Link Structure Analysis of Urban Street Networks for Delineating Traffic Impact Areas

Tzai-Hung Wen, Wei-Chien-Benny Chin, and Pei-Chun Lai

Abstract With the growing number of developing large-scale cities, *traffic congestion* has becomes a global issue. Traffic congestion could be attributed to *topological structure* of street network and *traffic flow concentration*. It is necessary to investigate these two factors simultaneously to solve traffic congestion. Therefore, this study proposed an innovative analytical procedure of ranking algorithm, the *Flow-based PageRank (FBPR)*, for investigating the traffic flow concentration, complexity of street network structure and traffic impact areas. By overlapping these factors, street segments prone to traffic congestion are identified. A network modularity algorithm is used for delineating the traffic impact areas that will be affected by traffic congestion. Our results indicate that only relying on the topological structure of the street network, this framework could identify the Central Business Districts (CBD), and the areas proximate to the stations of the combination of MRT and train railway systems are prone to traffic congestion. Meanwhile, the delineation of traffic impact areas could be spatially targeted at priorities of traffic improvement for city planners.

1 Introduction

With a growing number of developing cities, traffic congestion has become a global issue. In developing countries, the capacity of streets cannot meet the demands of drivers, causing congestion. Some cities in developed countries have special street network structures that also cause traffic congestion. Many cities suffer from congestion, and some cities stipulate congestion pricing to reduce traffic by requiring drivers to pay a surcharge. Congestion can be grouped into different types; slight congestion such as single interactions only makes the velocity of individual vehicles slower, whereas severe congestion such as network and control congestion

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(Vickrey 1969) slows the velocity of the whole network and requires additional traffic control. Congestion increases commuting times and fuel usage and causes environmental deterioration.

Traffic congestion is a spatio-temporal process (Kerner 1999). When the traffic volume increases on a street, the flow rate will decrease but the flow rates upstream remain the same, resulting in congestion (Kerner 1999). Apart from being triggered by recurring factors such as inadequate capacity or recurrent weather (Kwon et al. 2006), congestion is often triggered by unexpected factors such as accidents, lane closures, and special events (Kwon et al. 2006). Therefore, to measure and detect unexpected congestions have become an important issue for resolving traffic jams. Physical traffic congestion can be measured by using a fundamental diagram (FMD) which illustrates the absolute congestion state under a certain volume, speed, and density. However, the feeling of psychological congestion is relative. Some people are accepting of slight congestion, whereas others are not; thus, fuzzy logic has been discussed for the evaluation of congestion (Lu and Cao 2003; Pongpaibool et al. 2007). Some studies focus on developing methods to detect congestion, whether it is psychological or physical congestion. In early studies of congestion, point-based or short-section (for examining volume over a unit distance) detectors were used (Coifman 2003; Gall and Hall 1989). In recent studies, development of vehicle-to-vehicle systems has risen (Bauza and Gozálvez 2013; Lakas and Shaqfa 2011; Yang et al. 2004). A vehicle-to-vehicle system is a dynamic, non-location-based set of detectors. A vehicle-to-vehicle system utilizes nodes on the street-sides and the vehicle and uses short-range communication equipment to inform closed nodes of the current state of movement. The vehicle as a node is moving and the street side nodes are fixed and connect to a management center. By analyzing the dynamic characteristics of traffic movement, unexpected congestion can be detected, and the management center can make better decisions for traffic control.

From the view of transportation infrastructure, traffic congestion is related to the topological complexity of the streets network, in terms of turning probability. If the street structure is designed to be more complex, the moving vehicles might be easily turning from one street to another, hence, the moving speed would be slower; if the structure is relatively simple, most of the vehicles might be choosing to the same direction, and the moving speed would be faster. In other words, the spatial design of the infrastructure of streets, namely the topological complexity of streets network, would influence the turning probabilities between streets, which would then affect the moving speed along the streets. The streets with higher moving speed could have higher traffic flow rate (number of vehicles passing by per hour) compare with the street segments with lower moving speed. Therefore, if lots of vehicles are moving between street segments with low moving speed, the street would get into a congested situation.

From the view of traveling demand along the streets, the occurrence of traffic congestion is related to the functionalities of destinations, and the connectivities of the street network. The functionality of a destination includes the types of buildings, facilities, or land use at a specific location. In a city, the commercial districts and the area where most office buildings concentrated are where most of the people work.

Therefore, high commuting needs are expected in those areas and the nearby areas. For example, the transportation system near to central business districts (CBD), science and industrial parks, and financial districts would be busier than a residential area. On the other hand, the connectivity of a street represents the degree of the street connected with each other and facilitating people to their destination. As people tend to choose the shortest or fastest ways of moving towards their destination, the selection of the route of each moving person could be dependent on the connectivity of the street system. For example, a street with a higher connectivity to the city center means that it is easier for getting to the city center through the street. Therefore, the high connectivity of the street network could reflect high traffic flow concentration. And it could have high potential to cause traffic congestion.

In sum, traffic congestion could be attributed to topological structure of street network and traffic flow concentration. To solve traffic congestion, it is necessary to investigate these two factors simultaneously. Therefore, the objective of this study is to propose an innovative analytical procedure for investigating the traffic flow concentration, complexity of street network structure, and the traffic impact areas. By calibrating the probability of turning between street segments with the actual traffic volume data, the complexity of the streets topological structure could be measured. The geographical extent of traffic impact areas can be delineated by illustrating geographic regions with high turning probability between street segments. Profiling the characteristics of traffic congestion would provide more comprehensive insights for the city planners, and would also be useful for further understanding of the congestion spreading.

