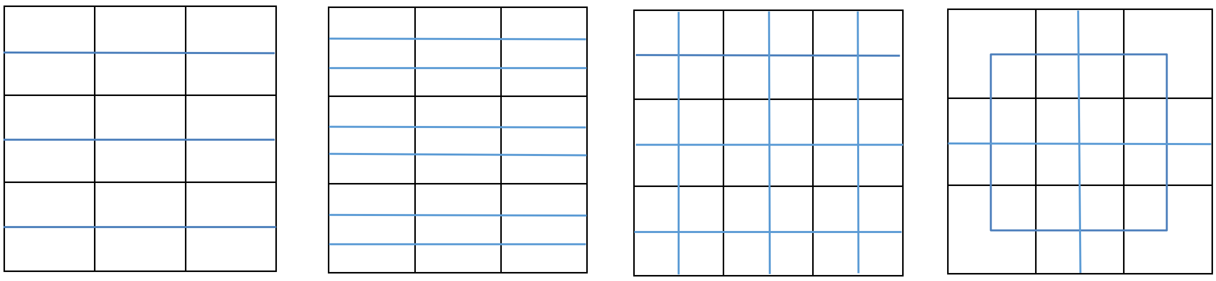

Influence of urban blocks on road traffic： analysis of the patterns shape using simulation techniques

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Abstract

Network connectivity, continuity and efficiency in urban areas depend on the patterns defined by the roads and the location of the buildings. Urban blocks affect the traffic operational performance in aspects such as travel time, average travel delay, average speed and resilience from congestion.

This paper analyzes the impact of urban blocks on road traffic by considering urban block patterns. For this purpose, traffic performance and propagation of traffic congestion are evaluated on different urban blocks by applying two techniques: MFD (Macroscopic Fundamental Diagram) and NEF (Network Exit Function). Furthermore, presence and influence of both arterial and local streets are discussed. DTA (Dynamic Traffic Assignment) function is used to capture dynamic effects that arise in congested scenarios in simulation. Results obtained evaluate and quantify the influence of urban block shape on the traffic performance.

Keywords

Urban block – Macroscopic Fundamental Diagram – Network Exit Function – VISSIM simulation – congestion

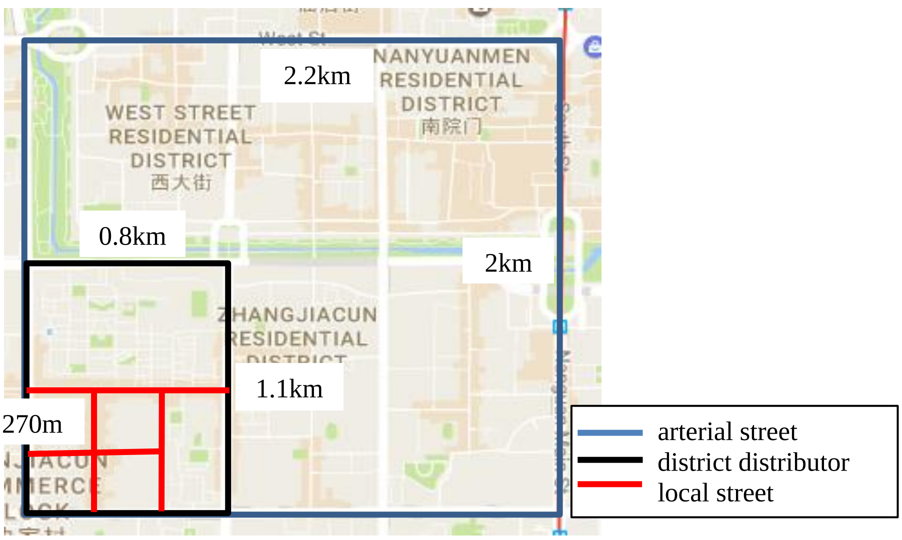
1. Introduction

In the cities of China, the average block size is relatively big (the link length can be 1 km) and recently the government proposed a strategy of '**open blocks**'(the newly-built blocks should share their internal road space to public while some built-up areas——such as universities, companies, need to be opened step by step).

There are two aspects of open blocks: reforming old neighbourhoods and planning new neighbourhoods. For new neighbourhood planning, the planning principles and evaluation criteria should be more clear. Shenzhen has done some related work. For old neighbourhoods, especially for some certain large urban areas such as enclosed universities, large residential quarters and large enterprises, with increasing density of urban centrals and tight land resources they have to gradually move to the periphery of cities. Open blocks will undoubtedly provide a new solution to these problems: big block can be divided by opening their gates and connecting inside local roads to outside roads.

By comparing many central urban areas in China's cities, the average local streets length between two intersections is about 500-600m in the central, and about 700-800m in the suburb. Figure 1 shows a part of an existing road network in Xi'an, China. The area is surrounded by 4 main streets with an average length of 2.1 km and contains a smaller area surrounded by 2 local streets and 2 main streets. The dimensions of this smaller area are 1.1 by 0.8 km^2. In this small area, there are a 600*800m^2 big block (university), a 500*260m^2 medium block (enterprise or institution), and a small block (residence community) of 270m in length surrounded by four branches.

