A Quantitative Analysis of Superblocks Based on Node Removal

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ABSTRACT Superblocks are city blocks whose size is significantly larger than average. Despite their widespread use across countries such as China, few studies have investigated how these superblocks affect network traffic performance. This paper aims to narrow that gap in knowledge. To that end, we use a grid network emulating a dense city environment. Then, multiple scenarios corresponding to size, location, shape, and number of superblocks are designed by removing nodes and related links. We evaluate network traffic performance by considering the factors of travel distance, travel time, volume-to-capacity ratios on nodes and links, as well as the level of traffic heterogeneity. The results indicate that superblocks with relatively small size (i.e. less than 1/4 of the network size) do not affect traffic significantly. The importance and connectivity of nodes and links related to superblocks are crucial factors affecting the overall traffic performance. In general, the more central the superblock, the larger its influence on the network traffic, except for extremely large superblocks that can significantly affect traffic when located in the periphery, as they lead to high traffic heterogeneities. Rectangular superblocks are more detrimental than square ones. Furthermore, traffic performance can be significantly improved by dividing the superblock into several relatively smaller blocks. Our results should be of direct interest to city-planning decision-makers in dense urban centers.

INDEX TERMS Urban traffic, block size, superblocks, traffic performance, node removal.

I. INTRODUCTION

Urban road networks can be generally divided into two categories, namely, small block size networks (i.e. dense road networks) and large block size networks (i.e. sparse road networks) [1]. The former have more road space and provide a larger number of alternative routes that distribute traffic flow faster. On these networks the travel routes for pedestrians are also shorter and safer, due to the higher density of smaller intersections. On the other hand, as a car-friendly system, the large block size type of network usually has lower road density and connectivity, but higher link and intersection capacity. These two types of road networks can be combined to different levels. As a matter of fact, many cities around the world contain dense road networks in their downtown areas, while they become sparser in the periphery. In other places, for example, many cities in China, the two networks can overlap, i.e. small blocks are combined with large blocks in the same area of the city. These large blocks, also called superblocks, can be rather large - up to 1 km or longer; in comparison with average blocks that can be 200 m long.

Recently, the Chinese government has proposed a policy named “Open Block” to divide superblocks into several smaller blocks. The main purpose of this is to optimize the road network layout and improve the utilization of land use through a more fine-grained urban pattern by transforming the internal roads nested in the superblocks into public streets [2], [3]. However, the impact of the resulting street patterns on network traffic performance is rarely considered by managers. In fact, there is limited quantitative research into the effects of the existing superblock infrastructure on traffic, i.e. the existing research focuses mainly on the qualitative properties of open blocks [4].

A good portion of the existing research on street networks has been mostly based on graph theory, focusing on the topology of the network. For example, since the concept of centrality was proposed [5], it has been widely applied in many different forms (e.g. degree centrality, closeness centrality,
betweenness centrality, straightness centrality, information centrality) to describe transport networks’ features and their efficiency [6]–[8]. The same is true for the concept of connectivity, measured by the cyclomatic number, meshedness coefficient, link to node ratio, γ index, etc. [9]–[13]; and node importance [14]–[16]. As a matter of fact, it is quite common to refer to road networks as graph networks, using a primal approach with the streets mapping into links and the intersections mapping into nodes [12], [13]. The dual approach, representing intersections as edges and streets as vertices, although less common, has also been used [9], [17]. This dual approach is based on the notion of spatial syntax proposed by Hiller [18], who recognized streets by their own functions, not merely as a connection between locations. Other concepts that allow us to capture different features of the transportation networks include the entropy to measure the heterogeneity (hierarchy) of the road speed, the Gini index to estimate the actual usage of the streets, and the ringness, webness, circuitness, and treelessness to measure the connection patterns of the street network [19], [20]. There are also other theories (e.g. game theory, percolation models) used to describe the networks and their dynamics [21]–[25].

In the last decades there have been also some studies linking specific aspects of the road network to the overall traffic performance [26]–[29]. All these studies aim to figure out how to allocate and organize urban space better, how to design streets more effectively, and how to determine which street configurations can handle traffic the best. However, so far, there is no consensus on the basic street configuration and block size. Zhang et al. [30] discussed the effects of different block sizes on the overall traffic performance. However, they only considered networks with uniform block sizes. For those cases, they showed that under low traffic scenarios, networks with smaller blocks lead to shorter travel distances, while networks with larger blocks lead to less turning maneuvers and shorter travel times. On high demand scenarios, networks with smaller blocks have a higher trip ending rate, while networks with larger blocks take longer to get congested and gridlocked. The questions remain, however, for networks with different block sizes: To what extent do superblocks affect traffic? Which characteristics of superblocks (e.g. size, location, shape, number) have the biggest impact on the overall network performance? Is it possible to minimize such impact?