2 Study Framework

The study framework is proposed in Fig. 1. We analyzed the real volumes of vehicle movements along street networks and the proposed flow-based ranking algorithm (Flow-based PageRank, FBPR) to determine the traffic flow concentration (travel

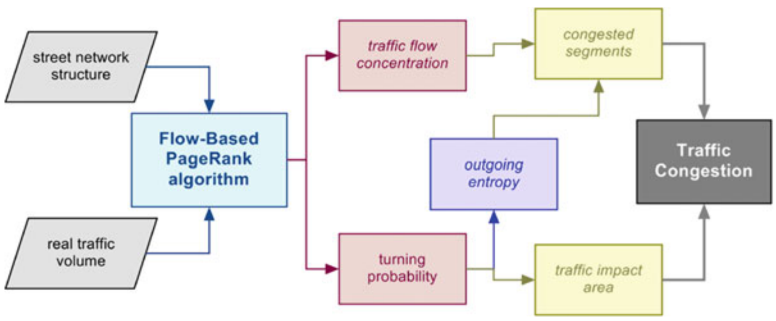


Fig. 1 The conceptual framework

demand), the turning probability (link relationships) and outgoing entropy (topological complexity). Congested segments are defined as the street segments that are prone to traffic congestion. By overlapping these factors, congested segments can be identified. Then, this study used the maximum modularity, a network partition method, to identify the community structure of the traffic flow, which represents the geographic extent of congestion, namely traffic impact area. Through integrating FBPR scores (traffic flow concentration), outgoing entropy, and the traffic impact area, the proposed framework could understand the urban traffic congestion in further. Taipei City, which is one of the major metropolitans in East Asia is used as a case study for demonstrating the feasibility of the proposed framework.

3 Data

3.1 Street Network

Taipei street network data were collected from the Institute of Transportation, Ministry of Transportation and Communication, Taiwan. The data contained the street names, types, and the locations. The street types contain national streets (freeway), elevated streets (viaduct), county streets, normal streets, country streets and lanes. This study focus on traffic conditions in the major planar street network, therefore, we filtered out the lanes, which has little influence due to low traffic volumes and elevated streets. There were approximately 5500 street segments in this study (Fig. 2).

To analyze link relationships of street segments, the street network was transformed into a dual graph (Fig. 5). A dual graph (Añez et al. 1996; Rodrigue 2013) or dual representation (Hu et al. 2008; Jiang 2009) has been proposed to illustrate link relationships and it is convenient for expressing turning relationships between streets when turning prohibitions exist in a street network (Añez et al. 1996). This study used a dual graph to form the network, and streets that are always taken as links were converted into nodes and turning movements between streets were converted into edges (Fig. 3). With the streets transformed into nodes, the movements between streets became the links. We also converted an intersection of three or more street segment into edges. For example, street segment A intersected with streets segments B and C and was coded as AB, AC, and AC (Fig. 4a) and then converted into edges AB, BA, AC, and CA (Fig. 4b).

3.2 Traffic Volume

Traffic volume data was provided by the Taipei Traffic Control Center and measured by vehicle detectors (VD). The date of the traffic volume was collected from July 1st to August 31st in 2012. The traffic information was updated every 5 min and the data