Figure 1 Part of road network of Xi'an, China



In this paper open blocks are mainly aiming at changing these big and medium blocks. For the big block in Fig. 1(600*800m^2), there are lots of internal streets we can chose to use, in the view of traffic performance, the bigger question is what the better local street pattern in a given network with big blocks would be.

There are some researches about the relationship between networks with traffic. (Xie and Levinson, 2006) found that network patterns determine the networks' connectivity, continuity and efficiency, and therefore they influence traffic operational performance such as network delay, travel time, average speed and resilience from congestion. Well-designed blocks could save urban space and provide a more efficient transportation system. Some researches have proved that higher connectivity allows us to better use the existing road resources to alleviate traffic congestion, especially on arterial roads (Oriol, 2015). (Wang, 2017) analysed data from 718 traffic analysis zones (TAZs) in Florida's Hillsborough County and developed a quantitative method for network pattern classification. Six quantitative metrics, geometric and topologic were analysed, and their ability to classify different road network patterns were compared. The results show that meshed coefficient, proportion of cul-de-sacs, and proportion of 4-legged intersections were the three most significant variables in determining network patterns. (Mühlich, 2014) investigated five different urban grid networks with different ratios of local and arterial streets. The patterns produced different MFDs and hysteresis loops of varying shape and size. (Ortigosa J, 2015) did a lot of work on urban grid networks, including the study to three street configurations: two-way streets, one-way streets, and two-way streets with prohibited left turns, which present very different traffic assignment levels of complexity, computational times and so on. (Oriol, 2015) modeled three networks with different block sizes in order to find networks that while fulfilling the space requirements, are also able to provide a good degree of mobility.

In this paper we focus on the relationship of block pattern and traffic performance, based on a grid original network, and we try to find a better block pattern for the fixed grid network. The MFD and NEF are used to assess network performance.

The MFD is a good way to integrate the physical and functional characteristics of the urban blocks and transport network. It gives an impression of the spatial-temporal patterns of congestion. It is shown how different land use and network structures affect the formation and dynamics of congestion (Tsekeris, 2013). (Daganzo and Geroliminis) did a lot of work about MFD. (Daganzo, 2007) describes an adaptive control approach (an idea consists in monitoring and controlling aggregate vehicular accumulations at the neighbourhood level) in to improve urban mobility and relieve congestion. (Geroliminis, 2008) enrich data for network MFD with data from GPS-equipped taxis, which covered the entire network and revealed that the new database were estimated better. (Buisson and Ladier, 2009) prove that the heterogeneity has a strong impact on the shape of the MFD by dealing with data from a medium-size French city. (Geroliminis, 2011) investigates what are the properties that a network should satisfy, so that an MFD with low scatter exists, such as the spatial distribution of vehicle density in the network is one of the key components that affect the scatter of an MFD and its shape. And he also shows (Geroliminis, 2011) the traffic hysteresis phenomena that freeway network systems not only have curves with high scatter, but they also have an exhibit hysteresis phenomena, where higher network flows are observed for the same average network density in the onset and lower in the offset of congestion. (Ludovic, 2014) makes a cross-compare existing estimation methods (vehicle trajectories, probes, loop detectors) for the Macroscopic Fundamental Diagram.

In order to have a better understanding of the impact of block patterns on traffic, we set up an abstract grid network and several block patterns in VISSIM simulation. Both traffic performance indicators and network performance indicators are considered to compare different networks.

2. Methodology

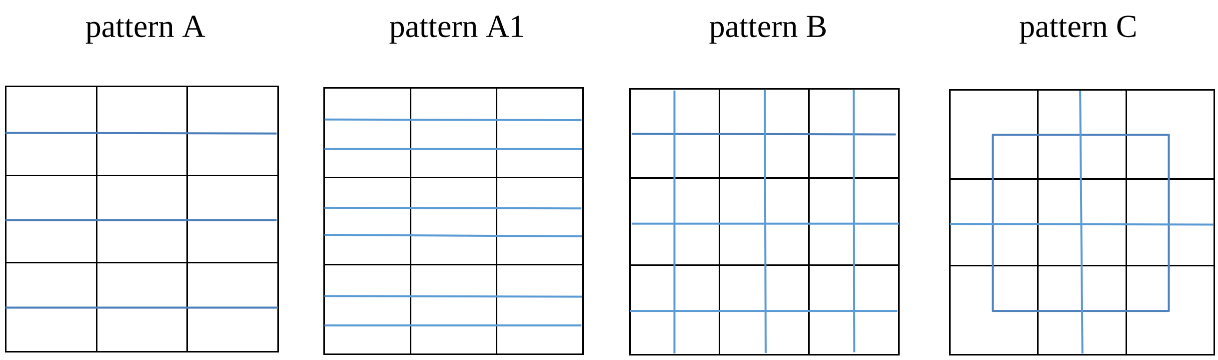
Four different patterns of open blocks were built into street networks within the simulation software VISSIM and we use a DTA model as the rule of traffic flow assignment. The DTA function runs every route in a network and calculate total delay of each route to give the better route dynamically. So for each pattern, the results are the last simulation runs for eliminate influence from route choice. And five simulations also were run with five different random seeds for each pattern. A 'random seed' is a number used to initialize a pseudorandom number generator. The numbers obtained from the pseudorandom number generator are used in order to consider the stochasticity of the different parameters in micro simulation models. To obtain the MFD of different patterns, the simulation output consists of lane density/flow, was aggregated over time and space within the computing environment MATLAB.

