assignment is defined as a mapping from the power set to $[0, 1]$ which represented by $m : 2^U \to [0, 1]$, the following conditions are satisfied,*

$$m(\emptyset) = 0 \ \ and \sum_{A \subseteq 2^U} m(A) = 1; \tag{6}$$

where $\emptyset$ is an empty set and A is a subset of 2^U, the function $m(A)$ represents how strongly the evidence supports A. Any propositions of which $m(A)$ is non-zero is called a focal element and the set of all the focal elements is core.

Definition 3 (Dempster's rule of combination). *For any two BPAs m_1 and m_2, the Dempster's rule of combination which can be represented by $m = m_1 \oplus m_2$ is defined as*

$$m(A) = \begin{cases} \frac{1}{1-K} \sum_{B \cap C = A} m_1(B) m_2(C), & A \neq \emptyset; \\ 0, & A = \emptyset; \end{cases} \tag{7}$$

with $K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C)$, where A, B and C are the elements of 2^U, K is a normalization constant which means the conflict coefficient of two BPAs.

Definition 4 (Weighted Dempster's combination rule). *In this paper, not all the BPAs are of the equal importance, so the weighted Dempster's combination rule is adopted. The modification of the Dempster's combination is conducted on the BPAs, the weights of the BPAs operate on the core of the power set, then the incomplete part is assigned to the frame of discernment. For the BPA which is defined in the frame work $\{A, \ B\}$, where $m_1(A) = a$; $m_1(B) = b$; $m_1(A, B) = 1 - (a + b)$. Its weight is denoted as w_1, where $w_1 \in [0, 1]$, Then the BPA is modified by weight as*

$$m_1(A) = aw_1; \ m_1(B) = bw_1; \ m_1(A, B) = 1 - (a + b)w_1; \tag{8}$$

Finally, we can use Dempster's combination rule for the BPAs combination.

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3.2.2 Agent's trust As explained, agent's trust is calculated from two aspects, the direct interaction experiences and indirect reputations. The direct trust evaluation is authenticity assessments consist of p aspects because the agents give their responses from p aspects. The users give their objective judgements by comparing the responses to the actual state of affairs, these judgement values $TrustE_{i,j,k}$ is between $[0, 1]$ where 1 means that the agent has provided an actual real response and 0 means that the agent was totally lying. We can use the Dempster-Shafer theory of evidence for the representation of the results, here the frame of discernment is defined as $U = \{Trust, NotTrust\} = \{T, nT\}$.

When translating the evaluating results into Dempster-Shafer theory of evidence, they can be denoted as

$$\begin{cases} m(T) = min\{TrustE_{i,j,1}, TrustE_{i,j,2}, ...TrustE_{i,j,p}\} \\ m(nT) = max\{1 - TrustE_{i,j,1}, 1 - TrustE_{i,j,2}, ...1 - TrustE_{i,j,p}, \} \\ m(T, nT) = 1 - [m(T) + m(nT)]. \end{cases} \tag{9}$$

For the trust evaluation, the current data is more reliable than the past ones because the characteristics of agents are always changeable. So we define a decay function that decays with time. Supposing the historical interaction happens at time T, we define decay function as

$$f_D(t) = \rho^{t-T}, \quad 0 < \rho < 1 \; and \; Limit \leq T \leq t. \tag{10}$$

we are now at time t and $Limit$ shows the interaction before this time is no longer reliable.

Similarly, the indirect reputations is also evaluated with the same approach of generating BPAs for direct trust. The final evaluation results can be represented as

$$\begin{cases} M_{DirectTrust} = M_{DT} = (m_D\{T\}, m_D\{nT\}, m_D\{T, nT\}); \\ M_{IndirectReputation} = M_{IR} = (m_I\{T\}, m_I\{nT\}, m_I\{T, nT\}). \end{cases} \tag{11}$$

Then the weighted Dempster's combination rule is used to combine both direct trust and indirect reputation,

$$M_{ij} = M_{DT}^{W_D} \oplus M_{IR}^{W_R}. \tag{12}$$

where $M_{DT}^{W_D}$ and $M_{IR}^{W_R}$ are the final evaluations about direct trust and indirect reputation, their weights represented by $W_D = f_D(t)w_{DT}$ and $W_R = f'_D(t)w_{IR}$ where w_{DT} and w_{IR} are the weights of direct trust and indirect reputation respectively, the values belong to $[0, 1]$. Of the final overall evaluation results, we would take more attention on the reliability value, i.e., $M_{ij}(T)$.