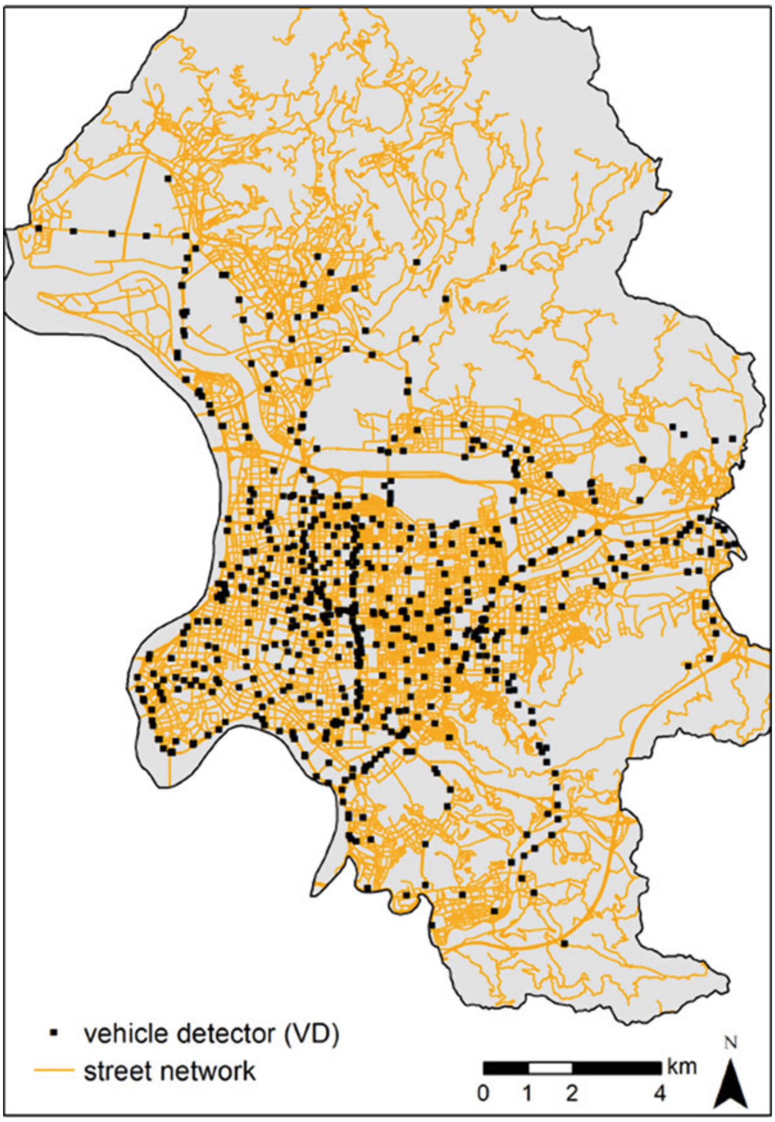


Fig. 2 Street network and spatial distribution of vehicle detectors of Taipei City

items included exchange time, device name (device_id), the name of the location, volume (total_volume), average speed, and the longitude, latitude coordinates of the VD. There are 379 VD are located on different street segments of Taipei City (Fig. 2).

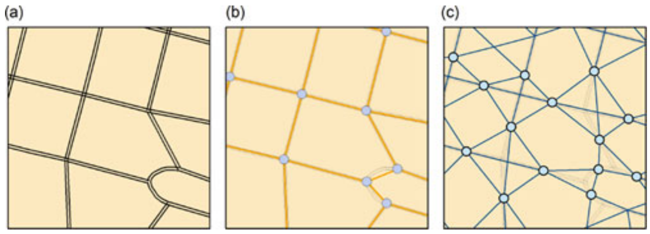


Fig. 3 From street network to dual graph. (**a**) An example street network, (**b**) axial map, (**c**) dual graph

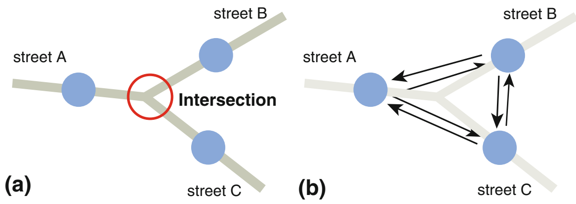


Fig. 4 Illustration of converting an intersection of street segments (**a**) into multiple edges (**b**)

4 Methods

4.1 The Flow-Based Ranking Algorithm

This study proposed a new flow-based ranking algorithm for ranking the significance of street segments, called the Flow-based PageRank (FBPR), which was borrowed from the concept of PageRank (PR). PR is an algorithm used by Google Search Engine (Brin and Page 1998) that uses weighting scores to rank web pages to identify the significant web pages from the enormous and complicated World Wide Web. Two factors make a web page become significance in PageRank algorithm: links from a high number of other pages and links from web pages that themselves have high importance scores. The calculation process of PR can be considered as a continuous process of pages voting for each other. At the beginning, all web pages are assigned the same amount of votes (also called scores); then, web pages pass their own scores to outgoing link-neighbors. The voting process is similar to the flow of vehicles into and out of a street network. The streets with higher volumes will lead a higher volume onto neighboring streets, and streets with more connections will have a higher volume.

However, some settings in PageRank do not correspond to the structure of street networks. For example, PageRank assumes that people move randomly between web pages, and thus the weights of all links are equal. But, human movement is not completely random, and it is influenced by both network structure and individual options (Chin and Wen 2015). Puzis et al. (2013) indicated that network analysis should consider the characteristics of the human movement. Social economic structures and the purpose of trips are often used as variables when simulating movement patterns (Jassbi et al. 2011; Yao et al. 2008). Therefore, PageRank cannot be used directly for street networks (Fig. 5).