2.1 Network design

The paper considers a 3x3 original grid network which consists of 24 links with each link 600m long. These links are all two-way arterial streets with 2 lanes each direction. The saturation flow of each original lane is 1400veh/h.

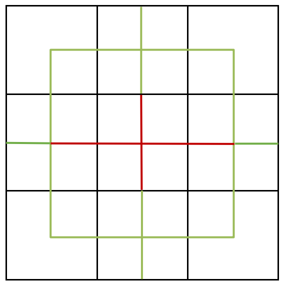
Open blocks can be realized by setting different patterns of local street networks and all the cross points are assumed as midpoint. Normally, there are two local street patterns: grid-based and linear-based. A grid-based pattern has high demand for landform, but it has a good connectivity and it is easy for building layout and one-way traffic organization. In this paper we consider four kinds of patterns, pattern A and A1 are all linear-based but with a different number of links. Pattern B is a typical grid-based and pattern C is a circular plus radial pattern. Fig. 2 shows four different patterns of open blocks. The saturation flow of each additional local lane is 1300veh/h.

Figure 2 Patterns of open blocks (black lines original show arterial streets and blue lines show additional local streets)



Every network has the same total lane length by adjusting the number of additional local lanes and using the same characteristics (signal timing, turn movements, traffic assignment) to compare the impact of different patterns on network performance. In this case all the local streets in pattern A are 2 lanes each direction and both pattern A1 and B has 1 lane each direction. In pattern C part of local streets are 4 lanes and others are 2 lanes (see Fig. 3).

Figure 3 Lane assignment of pattern C (green lines show streets with one lane each direction and red lines show streets with two lanes each direction)



There are three intersection layouts in these networks: arterial streets and arterial streets, arterial streets and local streets, local streets and local streets. All the arterial streets expand three turn movements (1 left, 1 straight and 1 right) in intersections and all the local streets expand two turn movements(1 left and 1 straight and right).

For arterial streets, the capacity for the left turn movement, straight turn movement and right turn movement are all 1000veh/h. For local streets, a total capacity for the straight and right turn movements combined is 1000veh/h, and 800veh/h for the left turn movement.

For each 4-leg intersection we considered 27seconds of effective green for the straight and right turn movements, and 13seconds for the left turn movement, out of a total cycle of 90seconds including 10seconds of lost time. Similarly, for each 3-leg intersection considered 30seconds of effective green for the straight and right turn movements, and 15seconds for the left turn movement, out of a total cycle of 60seconds including 15seconds of lost time.

2.2 Demand

In VISSIM, the demand is defined by Origin-Destination Matrix(OD Matrix), which displays the number of trips being executed from each origin to each destination in a fixed period of time, generally one hours (Oriol, 2015). The number of trips between origin i and destination j is:

$$T_{ij} = \begin{cases} T_{ij} = \alpha, i \neq j \\ T_{ij} = 0, i = j \end{cases} \quad (1)$$

There are some demand assumptions in this paper:

(1) We use parking plots (red circles in Fig. 4) to simulate the demand production and attraction in VISSIM and they are all located in the middle of links. Fig. 4 shows part of the pattern B network and Bp1, Bp2 ... Bp12 are all virtual demand points.

(2) The population is distributed uniformly in these areas

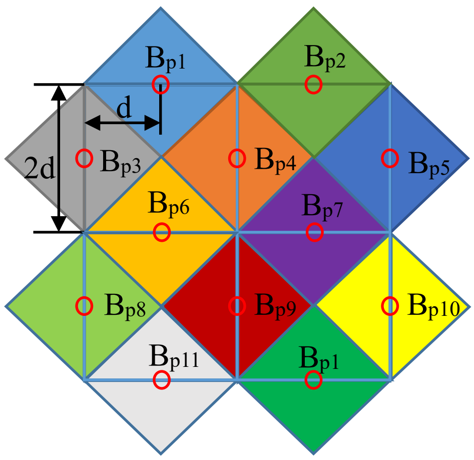
Road networks are not independently existing, and they are just extracted from a large network and there could be other demands and flows around network borders.

In this paper we assume population is distributed uniformly and different colors represent different areas which are covered by different parking plots (see Fig. 4). So Bp1, Bp2 ... Bp12 have same value.

(3) In all patterns, the total demand is assumed to be equal. As pattern B has the densest parking plots, we put it as the standard to assign other patterns' demand into virtual plots.