3.3 Probability of getting the selected shared bike

In dynamic bike sharing systems, all users can also rent the target bike before a user's arrival. In this situation, users prefer selecting a bike with high probability. Many research works consider bike appearance probability by population density

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[3]. In this part, we consider probability according to bicycle numbers in one domain within the user's reach.

Supposing $User_i$ needs to find a bike in time period $[0,t]$, her walking speed is V_{User_i}. Therefore, all the bikes in the circle whose radius is $V_{User_i} * t$ with user's position regarded as the center are available. As shown in Fig. 1, all the small blue circles in big dark circle are target shared bikes for the user represented by red five-pointed stars.

Firstly, we set a threshold $\sigma = t$. This threshold is also the time limitation for $User_i$ to find a bike. Then the travel salesman problem (TSP) algorithm is operated starts from any node with this threshold as the maximum traveling time. Traditional TSP is a shortest distance problem about traveling among x cities once and only once, starting and returning from the same place. Here we adopt TSP algorithm to classify all possible target bikes into sets which satisfies the traveling time in each set is smaller than the time limitation. If the time is still not exceed to the threshold when reaching at one node, the target bike is added to the set, otherwise, we start another TSP algorithm. Our goal is to obtain the minimum number of sets.

To the end, all reachable bikes have been divided into N sets, we can obtain the probabilities for $User_i$ to receive $Bike_j$ at time t by

$$p_{ij}(t) = \frac{Total\ numbers\ in\ set\ N}{Total\ numbers\ in\ the\ circle} = \frac{\sum(n_{set(i)})}{\sum(N_{Total})}. \tag{13}$$

where $\sum(n_{set(i)})$ shows the total number in set i and $\sum(N_{Total})$ shows the total numbers available for $User_i$.

3.4 The agent-based distributed approach

As explained above, in the bike sharing system contains n users and m shared bikes. At time t, $User_i$ needs to find a shared bike before time T, according to her requests and bike agents' responses, evaluations of the three main factors are all obtained. $pf_{ij}(t)$ represents her preferences, $M_{ij}(T)$ describes the credibility level and $p_{ij}(t)$ shows the probability of getting the bike. So a user needs to give overall evaluations to rank and decide to select which shared bike. The overall ranking results can be obtained by multiplication of the factors as follows

$$E_{ij} = pf_{ij}(t) \times M_{ij}(T) \times p_{ij}(t). \tag{14}$$

Then a user sets off for the best evaluated shared bike rapidly. If the ideal bike is still there when she reaches at the target location, she rents it. Otherwise, she immediately spreads her new requests for shared bikes. The distributed approach is summarized as choosing best bikes from i free sharing bikes for j requesters denoted as Algorithm $BBU(i,j)$, it is shown in Algorithm 1 as follows.

4 Practical example simulations

In this part, a practical example is given to show how the proposed approach works and its effectiveness for users to find needed shared bikes.

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Algorithm 1 BBU(i,j): Best Bikes for Users

Location Initializations: m Agents(Shared Bike Requesters) & n Agents(Free Shared Bikes);
if New requests for shared bikes appear at time t (Eq. 1) **then**
  Shared bikes responses (Eq. 2); Evaluate and rank all free shared bikes (Eqs. 3-15);
  Set off for the best one;
  if Target shared bike is still reachable; **then**
    Select the target shared bike;
  else
    BBU(i,j)
  end if
end if

4.1 A practical example

We suppose that three shared bike companies run a total 1000 shared bikes in a system, the shared bikes can be placed freely in anywhere safety in the city. At time t, 30 users are looking for shared bikes among 300 free bikes. Locations for bikes and users distribution are shown in Fig. 4.1, the small blue circles represent the free-parking shared bikes, users are denoted by small red five-pointed stars. The dark circles whose centers are red five-pointed stars denote that all shared bikes inside are available.