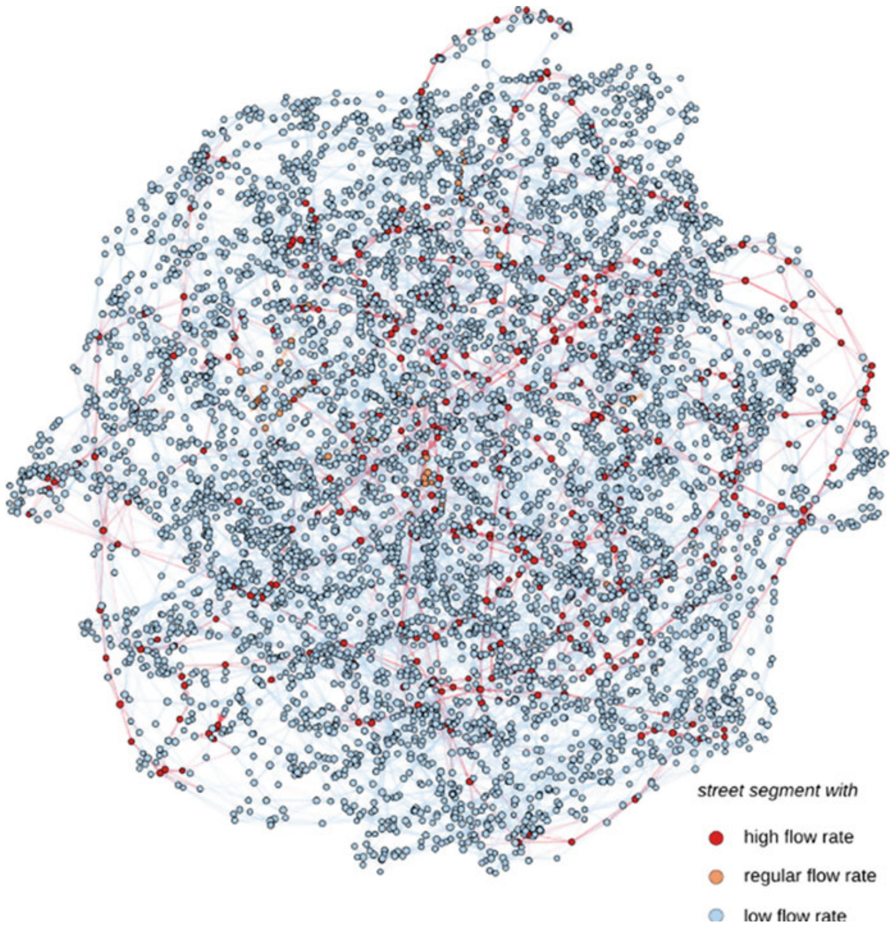


Fig. 5 Dual graph representation of Taipei City street network

Due to the problems mentioned above, the proposed Flow-based PageRank (FBPR) uses a composite index (weight) to replace those variables. The analytical procedure is illustrated in Fig. 6. FBPR uses different weighting schemes to emphasize the attractiveness of streets and decide the distribution of volume between streets (weight of link relationships) (Chin and Wen 2015; Xing and Ghorbani 2004). The weight is termed location attractiveness, which caused by land-use patterns, social economic factors. To correspond to its influence on traffic volumes, real traffic volume data were used to calibrate the attractiveness and link relationships to make the rank of FBPR scores fit the distribution of real traffic volumes. A genetic algorithm was used to determine the optimal values of weights and link relationships.

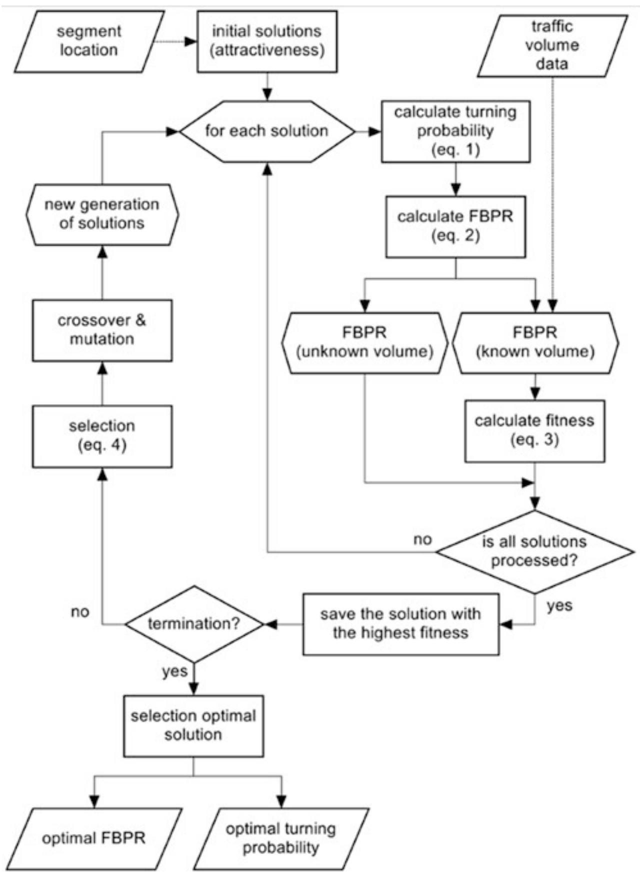


Fig. 6 Analytical procedure of FBPR

4.1.1 Attractiveness of a Node and Link Relationships Between Nodes

Attractiveness is defined as the level of a street segment to attract more traffic flow from neighboring streets. Its value ranges between integers from 1 to 100. The higher attractiveness of a node indicates that a street segment can attract a higher traffic volume from connected streets.

Link relationships were determined by the scores of attractiveness, and FBPR was used to capture link relationships. Equation (1) indicates the transfer proportion of attractiveness from street segment v to u. If $Weight(v, u)$ equals 0.5, then half of the traffic volume on street segment v move to street segment u. The FBPR score of the street segment u is defined by its attractiveness proportion among other outgoing street segments from street segment v, multiplied by the FBPR score of the street segment v in the previous iteration (Eq. (2)).

$$Weight(v, u) = \frac{Attr(u)}{\sum_{p \in R(v)} Attr(p)} \tag{1}$$

$$FBPR_t(u) = \sum_{v \in B_u} FBPR_{t-1}(v) \times Weight(v, u) \tag{2}$$

where: $Weight(v, u)$ is the link weight from street segment v to u; $Attr(u)$ and $Attr(p)$ are the value of the attractiveness of street segment u and p, respectively; $R(v)$ is the set of outgoing nodes of street segment v, which includes street segment u; $FBPR_t(u)$ and $FBPR_{t-1}(v)$ are the FBPR score of street segment u on iteration t, and FBPR score of street segment v on iteration $t-1$, respectively.