This paper aims to address these questions by first determining whether or not superblocks have an obvious impact on the network performance, and then determining the magnitude of such impact (if any). The contributions of this research are twofold. First, we propose a method to model the network structure of superblocks. By removing node(s) and adjacent links from the basic square grid network, superblocks with different features can be created. We use a grid network as the basic structure because it is prevalent in the real world and widely applied in network studies to simulate the urban traffic environment [31]–[34]. Second, we assess the impact of superblocks in regard to four different features, i.e. size, location, shape, and number. To do so, four scenarios are built to quantify the impact of each single feature of superblocks on network performance. To the best of our knowledge, this is the first study focusing on the relationship between size, location, shape, and number of superblocks and the overall network’s traffic performance. The results and other insights from this paper will aid transport and urban planners in the decision making process regarding superblocks. In China, in particular, this analysis could be crucial to the controversy and policy decisions regarding the opening of the existing superblocks.

The rest of the paper is organized as follows. Section 2 introduces the methodology used to perform the whole analysis (network design, demand, traffic assignment, superblocks creation, traffic indicators). Section 3 presents the results of the analysis. Section 4 discusses other possible scenarios, including different network sizes and other demands. In Section 5, conclusions and future work are presented.

**FIGURE 1.** Flowchart of the methodology.

### II. METHODOLOGY

A flowchart illustrating the overall methodology is shown in Fig.1. First, we build the basic network by using a square grid with a small block size. Loading a uniform demand on the network, we assign the traffic trips according to a static traffic assignment model that leads to the user equilibrium. Both, the road impedance and the intersection delay are considered in the travel time function. The overall network performance is evaluated using travel distance, travel time, volume-to-capacity ratios on nodes and links, as well as the level of traffic heterogeneity across the network. Later, the node removal process is employed to generate superblocks paying attention to four different features (i.e. size, location, shape, number). Multiple scenarios reflecting changes to these four features are designed to analyze how each of these features impacts the overall network performance. To maintain a consistent demand, we re-assign the demand of the removed

![Flowchart of the methodology.](image-url)
node(s) to the remaining nodes on the modified networks. For each network configuration we then run a static traffic assignment to evaluate the network performance. The impact of superblocks, that is, the extra delay caused by superblocks is estimated by comparing the performance of the modified networks to that of the basic network.

**A. NETWORK DESIGN**

We consider a regular grid network with nine nodes on each side to represent a dense city environment. Each node simulates a four-leg intersection (except those in the perimeter), and acts as an origin/destination to generate/absorb traffic demand. Demand is assumed to be uniformly distributed over the whole network, with each node exchanging the same number of trips with each other node. Based on data from Chengdu, China, every link is set as a 150 m-long two-way street with one lane for each direction. In other words, basic blocks all have a length of 150 m, so that the total area of the network is 1.44 km². Superblocks are then considered to be at least two times larger than the basic blocks (i.e. the sides of a superblock must be at least 300 m). Although streets only have one lane per direction, in intersections, for every incoming direction an extra lane is added to separate cars that want to turn left. The saturation flow for each lane is 1,800 veh/h, and the free flow speed is 50 km/h. Notice that although the basic network shows a relatively low demand level, some links will become quite saturated as soon as nodes are removed.

Changes in street patterns are normally accompanied by changes of land use types, which could lead, in turn, to changes in demand. In order to focus on the change of traffic performance caused only by street patterns, the total demand for the network is assumed to remain invariant even during the node removal process. In other words, the demand from the removed nodes is transferred to the adjacent nodes that are still part of the road network. In the example from Fig.2, the demand associated with node 7 is transferred equally to each of the four corners of the superblock, i.e. nodes 2, 4, 10, and 12.

