Allocation strategies in a dockless bike sharing system: a community structure-based approach

J. Zhang¹, M. Meng², David, Z.W. Wang³*, B. Du⁴,⁵

1. Institute for Manufacturing, University of Cambridge, Cambridge, UK, CB3 0FS
2. School of Management, University of Bath, Bath, BA2 7AY, UK
3. School of Civil and Environmental Engineering, Nanyang Technological University, Singapore 639798
4. SMART Infrastructure Facility, University of Wollongong, Northfields Ave, Wollongong, NSW, 2522, Australia
5. School of Civil, Mining and Environmental Engineering, University of Wollongong, Northfields Ave, Wollongong, NSW, 2522, Australia

*Corresponding author: Email: wangzhiwei@ntu.edu.sg

Abstract: This study develops a methodology to determine the optimal allocation position to deploy the bikes in a competitive dockless bike sharing market. The community structure approach in complex network theory is utilised to offer the bike allocation strategies to the market leader in two specific market regimes, with a potential competitor, and without a potential competitor. Two different heuristics are proposed to handle the two scenarios respectively due to different design objectives, wherein the first one aims to attract maximum users and the other one aims to use minimum resources to cover maximum service area. Two hypothetic networks are adopted to illustrate the difference in design under these two regimes. Two numerical studies – a simplified Sioux Falls network and a real network in Singapore – are used to demonstrate the algorithm performance and show the applicability of the model for the scenario that no potential competitor exists.

Keywords: Bike allocation; service catchment; complex network; community structure

1. Introduction

Bike sharing has been flourishing over the past decades since its first introduction in Amsterdam in 1965 (Zhang et al, 2017). It is one mobility strategy to share use of a bicycle fleet. It has many benefits, such as offering alternative public transport, encouraging more cycling, improving city image, providing complimentary service linking transit stations, reducing congestion and increasing accessibility (Manzi & Saibene, 2018; Almannaa et al., 2019). Bike sharing system has developed from station-based system to dockless system, wherein users do not have to return the bike to a designated place and can leave the bike nearby their destinations. Users can easily find an available bike to use if the system is sufficiently saturated with bikes. This system has already been practically implemented in many cities around the world such as Beijing, Singapore, Sydney, Munich. Ofo, one of the largest dockless
bicycle sharing companies has provided global users in many cities with over 6 billion efficient, convenient and green journeys from 2014 to 2018 (Love, 2018).

Extensive research attentions have been paid to bicycle sharing schemes in the past decades. At present, most of the existing studies with modelling framework development focus on station-based bicycle sharing problems, such as station location selection, demand prediction, inventory rebalancing, vehicle routing, and pricing analysis (Szeto et al., 2016; Ho and Szeto, 2017; Bulhões et al., 2018; Shui and Szeto, 2020). Many interesting approaches have been developed in these studies and the research outcomes have been practiced in applications.

Very recently, the advances of the dockless bicycle sharing system have been extensively analysed. Shen et al. (2018) studied the spatiotemporal patterns of bike usage through an autoregressive model using the dockless bikes’ Global Positioning System data in Singapore. The models explored the impact of bike fleet size, surrounding built environment, access to public transportation, bicycle infrastructure, and weather conditions on the usage of dockless bikes. Ai et al. (2018) measured the transfer tolerance for dockless bike sharing models. Results indicated that dockless bike-sharing users are more concerned with the time cost of finding available bike and the delay in traffic signals. Cheng et al. (2019) developed a site selection method to solve the inadequate utilisation and unreasonable distribution of the geographical resource in dockless bicycle sharing system. Rahim Taleqani et al. (2020) discussed a new paradigm to identify candidate locations that could be geo-fenced in dockless bicycle sharing. The above studies show dockless bike sharing has different unique characteristics than station-based bike sharing (Xu et al., 2019; Yang et al., 2019). The research outcomes from station-based bike sharing could not be directly applied in dockless bike sharing planning.

There is only one or few limited bike sharing operators in the market at the initial stage. For example, in China, there are two main dockless bike sharing operators, Ofo and Mobike, which takes a total market share of more than 90 percent (Ouyang, 2018). When the market leader first enters the market, it is natural to consider the competition risk when designing the allocation strategy. This study considers the two scenarios - with or without competitors – for the market leader to design the allocation strategy. That is to find the answer to the optimal allocation position to deploy bikes and identify the service area for each allocation point.