The procedure of FBPR was demonstrated in the following example. The sample network is presented in Figs. 7 and 8a. The street segment (A) has three out-

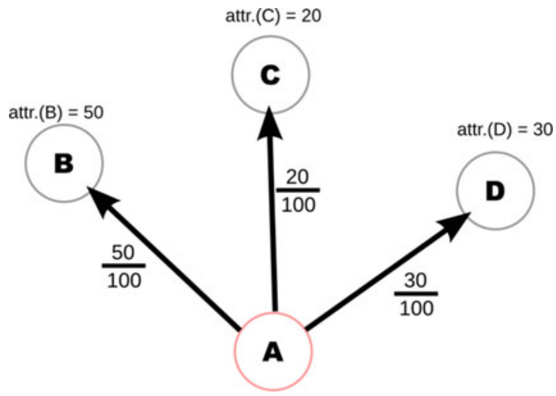
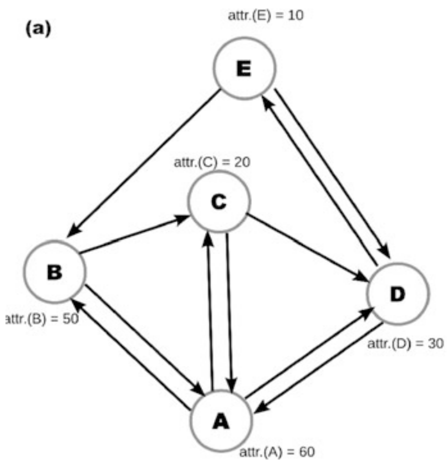


Fig. 7 A partial network including node A and its outgoing nodes, for demonstrating the calculation of the weight from the target nodes' attractiveness



(b)

to \ from	A	B	C	D	E
A	0	6/8	6/9	6/7	0
B	5/10	0	0	0	5/8
C	2/10	2/8	0	0	0
D	3/10	0	3/9	0	3/8
E	0	0	0	1/7	0

Fig. 8 The same network for demonstrating the calculation of the weight matrix from the attractiveness of each node

link neighbors, street segments (B), (C), and (D) (Fig. 7). The $Weight(A, p)$ was determined by attractiveness of the target nodes $Attr(p)$. The attractiveness of nodes (B), (C), and (D) are 50, 20, and 30, respectively. Therefore, the values for $Weight(A, B)$, $Weight(A, C)$, $Weight(A, D)$ are 50/100, 20/100, and 30/100. In the beginning of the process, all nodes received a same scores (there are five nodes in the network, so the initial scores are all $1/5$), and then node (A) distributed 50 % of scores to node (B), 20 % of scores to node (C), and 30 % of scores to node (D). The calculation of transfer proportions within the network is showed in Fig. 8b. The link relationships were determined as the matrix form, which was used as the turning probability in the procedures for calculating outgoing entropy and delineating traffic impact area. The process of transferring scores will repeat until no change occurs in the score of all nodes.

4.1.2 Model Fitting and Parameter Estimation

To capture the real movement along the street network, actual traffic volume data from the VD system is used to calibrate the attractiveness of each street segment. Since, the transfer process described above is similar to the movement behavior in a street network, turning weight can be estimated when the ranking of FBPR scores for each street segment is in agreement with the ranking of actual traffic volume. Therefore, the FBPR model was combined with a genetic algorithm (GA) to identify the optimal distribution of street segment's attractiveness. The fitness function of GA is to maximize the Spearman's Rank correlation among FBPR scores and actual traffic volume (Eq. (3)). If the rank of FBPR scores was highly correlated with the rank of actual traffic volume, the fitness of the candidate solution would be relatively high.

$$fit(s) = \frac{\sum_i (Rank_{FBPR}(i) - \overline{Rank_{FBPR}})(Rank_{volume}(i) - \overline{Rank_{volume}})}{\sigma_{rankFBPR}\sigma_{rankvolume}} \tag{3}$$

where: $fit(s)$ is the fitness of solution s; $Rank_{FBPR}(i)$ is the FBPR rank of node i; $\overline{Rank_{FBPR}}$ is the average FBPR rank of all nodes; $Rank_{volume}(i)$ is the volume rank of node i; $\overline{Rank_{volume}}$ is the average volume rank of all node; $\sigma_{rankFBPR}$ and $\sigma_{rankvolume}$ are the standard deviation of the FBPR ranks and volume ranks, respectively.

GA is an iterative process, which procedures included selection, crossover, and mutation in each iteration. The selection procedure takes fitness as the selecting basis, in which a candidate solution with better performance would have a higher probability of being selected. In this study, the fitness was transformed into relative probability, which represents the probability of each solution being selected from all solutions (Eq. (4)). The selected solution would enter the mating pool for crossover procedure.

$$P(s) = \frac{fit(s)}{\sum_{r=1}^{N} fit(r)} \tag{4}$$

where: $P(s)$ is the probability of the solution s being selected; $fit(s)$ and $fit(s)$ are the fitness of solution s and r, respectively; N is the total number of solutions in one generation.