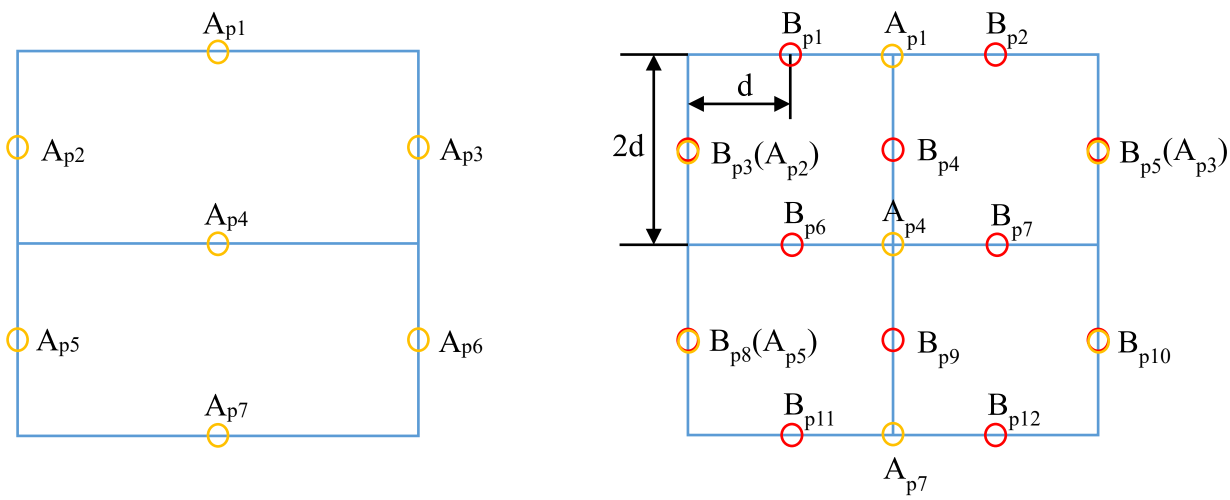
(4) The demand assignment is only related to the distance between each parking plot and if the distance is greater than 2d (Fig .4), the demand isn't be assigned.

Figure 4 Demand virtual points



For example, as shown in Fig.5, the left network is 1/9 of pattern A and Ap1, Ap2 ... Ap7 are virtual parking plots (total number is m) while the right one is part of 1/9 of pattern B and Bp1, Bp2 ... Bp12 are its parking plots (total number is n). Then we compare and calculate the value of Ap1, Ap2 ... Ap7 according to the location of the virtual parking plots of this two patterns. The traffic flows from P4 to P6 can be regarded as the sum of all the flows through P4 to P6.

Figure 5 Example of demand assignment



In this way we can get some relationships between two networks' demand virtual plots. For Bp5, it has the same location with Ap3 so it is assigned to Ap3 totally while for Bp4, there are Ap1 and Ap4 in its 2d distance range and both the distances from Bp4 to Ap1 and to Ap4 are 1d, so we assign ½ Bp4 to Ap1 and other ½ Bp4 to Ap4.

For the same total demand of all networks, there is a coefficient $\frac{n-1}{m-1}$ that also needs to be considered. Finally, parking plot values of pattern A can be described as:

$$A_{p4} = \left(\frac{1}{2}B_{p4} + \frac{1}{2}B_{p6} + \frac{1}{2}B_{p7} + \frac{1}{2}B_{p9}\right) * \frac{n-1}{m-1} \quad (2)$$

$$A_{p2} = \left(B_{p3} + \frac{1}{4}B_{p6} + \frac{1}{3}B_{p1}\right) * \frac{n-1}{m-1} \quad (3)$$

…

3. Results

To cover both uncongested and congested situations, six different demand levels ($\alpha = 0{,}5{,}0{,}8{,}1{,}1{,}5{,}2{,}3$)are chosen to run during one hour and five different random seeds were considered for stochastic variation in the trip generation for each network pattern.

Two kinds of parameters are considered to evaluate these block patterns: traffic performance indicators and network performance indicators. The traffic performance mainly focus on assessing uncongested scenarios or the process of traffic from uncongested to congested scenario. The indicators such as travel distance, travel delay and number of stops are derived from VISSIM results directly. The network performance indicators will be used to compare different network patterns under congested situation.

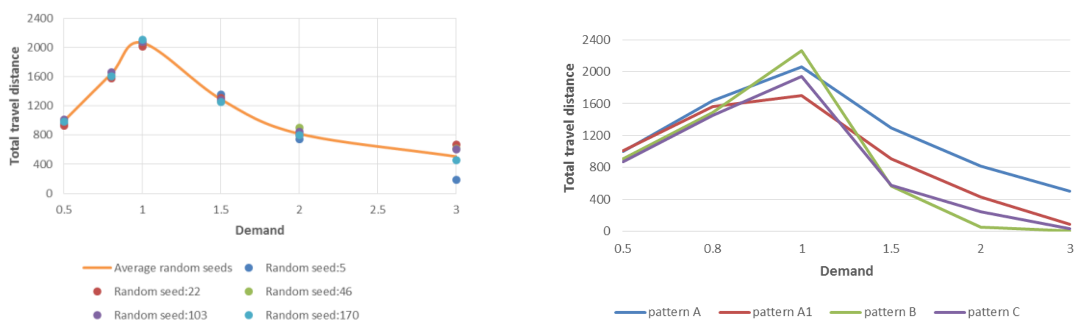
3.1 Traffic performance indicators

3.1.1 Travel Distance

The travel distance is the distance between the origin and destination of each trip of travellers. Fig.6 a) shows the variation among different random seeds for total travel distance of pattern A. It can be observed that the effect of random seeds on total travel distance is larger under the highest demand level than in uncongested scenario.