As dockless bike sharing is a new service in transport system, it is in principle difficult to gauge and predict its demand accurately. On the other hand, oversupply of bikes, despite of being able to meet the travel demand and increase the market share, leads to the waste of both road spaces and capital investment. Besides, regular bikes repositioning is not considered due to the system’s dockless nature and its high operation costs. Not being able to address these characteristics of the dockless bike sharing service, the existing methods for optimal bike allocation would not be applicable any longer. This motivates us to develop a new framework to solve the allocation problem in dockless bike sharing. It is different to bike relocation problem, as relocation aims to balance the distribution of the bikes at the operational level, while allocation aims to maximise the market coverage at the strategic level. The results would be a practically useful and theoretically interesting issue for providing guidance to the operators of the emerging dockless bike sharing market.

In this study, we propose to apply the community structure approach in complex network theory to obtain the bike allocation strategy. It is suitable to apply it in analysing the dockless bike sharing system based on the following reasons: (1) The whole bike sharing system can be
treated as a type of complex network. The bike allocation points are the vertices in the traffic analysis zones (TAZs) while the connections among vertices are the edges. The analysis method in complex network, e.g. community structure approach, can be applied in investigating the allocation problem in bike sharing system. (2) Dockless bike sharing allocation has high similarity to community structure formulation. Some vertices easily group together in a complex network due to high connections. This group is called community structure (Girvan and Newman, 2002). Vertices in one community structure have dense and frequent connections and vertices in different community structure have few connections. Bikes sharing in urban city mainly serves for short-distance trips. The origins and destinations are nearby the residential buildings, office buildings, public transport stations, etc. Assuming these places are regarded as vertices, the community structure can be found based on the bike sharing trips among vertices. The bikes that are allocated in the central of the community are likely to be used within this area. To effectively cover the network using limited number of bikes, bikes should be initially allocated to those positions with the strongest effect, i.e., the vertices with the highest weight in the community.

There are only few papers that study the initial bike allocation problem in a competitive market. Zhang et al. (2019) considered a competitive dockless bike sharing market and developed the allocation strategies for both market leader and market follower; Jiang et al. (2020) studied the competition in the bike-sharing market to help companies maximise their profit by making optimal investment and allocation decisions. This paper builds on the community structure theory to acquire the bike allocation strategies for the operator in different market regimes. We target to provide decision support for the market leader, who is the first operator in the market. Two scenarios have been considered, wherein the first one has potential competitor and the second one does not have potential competitor in the near future. The contributions of the study are two-fold: (1) To the authors’ best knowledge, this is the first study applying the community structure approach in transportation resource allocation problem. Besides, this is the first attempt to explicitly consider the forthcoming competition for the market leader when determining the bike allocation strategy. (2) Authors extend the community structure identification approach into two weighted networks and improve the classical Fast Newman (F-N) algorithm to solve the two problems separately.

Having established the study’s motivation, we organise the remaining of this paper as follows: Section 2 gives a brief explanation of basic definitions. Section 3 defines two scenarios and proposes a set of algorithms to design the allocation strategy for each scenario. Numerical examples are given in Section 4, followed by conclusions and discussions in Section 5.

2. Community structure and modularity
Complex network is a graph (network) with non-trivial topological features that occur in graphs modelling of real systems. Complex network possesses many characteristics, for example spreading and immunization, community structure, robustness, vulnerability and so on. Researchers have applied complex network theory to studying real networks in many fields, such as social network, informational network, neural network, transport network and so on (Huang et al., 2005; Kaluza et al., 2010; Rubinov and Sporns, 2010; Sporns, 2011). However, the research works applying complex network approach in solving urban transportation problems are limited, mainly focusing on finding methods to represent the transport system and evaluate transport networks (Yang et al., 2014; Murali et al., 2016; Meng et al., 2016).

A sketch of a small network is shown in Figure 1, where there are three communities based on the connection relationships among the vertices. Vertices in the same community have strong connections while vertices in different communities have less connections between each other. Under this circumstance, stations (vertices) could be grouped into different community structure-based on the bike distribution relationship, which is determined by the travel demand. Therefore, bikes are frequently distributed from one vertex to another vertex in the same community, which is formed based on the demand level.