**B. TRAFFIC DEMAND**

The intersection nodes are regarded as the origins and destinations of travel demand. An Origin-Destination Matrix (OD Matrix), used to describe the traffic demand in this paper, displays the number of trips exchanged between each origin and destination in a fixed period, generally one hour. The number of trips exchanged between origin \( i \) and destination \( j \), \( T_{ij} \), is given by the following equation:

\[
T_{ij} = \begin{cases} \tau, & i \neq j \\ 0, & i = j \end{cases}
\]

(1)

where \( \tau \) represents the number of trips per hour exchanged between any two given intersection nodes. Different values of \( \tau \) account for different demand levels. Inspired by the travel data from Chengdu, here we use \( \tau = 3 \). Thus, the total number of trips in the basic network is 19,440 per hour. Notice that although the basic network shows a relatively low demand level, some links will become quite saturated as soon as nodes are removed.

The STA model, assigning traffic to the different roads according to the user equilibrium [36], is solved with the Frank-Wolfe (FW) algorithm [37]. FW is widely used to solve the traffic assignment model, as it has reasonable computational times and low memory requirements. Both road impedance and intersection delay are considered as part of the travel time function during the traffic assignment process. To improve the operation speed of the traffic assignment model, we transform each intersection into multiple virtual nodes and links. As shown in Fig.3, the center of a 4-leg intersection can be regarded as a virtual main node, while the inlets and outlets of the four directions are regarded as 12 virtual sub nodes. In this way, the intersections are converted into links for the shortest path search. These dummy links have either a zero cost (for loading and unloading the
 FIGURE 3. Links on a 4 leg intersection. Dashed lines represent inlets and outlets of the intersection, to load and unload the demand into the network. Continuous lines represent traffic movements associated with some specific delay due to the signal phases.

 FIGURE 4. (a) Average travel distance (indexed). (b) Average travel time (indexed).

demand into the network, or for splitting the straight and right turn movements) or a positive cost (to account for the delay associated with the different signal phases). A similar setting was used in other reports [35].

D. ROAD IMPEDANCE FUNCTION

The classic BPR [38] function is utilized as the road impedance model; thus, the travel time on the link is given by:

$$t_a = t_0 \left( 1 + \alpha \left( \frac{x_a}{C_a} \right)^\beta \right)$$

(2)

where $t_0$ is the free flow travel time on the link $a$ (i.e. the ratio of link length (traveled distance) and free flow speed), $x_a$ is the link flow in veh/h, $C_a$ is the link capacity also in veh/h, $\alpha$ and $\beta$ are parameters obtained by experimental observations. Here, we use the default values typically used in the literature, $\alpha = 0.15$ and $\beta = 4$.

E. INTERSECTION DELAY

All intersections in the network are assumed to be signalized intersections. For simplification purposes, we adopt a fixed signalized control for intersections, i.e. the signal timing is invariant to the demand. Based on the data of Chengdu, we consider a total cycle of 60 seconds for each four-leg intersection (without node removal), with green phases for the straight and right turn movements lasting 17 seconds, and 8 seconds for left turning, with 10 seconds of lost time. Recall that a saturation flow of 1,800 veh/h for each lane is used. Therefore the total capacity for the straight and right turn movements combined is 510 veh/h, and for the left turn movement 240 veh/h. Since the straight and right turn movements share the capacity, the delay is allocated jointly. When we create a superblock by removing nodes and links, some four-leg intersections become three-leg intersections. Then another signal timing is considered for these new three-leg intersections, with three phases of 15 seconds each and a total of 15 seconds lost time. All the movements are separated and have an equal capacity of 450 veh/h.

The intersection delay formulation in HCM-2010 [39] is used here to calculate the delay at each intersection. It is worth noting that the delay formulation in HCM-2010 cannot be used directly for the traffic assignment model because it is non-differentiable. Therefore, we use the same transformation proposed by Ortigosa and Menendez [35] and adjust the HCM-2010 formulation into a 3 piecewise function that is continuous and differentiable. For the resulting function, the middle piece is a 3rd degree polynomial function, while the first and last pieces are linear.

F. SUPERBLOCKS

In this research we focus on four variables to describe the presence of superblocks: size, location, shape, and number. Therefore, we design four types of analyses, each addressing one of these variables. Nodes and links are removed accordingly.

This removal process not only changes the topology of the network, but that of the intersections themselves: many four-leg intersections become three-leg intersections and three-leg intersections are turned into two-leg nodes. The latter are regarded as normal links without any intersection.