Figure 6 a) Total travel distance of pattern A b) Total travel distance for all four patterns

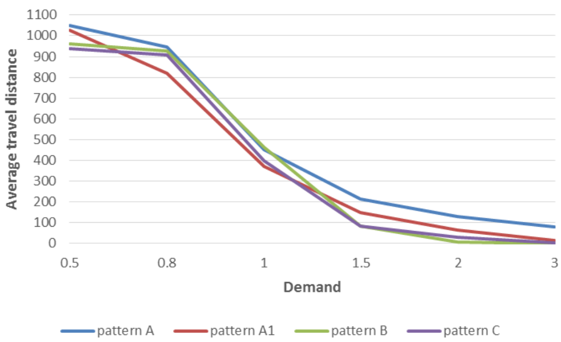
a) b)



In Fig.6 b) the TTD (total travel distance) of all patterns are drawn for each demand level and they all have similar shapes. TTD of pattern A and A1 are better than pattern B and C with a demand of $\alpha = 0.5$, but when $\alpha = 1$, total distance of pattern B become the largest one and better than pattern A and C, whereas pattern A1 is the lowest. At this demand level there is a certain point that TTD of all networks decreased with demand increasing since there are more cars on the roads and congestion happened. We can also find that pattern A has a best performance and much better than others in the congested scenario.

The average travel distance (ATD) can be calculated by dividing the TTD by the number of vehicles that still on the networks and arrived at their destinations. It is an indicator that can be used to make reliable comparisons of the results.

Figure 7 Average travel distance for all four patterns



It is visible in Fig.11 that with the increase of traffic flow, curves of average travel distance are all fall down especially during demand level α from 0.8 to 1.5. No matter if in uncongested or congested scenarios drivers in network of pattern A always travel longer distances. Besides, there is not a clear difference between pattern B and C.

3.1.2 Delay and Stops

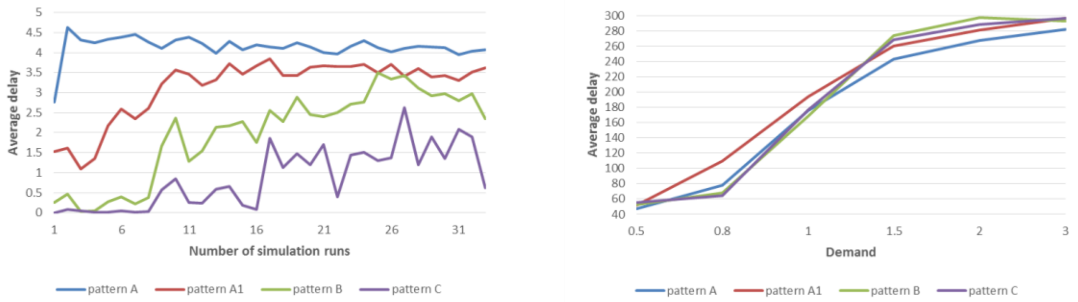
Average travel delay got directly from the simulation results and it also got an average value of six different demand levels. We can also get percentage of delay stopped and it can be used to analyze the effect of intersections and route redundancy.

$$percentage\ of\ delay\ stopped = \frac{average\ stopped\ delay}{average\ delay} * 100\% \qquad (4)$$

It is shown the relationships between average delay and number of iterations with a demand of $\alpha = 1$ (Fig.8 a)). Average delay of pattern B and C changed a lot with the number of simulation runs because they have more links and routes than other patterns. After the third simulation runs pattern A keep a more steady result.

Figure 8 a) Average delay for all networks ($\alpha = 1$) b) Average delay for all networks

a) b)



It can be obtained in Fig.8 b) that the shapes of average travel delay of all networks are similar but we can still conclude some rules such as with an increase of demand level from 0.5 to1, the average delay of pattern A1 is much higher than others and pattern A is lower than other three patterns with a demand of $\alpha = 1$.

Figure 9 % Delay stopped for all networks

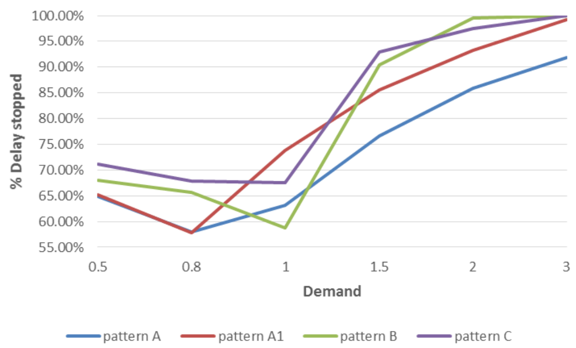
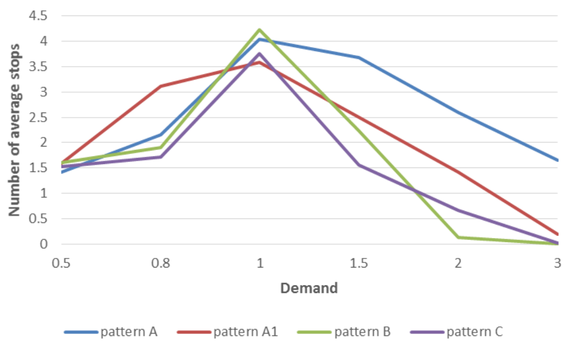