The crossover procedure in GA chooses two chromosomes as parent solutions from a mating pool and uses the parent solutions to generate child solutions with a certain probability. The multiple-point crossover was selected in this study. Multiple points were randomly selected, and there were 1000 crossover points in the model. The parent chromosomes between two points were swapped, and child chromosomes were generated. For example, solution A and solution B were selected as parent chromosomes, and the attractiveness was swapped between the crossover points, generating a new solution A and solution B. For crossover methods, the crossover rate should be set carefully. The crossover rate was the probability of mating and was set at 0.95. The mutation procedure imitates the phenomenon of natural evolution and maintains diversity in genes. The mutation occurs with a certain probability and generates one or more genes that have no relationship with previous genes. In this study, the GA process iterated for 1000 generations per run before the termination, and then output the optimal solutions.

4.2 The Outgoing Entropy

If most outgoing flows of a street segment is moving toward one street segment, this indicates that the two street segments are forming a major stream of vehicle flow. The existence of major stream suggests that the moving speed of the street segment would be relatively higher. In contrast, if a node's outgoing flow is moving equally toward its outgoing nodes, it represents every vehicle moving along the street segment might take a turn to any direction in the junction, this situation leads to a lower moving speed. The possibility of taking a turn is defined as turning probability. It can be calibrated when fitting the fitness function. Then the entropy of the outgoing flow is used to measure the homogeneity of turning probability of a street segment (Eq. (5)). If the outgoing entropy is high, the outgoing flow is equally divided, and it can reflect low moving speed of the street segment. Hence, the distribution of the outgoing entropy could provide a clear picture of the turning probability and moving speed of the street segments.

$$Entropy(v) = -\sum_{p \in R(v)} (Weight(v,p) \times \ln(Weight(v,p))) \tag{5}$$

where: $Entropy(v)$ is the entropy of street segment v; $Weight(v,p)$ is the link weight from street segment v to p; $R(v)$ is the set of outgoing nodes of street segment v.

4.3 Delineation of Traffic Impact Area

This study used the concept of network modularity to delineate the traffic impact area. The principle of modularity uses the difference between the number of connections inside communities and the number of expected connections to determine the quality of grouping. A higher modularity indicates better grouping. The original modularity was proposed by Newman (2006), but the modularity used in this study is revised by Blondel et al. (2008), also called the Louvain method. The algorithm comprises the iterative two-step procedure: the first step is to group the nodes into different communities and uses Eq. (6) to measure the grouping performance. The second step considers the communities as new nodes, and the links between the communities are converted to the links of the new network. After the new network is formed, the process of the first step is repeated. The node moves to different communities, and the process will repeat until there is no further increase of ΔQ.

$$\Delta Q = \left[\frac{\sum_{in} + k_{i,in}}{2m} - \left(\frac{\sum_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{tot}}{2m}\right)^2 - (\frac{k_i}{2m})^2\right] \quad (6)$$

where: ΔQ measured the increasing value of each movement of i; $\sum_{in}$ is the total weight of links inside the destination community; $\sum_{tot}$ is the total weight of links connecting the nodes in the destination community with other communities; $k_{i,in}$ is the weight of links connecting node i with the nodes located inside the destination community; k_i is the weight of links connecting with node i; and m is the sum of the weights of all links in the network.

5 Results and Discussions

5.1 The FBPR Scores

The FBPR scores refer to the tendency of traffic flow concentration. High FBPR score on a street segment indicates more vehicles would flow through the street segment, thus, the flow demand of the street segment is high. Figure 9 shows the distribution of FBPR scores. The result shows that the streets segments with high FBPR scores are concentrated mainly at the center part of Taipei City, which is the location of Taipei's emerging-CBD (the area-A in Fig. 9); the other areas with high FBPR scores are mainly scattering at the western part of Taipei, including the Taipei's old-CBD (the area-B in Fig. 9), and part of the high FBPR score areas are distributed at the corridor area from the western part area towards north (the area-C in Fig. 9). This means these areas, especially the emerging-CBD of Taipei, have a higher demand for traffic volumes and might result in possible traffic congestion problems.