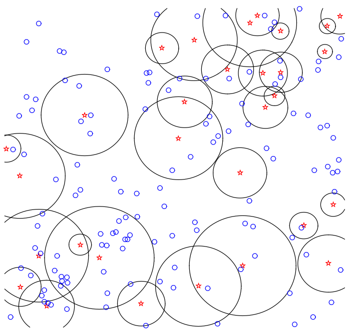

Fig. 1. Distribution of the shared bikes and users

We suppose $User_i$ is interested in four aspects when explaining her preferences, they are bike types ($Aspect_1$), whether there is a basket ($Aspect_2$), old and new degree ($Aspect_3$) and size ($Aspect_4$). All the influential aspects have influential sub-factors, the details are shown as below,

$$\begin{cases} Subf_{11} : V'Lille, Subf_{12} : Mobike, Subf_{13} : \ OfO; \quad Subf_{31} : New, Subf_{32} : Old; \\ Subf_{21} : With\ a\ basket; \ Subf_{22} : Without\ a\ basket; \quad Subf_{41} : Big, Subf_{42} : Small; \end{cases} \tag{15}$$

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$User_i$ needs to send her requests to available bike agents. This process completes in her phone according to the API connected to the system. For example, $User_i$ can give her requires as $e_{i,j,1} = (0.8, 0.2, 0)$, $e_{i,j,2} = (1, 0)$, $e_{i,j,3} = (0.4, 0.6)$ and $e_{i,j,4} = (0.5, 0.5)$. As is shown, we find that user i chooses $V'Lille$ or $Mobike$, and she prefers $V'Lille$. she needs the bike with basket so the bikes without basket are no longer considered. she prefers old shared bikes. From the forth aspect, bike size makes no sense.

By analyzing the original data entered by user i, weights of the corresponding aspects are obtained based on the coefficient of variation method shown in Eq. 3. The corresponding average value $\overline{\mu_k}$, standard deviation σ_k and weights are shown in Table 2.

Table 2. Weights of the four main influential aspects

$Aspects$	$Aspect_1$	$Aspect_2$	$Aspect_3$	$Aspect_4$
$user_i$	(0.8,0.2,0)	(1.0, 0)	(0.4, 0.6)	(0.5, 0.5)
$\overline{\mu_k}$	$\frac{1}{3}$	0.5	0.5	0.5
σ_k	$\frac{\sqrt{26}}{15}$	0.5	0.1	0
$W_{(i,j,k)}$	0.36	0.53	0.11	0

All shared bikes respond if $User_i$'s requests is received. Here we suppose three bikes give their responses as shown in Table 3.

Table 3. Three bikes' responses to user i

$Aspects$	$Aspect_1$	$Aspect_2$	$Aspect_3$	$Aspect_4$
$r_{1,i}$	(1,0,0)	(0, 1)	(0, 1)	(1, 0)
$r_{2,i}$	(1,0,0)	(1, 0)	(1, 0)	(1, 0)
$r_{3,i}$	(0,1,0)	(1, 0)	(0, 1)	(0, 1)

Preference evaluations can be obtained by Eq. 4. For $User_i$, the evaluations of the three bikes are $pf_{i,1} = 0.354$, $pf_{i,2} = 0.862$ and $pf_{i,3} = 0.668$. Then the responses' reliability are calculated according to the historical experience. $User_i$ has used shared bike 1 twice which happened three and five days ago respectively. she has used shared bike 2 five hours ago and never uses shared bike 3, so from her own point of view, she has to evaluate bikes from four aspects whether the bike has replied with exact results and she gives bike 1 two evaluations as $TrustE(i, 1)(t_1) = (1, 1, 1, 0.8)$ and $TrustE(i, 1)(t_2) = (1, 1, 0.9, 0.8)$. Then the information can be denoted by Dempster-Shafer theory of evidence as

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$m_{i,1}^1(T) = 0.8$, $m_{i,1}^1(nT) = 0.2$, $m_{i,1}^1(T, nT) = 0$ and $m_{i,1}^2(T) = 0.8$, $m_{i,1}^2(nT) = 0.2$, $m_{i,1}^2(T, nT) = 0$.