Fig.9 shows the proportion of stopped delay in total delay with the change of demand level. The % delay stopped of pattern A and A1 begin to increase with a demand of $\alpha = 0.8$ and the drivers in pattern A1 always have higher proportion of stopped delay than pattern A for 10% . When the demand level raise to $\alpha = 1$ pattern B and C start to increase.

Figure 10 Number of stops for all four patterns



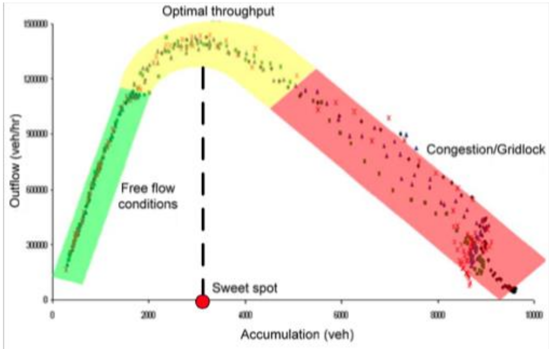
If there are too many trip stops because of congestion or signal lights it will decrease comfort and of course, increase total travel delay. It also will bring more emissions to the air. Fig.10 shows the performance of average number of stops for all networks. Similarly as TTD, the number of stops go raise with the increase of demand level and have a turning point at the demand level of $\alpha = 1$. In the congested scenario, pattern A is still perform worse than other networks.

3.2 Network performance indicators

3.2.1 Macroscopic fundamental diagram (MFD)

The Macroscopic fundamental diagram (MFD) is an effective instrument to study congestion propagation of networks. The model developed by Gerolomins and Daganzo in 2007 is the widely used one (Fig.11 shows). The sweet spot is the accumulation at which the system reaches the maximum flow.

Figure 11 MFD for a network



Source: Geroliminis and Daganzo (2007)

The MFD focus on the whole network rather than a single link or some links. The weighted average flow (q_t) and weighted average density (k_t) are applied to get the MFD (Geroliminis and Daganzo, 2008). These average flows per lane, q_t, and average densities per lane, k_t, are obtained for every time slice t, e.g. every 5 min. q_t^i and k_t^i correspond to the total flow and density of link i for time slice t, m^i corresponds to the number of lanes on link i, and l^i corresponds to the length of link i.

$$q_t = \frac{\sum_i q_t^i l^i}{\sum_i m^i l^i} \quad (5)$$

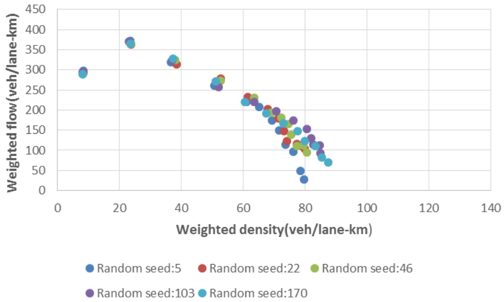
$$k_t = \frac{\sum_i k_t^i l^i}{\sum_i m^i l^i} \quad (6)$$

Link evaluation output of VISSIM was collected to get the MFDs of all four networks.300 seconds has been chosen as the time interval to calculate average weighted density and average weighted flow. Six different demand levels need to be considered to draw the MFD.

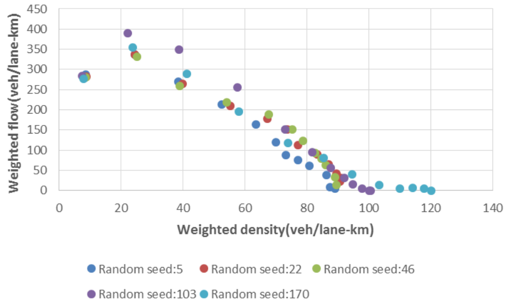
In Fig.12 all the networks have similar results for five different random seeds. Results show larger variations among random seeds in pattern A1 than other patterns, both in vehicle capabilities and congestion indicator. Different random seeds have less influence on the results of pattern A because it has less route choices.