The most popular method to determine the community structure was developed by Newman (2004), which is an agglomerative hierarchical clustering method. The core concept is that the community structure leads to the largest modularity in the complex network. Modularity is a function to test whether a clustering is meaningful in community structure theory. The modularity can be either a positive or negative value, wherein the positive value indicates the possible presence of community structure. Therefore, the community structure can be precisely identified through looking for the divisions of a network that have positive, and preferably large, values of the modularity (Newman, 2006). For a given network \( G = (V, E, W) \), where \( V, E, W \) represent the set of vertex, edge and weight, respectively, modularity \( M \) is calculated by

\[
M = \frac{1}{2m} \sum_{uv} \left[ A_{uv} - \frac{k_u k_v}{2m} \right] \delta(c_u, c_v)
\]

(1)

where \( m \) is the total number of edges in the network, \( A_{uv} \) is the number of edges between vertices \( u \) and \( v \), \( k_u \) and \( k_v \) are the degrees of the vertices \( u \) and \( v \). The degree of the vertex is the number of connected edges of this vertex. \( \delta(c_u, c_v) \) is the relationship function of \( c_u \) and \( c_v \). \( \delta(c_u, c_v) \) is defined as follows: if vertices \( u \) and \( v \) belong to the same community, that is \( c_u = c_v \), then \( \delta(c_u, c_v) = 1 \); Otherwise, \( \delta(c_u, c_v) = 0 \).

Suppose the network contains \( n \) \((i=1,2,...i,..,j,..n)\) number of communities, we define the two variables \( e_i \) and \( a_i \) as follows:

\[
e_i = \frac{1}{2m} \sum_{uv} A_{uv} \delta(c_u, i) \delta(c_v, j)
\]

(2)

\[
a_i = \frac{1}{2m} \sum_u k_u \delta(c_u, i)
\]

(3)
where $e_{ij}$ is the fraction of edges in the network that connect vertices in group $i$ to those in group $j$, and $a_i = \sum_j e_{ij}$. Therefore, Eq. (1) can be modified as:

$$M = \sum_{i=1}^{m} (e_{ia} - a_i^2)$$

Newman (2004) proposed a F-N algorithm to identify the community structure. It is a bottom-up agglomerative algorithm, which only works for unweighted network. The next section applies the community structure approach in dockless bike sharing system, which is a weighted network, and improved the F-N algorithm to solve the practical problem in two scenarios.

3. Optimal bike allocation strategy
According to the reality in dockless bike sharing system, we establish five assumptions as follows:

A1: We consider the initial operational stage, where the operators have limited number of bikes. Therefore, the objective of bike allocation is to use minimal number of bikes to achieve best operation performance.

A2: The initial bike usage demand is not predictable so that the allocation needs to be made in batches repeatedly to seek the potential maximum bike usage.

A3: There is no repositioning vehicle arranged in the system. Bikes can only be distributed by usage.

A4: Operators can obtain bikes’ real time position and usage.

A5: The price for all systems is identical.

The general allocation framework is developed as shown in Figure 2. The difference between two scenarios is to find different key vertices based on the operational objective.

Figure 2 General allocation framework
3.1 Scenario one

In this scenario, the market leader needs to grasp the market quickly before the market follower enters the market. The operational objective for market leader is to obtain maximum users as quickly as possible. Based on complex network concept, each edge has its weight based on the connection relationship between the adjacent vertices, which is called the weight of the edge. Each vertex also has its weight, which is the sum of the weights of the connected edges. Higher weight of vertex means that this vertex has a significant influence onto the connectivity of the network. Therefore, the key vertex during allocation in this scenario is to distribute bikes at the vertex with the highest weight in the community. For example, in Figure 1, vertices 5, 9 and 15 are the key vertices in each community.

An improved community structure detection algorithm based on Fast Newman (F-N) algorithm is proposed to allocate the bikes in this study. Since the dockless bike sharing system has weightage on each edge, some adjustments have been made.