The weighted Dempster' combination rule is adopted for the combination. We define $\rho = 0.95$ in delay function. The two times are separately three and five days ago, so the decay values are $0.95^3 = 0.8574$ and $0.95^5 = 0.7738$, they are regarded as the weights for combination of direct trust. The modified evaluations according to Eq. 8 are denoted as follows,

$$\begin{cases} m_{i,1}^1(T) = 0.6859 \\ m_{i,1}^1(nT) = 0.1715 \\ m_{i,1}^1(T, nT) = 0.1426 \end{cases} and \begin{cases} m_{i,1}^2(T) = 0.6190 \\ m_{i,1}^2(nT) = 0.1548 \\ m_{i,1}^2(T, nT) = 0.2262 \end{cases} \tag{16}$$

Then the combined results are $M_{i,1}^1(T) = 0.8480$; $M_{i,1}^1(nT) = 0.1110$; $M_{i,1}^1(T, nT) = 0.0410$. Similarly, another user K provides him the indirect reputation evaluation and the results are $M_{K,1}^2(T) = 0.5$, $M_{K,1}^2(nT) = 0.3$, $M_{K,1}^2(T, nT) = 0.2$

For direct trust and indirect reputation, she trusts herself more and the weights are $W_D = 1$ and $W_R = 0.7$. Finally, the overall trust evaluations are calculated from both direct experience and indirect reputation by Eq. 12, the combined results for $Bike_1$ are $M_{i,1}(T) = 0.8738$, $M_{i,1}(nT) = 0.1032$ and $M_{i,1}(T, nT) = 0.0230$.

Similarly, the trust evaluations about bike 2 and 3 are conducted. Here we suppose the trust values respectively are 0.832 and 0.65 to bike 2 and 3. Simultaneously, the probabilities are conducted while we suppose they are 0.7, 0.553 and 0.75 respectively.

To the end, we would like to choose not only an ideal and reliable bike, but also a bike with high probability to be received. For the three bikes,

$$\begin{cases} E_{i1} = pf_{i,1} \times M_{i,1}(T) \times p_{i,1} = 0.354 \times 0.8738 \times 0.7 = 0.2165 \\ E_{i2} = pf_{i,2} \times M_{i,2}(T) \times p_{i,2} = 0.862 \times 0.832 \times 0.553 = 0.3966 \\ E_{i3} = pf_{i,3} \times M_{i,3}(T) \times p_{i,3} = 0.668 \times 0.65 \times 0.75 = 0.3257 \end{cases} \tag{17}$$

The final results are compared and $User_i$ chooses bike 2. With the same process, all users rank reachable shared bikes and set off for the best one.

4.2 Results Comparison and analysis

As discussed in the last subsection, three aspects, namely bike evaluations, agent trust and probability are evaluated for 30 users to select best bikes from 300 free bikes. Looking for bikes randomly is used for the comparison with the proposed method in this paper. Moving randomly is the method that frequently be used nowadays. When a user and a bike gets close, the user evaluates whether this bike is acceptable. If she is satisfied about the bike, then the bike is selected and both the shared bike and user are removed to satisfied set. Otherwise, the user sets off randomly again to search for a needed bike.

The proposed method in this paper is regarded as another approach. A user evaluates all the possible bikes firstly and then sets off for the appropriate bike. Obviously, this method is more efficient and a user can receive the satisfied bike much more faster than the randomly approach.

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5 Conclusions

In the bike sharing system, fixed bike stations are always the main restriction for the users to rent and return the shared bikes freely, the redistribute strategy are widely considered for the imbalances of supply and demand in the fixed stations in order to satisfy all the users. In this paper, we discussed a more freely environment for bike sharing system where the fixed stations are no longer existed. Users rent and return bikes anywhere in the city. We also considered for the users to choose satisfied shared bikes according to her own demands or preferences. There are many other future works, the proposed method needs to be compared to other approaches, more methods about uncertainty and data fusion will be adopted for trust evaluations.

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