Figure 12 MFD for all networks among five random seeds

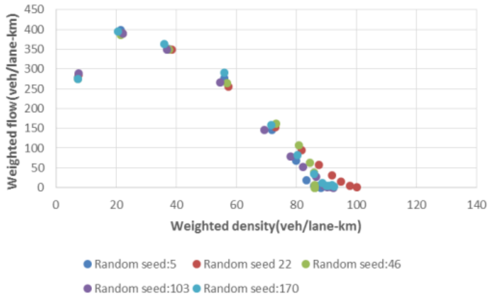
a) pattern A



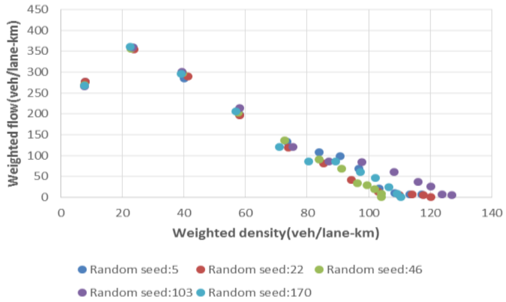
b) pattern A1



c) pattern B



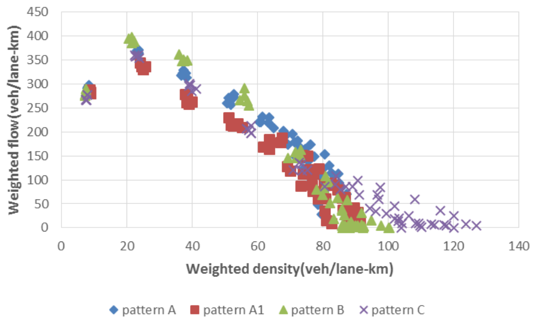
d) pattern C



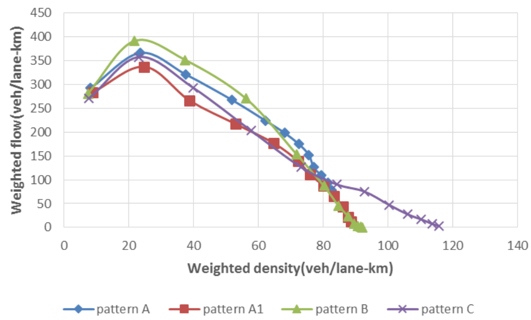
Then we put all MFDs of five random seeds for each networks into a diagram (Fig.13 a)) to analysis the different among networks. The difference among networks are more clear in Fig.13b) which contains average results for five random seeds.

Figure 13 a) MFD for all networks b) MFD for all networks with average results of five random seeds

a)



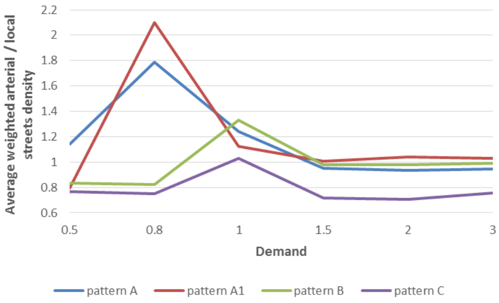
b)



We also care about performance of arterial streets and local streets. Fig.14 shows the ratio of average weighted lane density of all arterial streets over the average weighted lane density of all local streets. It can be observed that the ratios of pattern A1 and pattern A are much higher than pattern B and C. Especially, the ratio of pattern A1 is tripled over pattern C.

It is obvious that most drivers chose arterial streets when the total demand level is low meanwhile both arterial streets and local streets have similar density with the increase of demand level. The average weighted lane density of arterial streets of pattern C is much steady with the change of demand level. Differently, the variation of ratio of arterial street density to local street density of pattern A is much higher than others.