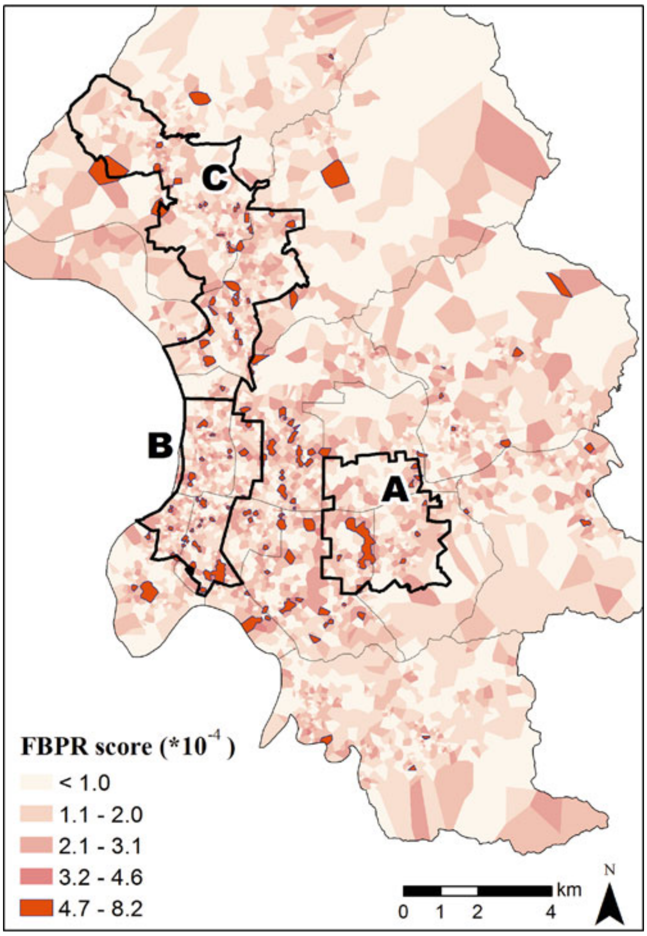


Fig. 9 The FBPR scores distribution in the Thiessen polygon generated by the streets segments (nodes), the emerging-CBD area (*A*), the old-CBD area (*B*), and the corridor bridging the old-CBD and the town located at the north of Taipei City (*C*)

5.2 The Outgoing Entropy

The link relationship indicated the turning probability ($Weight(v, p)$) between two street segments, from v to p. Using the link relationship, we calculate the outgoing entropy ($Entropy(v)$) of each street segment, which represent the equality of turning probability. Higher outgoing entropy indicates that the turning probability toward each direction in the junction is more even. Figure 10 displays the spatial distribution of outgoing entropy. Most of the areas with high entropy are located at the old-CBD (the area-B in Fig. 10), the emerging-CBD (the area-A in Fig. 10), the corridor toward the north (the area-C in Fig. 10), and also the transition areas between the

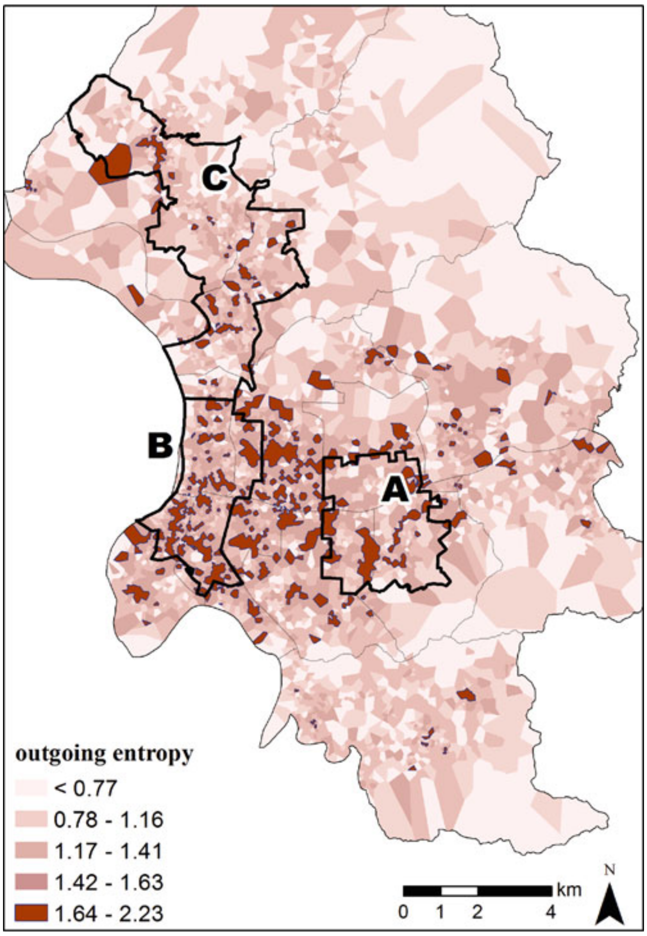


Fig. 10 The outgoing entropy distribution, which is also processed by transforming the entropy index into the Thiessen polygon generated by the streets segments, the emerging-CBD area (*A*), the old-CBD area (*B*), and the corridor bridging the old-CBD and the town located in the north of Taipei City (*C*)

two CBD. This finding suggested that the moving vehicles in the streets at old-CBD areas might turn to different directions from one vehicle to another, and leads to a lower moving speed. This is consistent with the reality since the old-CBD is developed while Taipei City is in its early development stage, and most of the streets were not built for vehicle flows as heavy as today.

5.3 The Congested Segments

Traffic congestion is supposed to have happened at the locations where the traffic flow demand and the complexity are both higher than other places. While the FBPR score could reflect the relative traffic flow demands, and the outgoing entropy could capture the degree of complexity, the streets segments prone to traffic congestion could be identified by overlapping the streets segments with high FBPR score with streets segments with high outgoing entropy, namely the congested segments. We classified FBPR score and outgoing entropy into five levels by using Jenks natural breaks classification (Jenks 1967), which is a data clustering method designed to determine the best arrangement of values into different classes. Jenks natural breaks classification method seeks to minimize the variance within classes and maximize the variance between classes. Then, we used the highest level as the groups of streets segments with the highest indexes. Figure 11 shows the streets segments with highest outgoing entropy, streets segments with highest FBPR score, and their overlapped street segments. The result indicated that although many places at the old-CBD have the highest outgoing entropy, but only some of them are overlapped with the highest FBPR score. This suggested that these streets segments have relatively low traffic flow demands. On the other hand, the streets segments near to the CBD area, some streets segments between the CBD and old-CBD areas, and some streets segments at the southern part of the old-CBD, which have the highest FBPR score, is partially overlapped with the outgoing entropy, suggested that these locations might be easy to get into congestion situation.