G. TRAFFIC INDICATORS

This paper calculates traffic indicators, including average travel distance, average travel time, intersection delay, node saturation, and link saturation, to evaluate the impact of superblocks on the network traffic performance. The average travel distances/times are estimated as the ratio of total travel distances/times (i.e. the sum of travel distances/times between all OD pairs) to the total number of trips. They are useful to understand the efficiency of the network. Intersection delay mainly refers to traffic signal delay, and reflects the role that intersections play on the total travel time. The node/link saturation, which is also known as volume-to-capacity ratio (V/C), indicates the network level of congestion and the importance of a given node/link within the whole network.
H. COMPUTATIONAL COMPLEXITY

For the basic network, which has 81 origin/destination nodes, and 1053 nodes/1948 links after considering the more complex design for the intersections (Fig.3), our algorithm achieves a relative gap in travel time of 1E-4 under a small demand scenario. This is achieved in less than 10 minutes using the i7 processor. That usually happens after approximately 30 iterations. Although this number of iterations might seem low, for our purposes the obtained level of accuracy is reasonable. To account for each superblock feature, we generate thousands of scenarios leading to different traffic assignment processes. The traffic assignment is performed using a FW algorithm, that accounts for both, road impedance and intersection delay (details were given in Sections II-C, D, E). Notice that compared to the Gradient Projection (GP) algorithm, the FW shows a similar convergence speed, but lower memory requirements (16% less than the GP algorithm). The computational cost in all cases was similar to that of the basic network, yielding also a similar quality of results.

III. EFFECTS OF SUPERBLOCKS

Here we regard the area of the basic blocks (150 x 150 m²) as a unit value. Superblocks can have a square or rectangular shape. The area of a square superblock can be 4, 9, 16, 25, and 36 times the unit value. Such setting of superblock parameters is based on realistic values from cities across China. Recall that no more than half of the nodes can be removed at any given time, and removed nodes cannot be in the perimeter of the network. Below we conduct four types of analysis to evaluate the impact of the superblocks. For each analysis, networks with different superblocks are simulated, and the traffic indicators described above are calculated.

A. SIZE OF SUPERBLOCKS

In this analysis, 1, 4, 9, 16, and 25 nodes are removed from the basic network to generate new networks with square superblocks whose areas vary from 4 times to 36 times the unit value. For superblocks of any given area, multiple simulations are run to cover as many locations as possible of the superblocks within the networks; then, the average results across all locations are calculated.

Fig.4 shows the average travel distance (ATD) and average travel time (ATT) as a function of the area of the superblocks. The black lines represent the average values, while the grey lines represent the range of values observed. Link density is computed as the total link length divided by the network area; its value is affected by the number of nodes and links removed. Node connectivity here is defined as the average number of nodes directly connected to each single node in the network (i.e. the average number of legs per node). Last, node saturation (i.e. V/C on nodes) is calculated as the ratio of volume-to-capacity on nodes. Compared to the basic network, the larger-sized superblocks involve a higher proportion of removed nodes and links, hence a lower overall road density and road connectivity, as shown in Fig.5a and Fig.5b. Furthermore, with the decrease of link density and node connectivity, not only the node V/C ratio increases, but also its variance (Fig.5c). As we know, higher node saturation leads to higher intersection delay, which contributes significantly to the average travel time (as seen in Fig.4b).

Fig.5 shows the link density, node connectivity, and node saturation. As before, the black lines represent the average values, while the grey lines represent the range of values observed. Link density is computed as the total link length divided by the network area; its value is affected by the number of nodes and links removed. Node connectivity here is defined as the average number of nodes directly connected to each single node in the network (i.e. the average number of legs per node). Last, node saturation (i.e. V/C on nodes) is calculated as the ratio of volume-to-capacity on nodes. Compared to the basic network, the larger-sized superblocks involve a higher proportion of removed nodes and links, hence a lower overall road density and road connectivity, as shown in Fig.5a and Fig.5b. Furthermore, with the decrease of link density and node connectivity, not only the node V/C ratio increases, but also its variance (Fig.5c). As we know, higher node saturation leads to higher intersection delay, which contributes significantly to the average travel time (as seen in Fig.4b).