Figure 14 Ratio of arterial street density to local street density

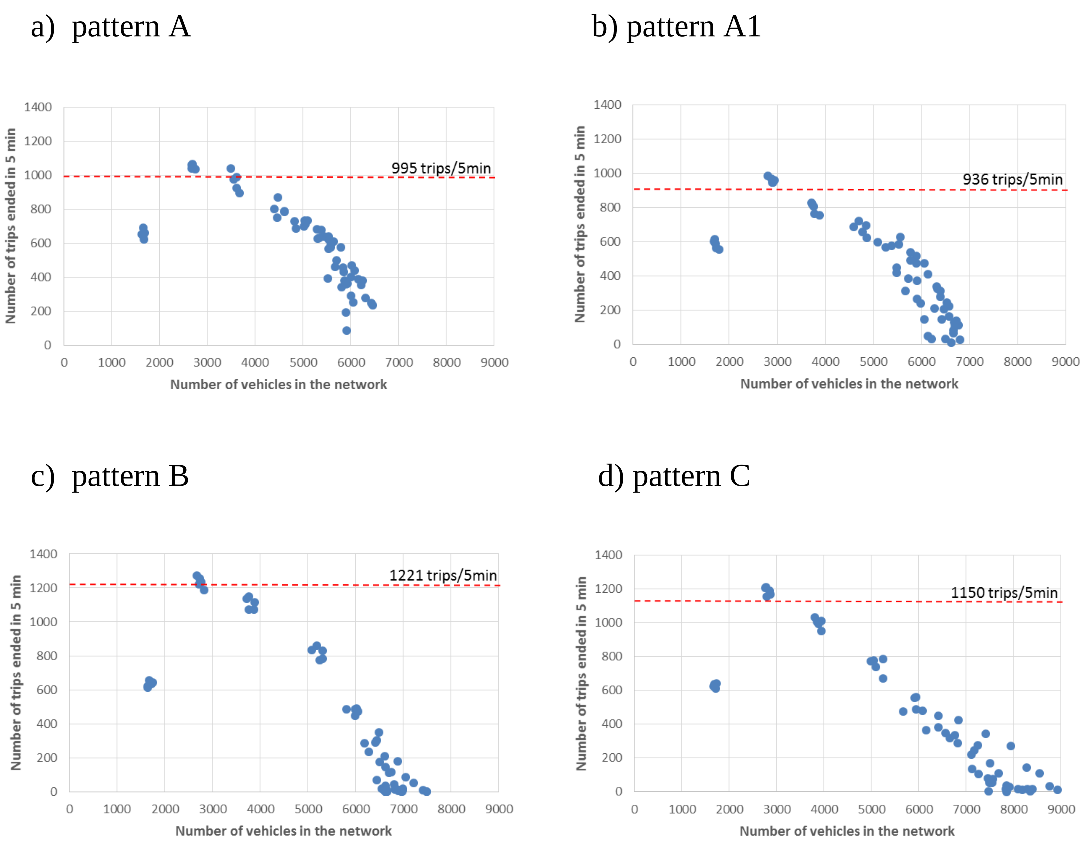


3.2.2 Network exit function

The Network Exit Function (NEF) plots the trips ending in a time interval versus the accumulation of cars in the network. Daganzo (2007) shows that the MFD can be used to derive the NEF and the needed data can be got from the network performance output in VISSIM.

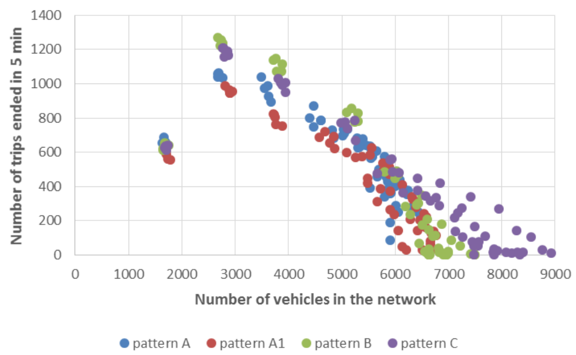
The shape of all NEFs of different four patterns are similar but they have different periods (Fig.15). It means that the four networks have different trip-serving capacities and pattern B has the highest capacity which is 1221 trips per 5 min, while pattern C network has 1150 trips per 5 min, greater than pattern A which has 995 trips per 5 min and 936 trips per 5 min. Both pattern A and A1 has lower capacities since they have fewer route choices and lower road connectivity. Pattern B and C are greater than the capacity of pattern A1 by 30.4% and 22.9%, and greater than A by 22.7% and 15.6%.

Figure 15 NEF for all networks



Besides, there are almost 9000 vehicles for accumulation in the network of pattern C when the completion rate is zero whereas around 7500, 7000 vehicles in pattern B and A1. With a same demand of $\alpha = 1$, there is still some capacity rest for pattern A but other patterns all have got into the congested scenario. Fig.16 contains all NEFs for four patterns.

Figure 16 NEF for all patterns



4. Summary and conclusions

The main goal of this paper is find out the different traffic performance of different block patterns. For this purpose four block patterns: linear-based with 4 lanes each local street, linear-based with 2 lanes each local street, grid-based and circular plus radial pattern, were built with same lane length and signal timing. They were evaluated by implementing a traffic simulation software with a DTA in VISSIM. Both traffic performance and network performance are considered to evaluate different patterns.

The results of this paper help us understand how four typical block patterns influence the traffic performance in uncongested and congested situations. Summarizing, we can get following conclusions:

-In the uncongested scenario, the trip length and the intersections of different patterns are two main factors that influent the networks. Although pattern B and C offer shorter travel distance but have a higher density of intersections. Compare with pattern A1, pattern A with less number of intersections have lower total average density.

-With the increase of demand level, the network is approaching the capacity states. In this process pattern B and C have a better performance than pattern A and A1. One reason is that pattern B and C have more route choices and higher road connectivity. They can disperse more crowded traffic flow.

-In the congested scenario, the NEF shows that pattern A1 has a lowest capacity value than others. It means that once the network reaches capacity conditions it gets highly congested very fast by increasing the density. It also shows that pattern B has multiple option to choose to reach a destination so it need longer time to get congested.

Some study shows that the way demand is distributed over the network has an influence over the results (Ortigosa J, 2015; Oriol, 2015). In this paper demand distribution of pattern B is uniformly and other three patterns have an unbalanced but centrosymmetric demand distribution. For the future more studies should consider on demand distribution.

Six different demand levels were considered in this study during one hour in VISSIM, but in real-life conditions demand is not constant over time. In this case it maybe consider longer simulation periods and much variations of demand levels.

Besides, different patterns bring different block size, and it will influent not only vehicle traffic but also public transport and pedestrians. Taking into account multi-modes of urban traffic to analyse block patterns will be a future research topic.

To sum up, the performance of pattern A1 is worse than others in many aspects and pattern C has a medium comprehensive assessment. Pattern A and B all have many advantages and disadvantages in performance and pattern A has a better mobility degree and also allowed to create friendly and green neighborhood living spaces.

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