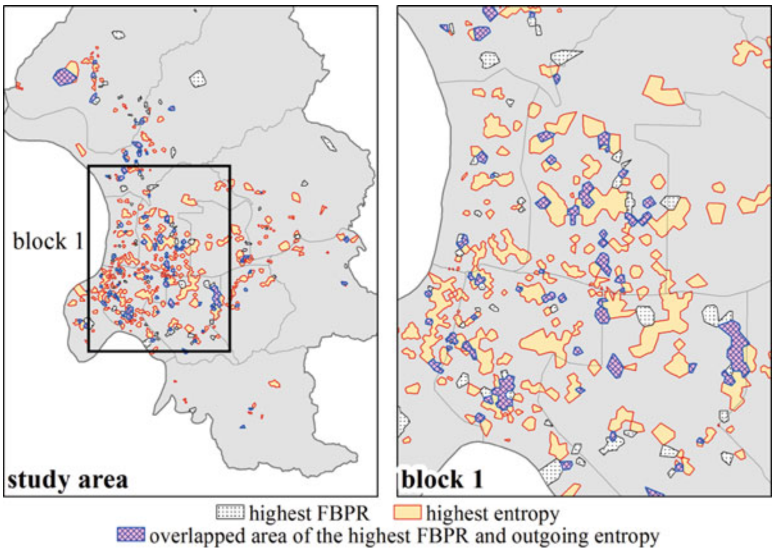


Fig. 11 The streets segments with highest FBPR score, streets segments with highest outgoing entropy, and their overlapped street segments (congested segments)

5.4 Traffic Impact Areas

The community structure algorithm was used to delineate the geographic extents of traffic impact areas. It is interesting to find that some of the boundaries of the traffic impact areas are similar to some of the administrative boundaries. This might be an outcome of the land use zoning, that is decided and planned by the city government. The land use zoning might cause the development of streets system tend to connect with each other within each zone, rather than between zones. The geographic extent of the traffic impact areas are the areas where the within-areas connectivity are stronger than the between areas connectivity.

The segments prone to traffic congestion are compared to the traffic impact areas in Fig. 12. We focused on two of the traffic impact areas in Fig. 12, both areas are located near to the two main railway stations in Taipei City, the Songshan station (block 1) and Taipei station (block 2). Both Songshan and Taipei stations have two types of rail systems, including the intra-city massive rapid transit (MRT) system and the inter-city train railway system. The stations are acting as the hub in terms of transportation connectivity, which implies that the nearby areas would have high transportation needs. In block 1, the traffic impact area (the area for discussion in block 1) has one group of segments prone to traffic congestion, which is near to the Songshan station. This indicated while the congestion occurs at the segments in the group, the congestion situation would probably spread to the northern zone in the traffic impact area. Three groups of segments prone to traffic congestion exist

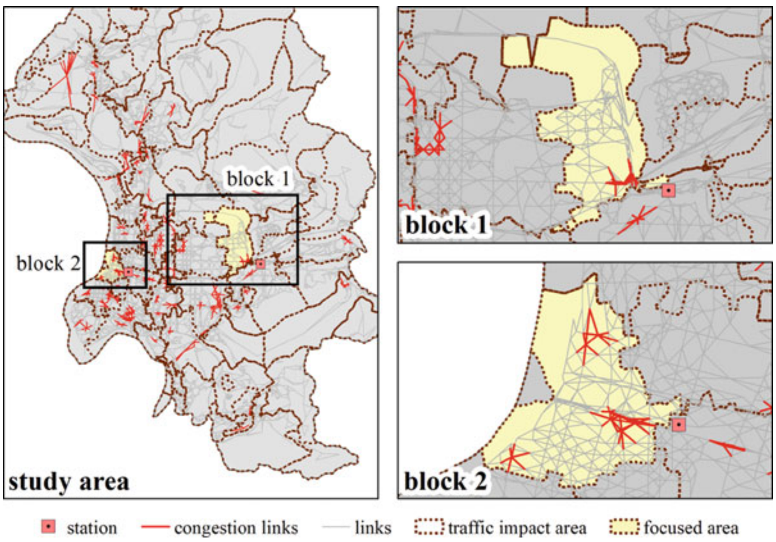


Fig. 12 The traffic impact area, the connected links of the segments with highest-entropy-and-highest-FBPR-score (links of h-h nodes), the other links, and two areas for discussion, which are near to the main stations in Taipei City

in the traffic impact area in block 2. One of them is near to the Taipei station, the other two are the centers of the old communities within the old-CBD. This means that this traffic impact area would get into congestion situation if any one of the three groups of segments has overflowed traffic volume.

6 Conclusions

Identifying characteristics of traffic congestion is currently a crucial issue for urban management. We proposed a new algorithm, FBPR, to determine the turning probability, traffic flow concentration and outgoing entropy for identifying traffic congested segments and impact areas. Only relying on the topological structure of the Taipei City street network, this framework could identify the CBD, and the areas around the stations of the combination of MRT system and train railway system are prone to traffic congestion. The traffic impact areas, which were delineated by the network partition method, could be spatially targeted at priorities of traffic improvement for city planners.

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