An increase in the size of the superblocks also leads to an increase in the links’ V/C ratios. Fig.6a shows the links’ V/C could be even 6 times higher than for the basic network. Such a large variance reflects the importance of the location of the superblock, which can lead to significant congestion levels, affecting the ATT much more than the ATD. In any case, this pattern is reasonable as such large superblocks include the removal of almost half of the links in the whole network. In other words, the size of the superblock is important mostly in relation to the size of the network, and its location is key in determining its impact (more details on this are given in sections 4.1 and 3.2, respectively).
B. LOCATION OF SUPERBLOCKS

In this analysis we use a square superblock and move it across the network to evaluate the impact of its location. We first focus on a square superblock of area 4 (i.e. an area equivalent to 4 times the unit value), for which the removed node defines its location within the grid. Afterwards, we increase the size of the square superblock, and evaluate its location just cataloging it as central or in the periphery (depending on whether any vertices of the superblock are located on the network edges).

Generally, for a regular grid network of finite size, with a uniform traffic demand, the most central nodes carry the highest flows (see Fig.6a). In other words, the central nodes are the most important ones, thus removing them have the biggest impact on the overall traffic performance [35]. To account for this, here when analyzing the superblocks of size 4, we use the importance level of the removed node to estimate the impact of its location. To assess the importance level of each node, we calculate its betweenness centrality [40]. Due to the network’s symmetry, we only investigate one-eighth of the network. Each grey dot in Fig.7 shows a node that can be removed. Fig.7a shows the betweenness centrality (BC) of each of the potentially removed nodes. Fig.7b shows the average travel time (ATT) for the networks generated after removing the corresponding nodes.

As expected, the more centrally located superblocks lead to the highest travel times. The differences, however, are not significant. This is not surprising, as the previous analysis had shown that a single superblock of size 4 has almost no impact on travel times. Notice that this might not be true for very high traffic demands. Moreover, as the size of the superblock increases, the differences become more significant. Recall the variance observed in Fig.4b for superblocks of size 25 and 36.

As previously stated, for superblocks with areas larger than 4, we only catalog its location as being central or in the periphery (if one of its sides in on the networks’ edge). Fig.8 shows the average travel time (indexed) of networks with superblocks of different sizes, located in the center, in the periphery, or anywhere in the whole network (any of the two prior classifications). These averages are obtained from simulations with many possible locations. Interestingly, for...
superblocks of size 4, 9 and 16, the highest travel times take place when they are located in the central area (although the differences across locations are not large). For superblocks of size 25 and 36, locations in the periphery are significantly the most detrimental. Below we explain the reason for such unexpected pattern.

**FIGURE 9.** The betweenness centrality (BC) of nodes in networks with a superblock (a) located in the center and (b) located in the periphery.

Fig.9 shows the BC of each of the remaining nodes for two networks with a superblock of size 36, located in the center and in the periphery, respectively. The dark grey shaded numbers represent the maximum values of BC among all the nodes, and the light grey shaded numbers represent the minimum ones. While the superblock located in the center leads, evidently, to a symmetric pattern, the one in the periphery does not. Moreover, it accentuates both the maximum and the minimum BC values. In other words, it generates much more traffic heterogeneities, leading to worse overall traffic performance (see Fig.8).

**FIGURE 10.** Gini index of V/C on links of networks with superblocks.

Fig.10 shows the average and variance of the Gini index of the V/C across all links for networks with a superblock in the center or in the periphery. A Gini index of 0 indicates equal V/C values across all links, whereas 1 indicates a high inequality. Results show that the Gini index of networks with superblocks located in the center is larger than the ones in the periphery when the size of superblocks is smaller than 16. This trend, however, reverses for larger superblocks, further confirming the traffic heterogeneities driven by very large superblocks in the periphery of a network.

**FIGURE 11.** Percentage of average travel time that happens at intersections of networks with superblocks.

Fig.11 shows the percentage of travel time that happens at intersections for superblocks of different sizes, located in the center, in the periphery, or anywhere in the whole network. It exhibits a similar pattern as Fig.8. Notice also that for superblocks of size 36, close to 80% of the delay takes place at the intersections, in particular those in the corners of the superblock (see Fig.6d and Figs.9a-b).

**FIGURE 12.** V/C on links of the network with (a) a square superblock and (b) a rectangular superblock.

**C. SHAPE OF SUPERBLOCKS**

In this analysis, we compare the impact of two different possible shapes for the superblocks (i.e. square vs. rectangular) on network traffic performance. To this end, two networks are designed: one contains a square superblock, which is generated by removing one node and the four adjacent links, and the other contains a rectangular superblock, which is generated by removing three parallel links (see Figs.12a and 12b, respectively). Square blocks are common in cities like Portland and Xi’an, while rectangular blocks are more popular in other cities such as New York and Miami. Both of the
superblocks are constructed to have the same area, equivalent to 4 unit values, and a location as similar as possible.