First, the weight is calculated based on the concept of Gravity model. Demand level between two vertices is decided by the demand at each vertex and the distance between two vertices. Set edge weight between vertices \( u \) and \( v \) be \( w_{uv} \), considering that people will not cycle the bikes in an overly short or long distance (e.g. less than 0.1km and over 3km), the edge weight is expressed as:

\[
 w_{uv} = \begin{cases} 
 (p_u p_v) / (d_{uv}^2), & \forall d_{uv} \in [0, 3] \\
 0, & \text{otherwise}
\end{cases}
\]  

(5)

where \( p_u \) and \( p_v \) are the demand of vertices \( u \) and \( v \), \( d_{uv} \) is the shortest distance between vertices \( u \) and \( v \). The more demand between two vertices, the higher weight on their direct connected edge.

Second, we define \( e_{ij} \) and \( a_i \) by considering the edge weight in the network.

\[
 e_{ij} = \frac{\sum_{uv} w_{uv} A_{uv} \delta(c_u, i) \delta(c_v, j)}{\sum_{uv} w_{uv}}
\]

(6)

\[
 a_i = \gamma \sum_j e_{ij} + (1-\gamma) \cdot k_i / (2m)
\]

(7)

where \( \gamma \) is a parameter \( 0 < \gamma < 1 \).

In this way, an improved F-N algorithm is developed to identify the community structure in the weighted network as follows:

**Step 1:** Network initialisation: divide the network into \( n \) number of TAZs, wherein each TAZ contains certain number of vertices and edges.

**Step 2:** Weight calculation and adjacency matrix construction. Based on the demand level at each vertex and the travel distance in the network, the edge weight is calculated based on Eq.(5).

**Step 3:** Set each vertex as one community and calculate the modularity in the system.

**Step 4:** Community combination. Combine communities together in pairs sequentially and compute the variation of modularity. \( \Delta M \) is given by the merging of any two communities of the running partition as follows:
\[ \Delta M = e_j + e_j - 2a_j = 2(e_j - a_j) \]  

(8)

**Step 5:** Direction identification. Find the largest and smallest increase in \( M \) during combination, and update \( e_j \) accordingly.

**Step 6:** Repeat steps 4 and 5 until all communities merge into one community.

This algorithm would carry out \( n-1 \) merging operations until completion, and hence, the entire computational complexity is \( O((m+n)n) \), or \( O(n^2) \) on a sparse graph (Newman, 2004). This algorithm is simple to obtain the optimal decision of the bikes allocation.

### 3.2 Scenario two

If there is no potential competitor in the market in the near future, the market leader has sufficient time to allocate bikes in the network. In this case, with limited number of bikes and available budget, operator would allocate bikes at a minimum number of locations while ensuring to cover the maximum service area. It could be regarded as a problem of finding the best \( k \) vertices which could affect the most vertices in the network.

As mentioned before, according to the characteristic of community structure, bikes are mostly used inside the community, and infrequently used among different communities. For example, as illustrated in Figure 1, there are three communities in the small unweighted network. Assume that only one public bike allocation vertex is required. If the operator still follows the method in scenario one, vertex 9 will be selected as vertex 9 is the one with the greatest degree in the network. In this case, most of the bikes will be circulated in community \( c_2 \) while few bikes could go to other communities. On the contrary, if vertex 6 is selected, bikes could be easily distributed to all the three communities so that the catchment area of the bike sharing service could be expanded.

A similar problem has been investigated by Domingos and Domingos (2001, 2002), and be further extended in social network algorithms (Palla and Derenti, 2005; Han et al., 2012; Morone and Makse, 2015). To extend the application of this idea to transportation network, an improved algorithm is proposed in this study. Three types of vertices are defined: the first type is the directly connected vertex (DCV) to the vertex where the bikes are initially allocated; the second type is the indirectly connected vertex (ICV) to the bike-allocation vertex which is in the same community with DCV; all of the rest vertices fall into the third type. The mathematical formulations of DCV and ICV could be expressed as

\[ \Delta N_{DC}^{u} = N_{DC}^{u} \cup N_{DC} \setminus N_{DC} \]  

(11)

\[ \Delta N_{IC}^{u} = N_{IC}^{u} \setminus \left( N_{DC}^{u} \cup N_{DC} \cup N_{IC} \right) \cap N_{IC} \]  