As we have already seen, superblocks can impact travel times in the network mostly by changing network connectivity and road density, which in turn leads to higher V/C ratios at specific locations.

The results show an average travel time of 96.6 s in the network presented in Fig.12a (square superblock), and 98.4 s in that of Fig.12b (rectangular superblock). The network with the square superblock has a shorter road network length (0.94 km vs. 0.96 km) given by the removal of 4 links instead of 3. However, it retains a higher overall road connectivity (3.5 vs. 3.48), which may contribute to the better traffic performance. For example, for the travelers that go from node $i$ to node $j$, the higher link connectivity offers a larger number of alternative routes, and also a lower number of turning maneuvers. The higher number of alternative routes distributes traffic more homogeneously throughout the network. The lower number of turning maneuvers reduces the average intersection delay. Moreover, the square superblocks generate on average shorter detours than the rectangular superblocks, with an average extra distance of 0.5% vs. 2.7% on top of that of the basic network.

D. NUMBER OF SUPERBLOCKS
In this analysis, we construct networks with different numbers of square superblocks. The area of each superblock is fixed (i.e. 4), while the number of superblocks ranges from 1 to 4. They are kept separated (no two superblocks are adjacent to each other) in the initial analysis. Afterwards, the results with four adjacent superblocks, each with size 4, are compared with the results from a single superblock of size 16. For each scenario, we run 50 simulations to cover as many locations as possible and then calculate the average results.

Fig.13a shows the average travel distance/time as a function of the number of superblocks. Both the ATD and ATT increase gradually, and the differences compared to the basic network are not very significant. Interestingly, different from before, the ATD increases faster than the ATT. In other words, the effects on travel detours are more pronounced than the effects on traffic congestion. We expect though, that as the demand increases or if we were to remove more links (i.e. the superblocks were larger), the system would become more congested and the ATT would increase more than the ATD. The results are similar when we look at the average node V/C ratio in Fig.13b.

When compared to networks containing a superblock of size 16, a network with four adjacent superblocks of size 4 yields better traffic performance. A single superblock of size 16 leads to average travel times of 122 s, around 24% higher than that of a network with the four superblocks of size 4. This is reasonable as the large superblock leads to a significant decrease in link density and network connectivity. This also proves that dividing a superblock into smaller blocks is an effective way of improving traffic performance in urban networks.

IV. OTHER VARIATIONS TO THE PROBLEM
A. NETWORK SIZE
As previously discussed, the impact of superblocks on overall network performance becomes significant when the area of the superblock is larger than 16 (i.e. the ratio of the area of the superblock to network size is 1/4). For better understanding the relationship between network size and network performance, here we keep the superblock size (i.e. 4) and vary the network area from 9 to 64.

As shown in Fig.14, the average travel time (indexed) of networks with a superblock increases as the area of the network becomes smaller. Interestingly, similar as above, when the ratio of the area of the superblock to the network size is smaller than 1/4 (4/16 in the graph), the ATT (indexed) of networks increases gently. For ratios larger than 1/4, the ATT increases by 8% (when the size of superblocks is 25), and by 34% (when the size of superblocks is 36) compared to the basic network. In other words, the impact of superblocks on overall traffic performance is not only a function of the size of the superblock but it is also related to the network size. The ratio 1/4 is observed in this paper as a turning point.
B. DEMAND

Recall that we assume a uniform demand distribution, emulating demand patterns in very dense city centers (this assumption will be relaxed later). The number of trips ($\tau = 3$, i.e. 19,440 trips per hour) corresponds to the daily demand level of Chengdu, China, and is considered to represent a common city environment. For the sake of completeness, however, here we run the analysis again for higher levels of demand, that is $\tau = 4$ (i.e. 25,920 trips per hour) and $\tau = 5$ (i.e. 32,400 trips per hour). The results still support the aforementioned findings, although for superblocks with relatively small areas, such as 4 and 9, the impact on traffic performance is significant under high-demand scenarios.

Different demand patterns might lead to different travel behaviors under the STA model. To understand whether the above results can be generalized to non-uniform demand patterns, the following two scenarios are constructed:

(a) the number of trips generated and attracted by nodes in the perimeter of the network is three times higher than that of the other nodes.