(12)

where \( N_{DC} \) and \( N_{IC} \) are the sets of all direct and indirect vertices. Take Figure 1 as an example: if vertex 9 is the allocation node, the vertices that are directly connected to vertex 9, i.e., the DCVs, include nodes 6,7,9,10,11,12,13. The vertices that are directly connected with DCVs and located in the same community, i.e., the ICVs, include vertices 1,2,3,4,5,8. A new indicator \( Q \) is defined to measure the importance of vertex in affecting the coverage area as

\[ Q_u = \omega_1 \sum_{v \in N_{DC}^{u}} \zeta_v + \omega_2 \sum_{v \in N_{IC}^{u}} \zeta_v, \forall \omega_1 + \omega_2 = 1 \]  

(13)
where $\zeta_u$ is the demand at vertex $u$; $N^u_{DC}$ and $N^u_{IC}$ are sets of DCV and ICV of vertex $u$. $\omega_1$ and $\omega_2$ are weight coefficients, which reflect the importance of DCV and ICV, respectively. When $\omega_1 = 1$ and $N^u_{DC}$ and $N^u_{IC}$ are not updated during calculation, and the results are same with the results from the algorithm for scenario one.

**Step 1:** obtain the community structure following the steps in scenario one;

**Step 2:** initialise the vertices set by setting $N_{DC} = \emptyset$ and $N_{IC} = \emptyset$;

**Step 3:** enumerate all the vertices and get $N_{DC}$ and $N_{IC}$ for each vertex;

**Step 4:** calculate the value of $Q$ for each vertex $\mu$ and select the vertex with maximum $Q$;

**Step 5:** update $N_{DC}$ and $N_{IC}$;

**Step 6:** repeat steps 3 - 5 until the total number of selected vertices is equal to a predefined value $k$ or the number of vertices in $N_{DC}$ is equal to the number of vertices in the network.

4. Numerical example

4.1 Simplified Sioux Falls network

Sioux Falls network is used to demonstrate the algorithm performance, as shown in Figure 3. Number on the edge is the distance between two vertices. The network information and parameters are from Chakirov and Fourie (2014). The demand level is simplified by 10% of the population data at each vertex, wherein the population data is listed in Table 1 (Zhang and Meng, 2019). The demand estimation has been partially tested by local field survey.

![Figure 3 Simplified Sioux Falls network](image)

![Table 1 Population data in study area](image)
Scenario one

After running the algorithm in Section 3.1, results of modularity changes during the whole process are shown in Figure 4 and the dendrogram of clustering results are shown in Figure 5. From Figure 4, the largest modularity $M = 0.465$ appears when there are 5 communities in the network. Therefore, 5 allocation vertices needed to be selected in total. Figure 5 reflects the details grouping results, wherein community 1 only has one vertex 1, community 2 contains vertices 2,5,6,8, community 3 contains 9,10,15,17,19, community 4 contains 7,16,18,20,21,22 and community 5 contains 3,4,11,12,13,14,23,24.

![Figure 4 Modularity of partition results](image)

![Figure 5 Dendrogram of clustering results](image)

The key vertex at each community and the community coverage area are shown in Figure 6. As mentioned in Section 3.1, the optimal allocation location in Scenario one should be the vertex with greatest weight in each community. The selected five allocation locations are vertex 1, 6, 10, 12, 18. After the first time allocation, if the demand is not fully covered, the demand should be updated by removing the number of used bikes. New allocation location could be
obtained following a similar approach. It should be noted that community 1 only has one vertex. It means that this vertex has less connection with other vertices. This could be also been reflected in Table 1 as well as vertex 1 has little demand. Therefore we can remove this community out from the allocation.

![Figure 6 First allocation strategy in Scenario one (dark nodes indicate the allocation position)](image)

**Scenario two**

Now, assuming scenario two is prevalent in the market, we apply the proposed solution algorithm in section 3.2 to find the best bike allocation strategy. It is assumed that $k$ allocation positions are to be found. Table 2 lists the best allocation positions and coverage areas when $k=1, 2, 3$. When $k=1$, only vertex 10 is selected as allocation position. If the number of bikes provided at vertex 10 is sufficiently large, the demand covered by the DCV set of vertex 10 is 24.84% of the total demand. Considering ICV set of vertexes 10, the total demand coverage by both DCV and ICV sets could increase to 88.28%. When $k=2$, an additional new allocation position vertex 7 is selected other than vertex 10, in which case the total demand coverage goes to 99.92%. When $k=3$, although the demand coverage by DCV increases to 59.87%, the total demand coverage remains the same with the case when $k=2$. That is, $k=2$ could almost satisfy all the demand requirements in this case. In principle, if $k$ is sufficiently large, the total demand coverage can achieve 100%. However, it would not be a cost-effective operation strategy. The results the demand coverage are also illustrated in Figure 8, where the vertices with dark background are the vertices in the set of DCV. For example, vertex 10 could cover three communities in the bottom of the network. The addition of vertex 7 for bike allocation could extend the coverage area to right-upper corner in the network. However, if vertex 20 is also included as a position for bike allocation, the total demand coverage area remains the same.

<table>
<thead>
<tr>
<th>$k$</th>
<th>Key vertex</th>
<th>DCV</th>
<th>Demand Coverage by DCV</th>
<th>ICV</th>
<th>Demand Coverage by ICV</th>
<th>Total Demand Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$k$</td>
<td>Allocation Positions</td>
<td>Demand Coverage (%)</td>
<td>bikes allocation %</td>
<td>bikes allocation %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>----------------------</td>
<td>---------------------</td>
<td>--------------------</td>
<td>--------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>10,10,11,15,16,17</td>
<td>24.84%</td>
<td>3,4,7,12,13,14,18,19,20,21,22,23,24</td>
<td>63.44%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>10,11,15,16,17</td>
<td>43.69%</td>
<td>2,3,4,5,6,12,13,14,19,20,21,22,23,24</td>
<td>56.23%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>10,17,15,16,17,18,19,20,21,22</td>
<td>59.87%</td>
<td>2,3,4,5,6,12,13,14,23,24</td>
<td>40.05%</td>
<td>99.92%</td>
<td></td>
</tr>
</tbody>
</table>

From Table 2 and Figure 7, selecting only two allocation positions (i.e., vertices 10 and 7) to allocate sufficient bikes could meet the demand requirements for this case. Along with demand updating, the allocation strategy can follow the same procedure in Scenario one.

Figure 7 Demand coverage area when $k=1, 2, 3$ (dark nodes indicate the allocation position)

4.2 Large scale network in Singapore
A bikes sharing network in Singapore is introduced in Figure 8 to illustrated the practical performance of the proposed allocation approach. Similar to the first case, the bike sharing demand is adopted from the population in the study area. The total running time for this network is 0.037 seconds. The first allocation locations for Scenarios one and two ($k=3$) have been pointed out in Figures 9 and 10.

Scenario one obtains 5 communities, where boundaries are rivers (lines 1 to 3) and expressway (line 4) in real. It fits the reality as the river and expressway will increase the travel distance, which will decrease the bike distribution. The distribution points are subway station (vertices 54, 77 and 81) and shopping centre (vertices 58 and 92). It is reasonable as they are with high demand level which leads close connections among vertices in the community. Results in Scenario two reflect that vertices are connected densely than Sioux Falls network. Although the study area is divided into 100 number of TAZs, 3 vertices could cover the 100% demand.
5. Conclusions

An optimal allocation strategy for market leader has been proposed in dockless bike sharing market, wherein both two situations with or without potentials competitor have been discussed. An improved community structure detection algorithm is proposed with considering the edge weight. If there is potential competitor, the bikes need to be allocated at the vertex with largest weight in the community. If there is no potential competitor, the allocation should find the best k vertices which could affect the most vertices in the network. Since the potential usage is hardly predicted at the initial stage, the allocation is arranged to be made in small batches. In Step 5, the bike demand is updated by subtracting previously allocated bikes that served a certain number of users. If there is potential competitor entering the market soon, the vertices with maximum weight shall be selected to allocate bikes. This strategy could allow the bikes to be distributed across the service area with the fastest speed. On the contrary, if there is no potential competitor, the bikes should be initially allocated to the vertices with maximum catchment area so that minimum number of bikes are required to cover all the service area.

The method proposed in this paper is a qualitative analysis approach, which cannot precisely provide the optimal number of bikes at each allocation. The community structure characteristics in the dockless bike sharing network has been discussed. However, other features in a dynamic complex network, such as memory and attractiveness, have not been investigated. These are the topics that can be investigated in the future.

Acknowledgement

This research is partly supported by the Singapore Ministry of Education (MOE) AcRF Tier 2 Grant MOE2016-T2-1-044.
Reference