(b) the number of trips generated and attracted by nodes surrounding the superblocks is three times higher than that of the other nodes.

![Diagram](Fig.15a and 15b show the average travel time of networks under the two non-uniform demand patterns mentioned above. Results are very similar to those of the network with a uniformly distributed demand (Fig.8). That being said, it is worth noting that under non-uniform demand patterns, the distribution of traffic tends to be slightly more heterogeneous (with trips being more concentrated on some links and nodes). This, in turn, leads to an earlier start of the traffic congestion, and a slightly faster increase of the average travel times.

V. CONCLUSION

Over the past few decades, the influence of block size on traffic performance has been discussed from the perspectives of both urban planning and traffic planning. The existing research mainly focuses on networks with different but uniform block sizes, and little attention has been paid to situations in which small and large blocks coexist in a network. Even fewer studies have conducted a quantitative analysis on the impact of superblocks on traffic performance, and whether it is reasonable or not to split them into smaller blocks. This paper provides some of these answers, and relevant insights for urban planning, promoting a deeper understanding of the relationship between network structure and traffic performance.

To do so, we use simulation tools to analyze the traffic performance of networks with different size, location, shape, and number of superblocks. In our study, all the streets have the same characteristics and the demand is uniformly distributed across the network, which means that under normal circumstances the central streets carry a higher flow. The FW algorithm is used to solve the static traffic assignment model, which describes the users’ traffic behavior in our networks. In this paper we focus on quantifying the impact of superblocks, not on developing new algorithms. The analysis presented here can be considered a first building block toward future optimization models for the design of urban networks with superblocks. Insights from this research shed light on the most important features of superblocks and how they affect traffic performance.

The results indicate that the size of the superblocks is the most important parameter to influence the overall network performance. Under a given demand ($\tau = 3$), a superblock up to a certain size (e.g. 3-4 times the size of a basic block) does not affect traffic significantly; only when the size of a superblock is more than 4 times the size of a basic block can its impact on the traffic performance no longer be ignored (the average travel time can increase up to 6 times). Furthermore, such impact is directly related to network size; when the ratio of the area of the superblocks to the network size is 1/4 or higher, the impact of superblocks can be significant.

Besides the size, the location of superblocks also contributes to the network performance. Very large superblocks can be highly detrimental when located in the periphery as they can lead to very high traffic heterogeneities. Similarly, the number of superblocks can affect traffic performance by changing the distribution of traffic in a network. Last, the shape of the superblock impacts the traffic performance as well. A rectangle superblock lowers the number of alternative routes and increases the number of turning maneuvers compared to a square superblock. Overall, the combined impact of these four parameters can be calculated to define if a superblock should be open up or not.

For superblocks that indeed influence the traffic performance of networks, dividing them into smaller blocks is an effective way to mitigate their impact. Sufficient node/link capacity and effective signal control can also help decrease the negative effects of superblocks.

The effects mentioned above are restricted to a very limited area. In practice, the road network could be limitless; therefore, the proper size of the analysis area needs to be determined first. There are multiple options for accomplishing this. For example, according to the results presented here, the superblocks only show significant influence in a very
limited area around them. Therefore, we could focus only on the area surrounding the superblocks, using a buffer of a few blocks, or simply until the first main road (or natural barrier such as river and railway) is reached. Alternatively, other methods, such as community detection [41]–[43] might also be used. In any case, how to properly delineate the study area requires further investigation, especially using empirical evidence. Ultimately, based on the resulting network, the characteristics of superblocks (i.e., size, location, shape, and number) could be calibrated, and their impacts (and also the impacts of different scenarios) could be estimated according to the methodology and results presented in this paper. Insights from this type of analysis would be indeed very important for the planning and/or design of urban networks involving superblocks.

Notice that the static traffic assignment model used here is a compromise between the accuracy and the complexity of the algorithm. However, this approach does not capture how the congestion spreads spatially. In addition, we assume that the travel demand remains invariant across different scenarios of superblocks, which ignores the changes in land use types and induced travel demand of different block sizes. Future research could use a more realistic network and demand pattern to extend this study. Also, here we look at the individual effects of superblock size, location, shape, and number. In the future, we could use more advanced sensitivity analysis methods (e.g., [44], [45]) to also analyze the combined effects of these variables, and to potentially find their optimal values in order to maximize the overall network throughput. Our work is an important first step in this future trajectory.

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