

**RESILIENCE OF URBAN STREET NETWORK CONFIGURATIONS UNDER LOW
DEMANDS**

By

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ABSTRACT

Urban street networks are subject to a variety of random disruptions and the impact of movement restrictions (e.g., one-way or left-turn restrictions) on the ability of a network to overcome these disruptions—i.e., its resilience—has not been thoroughly studied. To address this gap, this paper investigates the resilience of one-way and two-way square grid street networks with and without left turns under light traffic conditions. Networks are studied using a simplified routing algorithm that can be examined analytically and a microsimulation that describes detailed vehicle dynamics. In the simplified method, routing choices are enumerated for all possible origin-destination combinations to identify how the removal of a link impacts operations, both when knowledge of the disruption is and is not available at the vehicle's origin. Disruptions on two-way networks that allow left turns tend to have little impact on travel distances due to the availability of multiple shortest-paths between OD pairs and the flexibility in route modification. Two-way networks that restrict left turns only have a single shortest-distance path between any OD pair and thus experience larger increases in travel distance, even when the disruption is known ahead of time. One-way networks sometimes have multiple shortest-distance routes and thus travel distances increase less than two-way network without left turns when links are disrupted. These results reveal a clear tradeoff between improved efficiency and reduced resilience for networks that have movement restrictions and can be used as a basis to study network resilience under more congested scenarios and in more realistic network structures.

1 INTRODUCTION

2 Urban traffic congestion has increased significantly over the past two decades. In 2014, the average
3 annual delay for auto users in the United States exceeded 40 hours, which resulted in 3.1 billion
4 gallons of wasted fuel and \$160 billion in lost productivity to the US economy (1). Approximately
5 60% of congestion in the United States is caused by recurring sources—such as bottlenecks or
6 poor signal timing—and inclement weather (2). The other 40 percent is caused by non-recurring
7 sources that cause disruptions to portions of a network, such as traffic crashes, work zones, road
8 closures or special events. Designing networks that can minimize the impacts of these randomly
9 occurring disruptions might alleviate a significant portion of urban congestion.

10 The ability of a network to accommodate disruptions is generally referred to as network
11 resilience. Resilience has long been studied for freight systems (3–6), public transportation
12 systems (7–9), and general traffic networks (10–13). However, no standard metric has been
13 established to quantify the resilience of a transportation system, since resilience encompasses
14 various components and agencies focusing on different aspects of operational performance. A
15 previous study (10) summarized ten properties of a resilient transportation system and suggested
16 that the complicity and inter-dependence among these dimensions result in difficulty creating a
17 comprehensive resilience metric. Despite the different metrics used in analysis, there are
18 similarities when it comes to the measurement of network performance after disruptions. Some
19 examples include the ratio of recovered performance compared to a baseline case (11), the ratio of
20 recovery over loss (13), and the area surrounded by desired and actual key performance indicators
21 (KPIs) (14) after a disruptive event. All these measurements compare the metrics after disruptions
22 to some baselines (e.g., the case without disruptions or the case without specific treatments to
23 combat disruptions, as two sides). Some other studies (15–18) focused more on the importance of
24 a single link inside a network and aimed at identifying the most vulnerable area(s) in the network.
25 Regardless of the metrics used in evaluation, a common approach to measure link importance is
26 to compare the network performance with and without the link included in the network.

27 In recent years, there have been a growing debate regarding urban street network
28 configuration and urban space allocation. More specifically, many studies are discussing the
29 possibility of turning roads of one-way operation into two-way operation (19–21). However, the
30 issue of resilience has not been considered in the context. While several recent studies have
31 examined the operational performance of abstract grid networks under different street network
32 layouts, none have compared how these networks might perform when link disruptions occur.
33 Gayah and Daganzo (22) analytically compared the trip-serving capacity of complete networks
34 consisting of one-way streets (OW), and two-way streets with (TW) and without (TWL) left-
35 turning maneuvers allowed at intersections. This study found TW networks have higher capacities
36 than OW networks when mean trip lengths are short, while TWL networks always have higher
37 capacities than OW networks. DePrater et al. (23) used simulation to reveal that TW networks
38 allow vehicles to reach their destination more quickly in light traffic while TWL networks offer
39 improved performance in moderately congested scenarios. Ortigosa et al. (24) applied micro-
40 simulation methods to compare the TW, TWL, and OW network configurations under high traffic
41 volumes. The results revealed that a TWL network offers the best balance between trip distance
42 and intersection delay under low demand scenarios, but offer decreased performance at high
43 congestion levels due to lack of redundancy in vehicle routing. This provides the earliest indication
44 that TWL networks might be less resilient to disruptions, even though only complete networks
45 without disruptions were studied.

Some other studies have explored the impact of link and lane removals in TW and OW networks (25, 26). However, these studies assumed permanent roadway space removal from a planning perspective. User equilibrium is thus used in traffic assignment, which does not represent traffic behavior under unexpected disruptions. In addition, these studies only focused on one network configuration and did not provide comparison among different network configurations.

In light of this, the present paper studies the performance of different network configurations when disruptions impact regular network operation. Abstract grid networks of three different configurations are studied and compared: TW, TWL, and OW networks. Two modeling approaches—a simplified approach and microscopic simulation—were applied and their results were compared at low traffic demands. Light traffic is the focus here since networks typically operate under light traffic conditions during the majority of the day. The results indicate that the simplified approach can replicate traffic assignment under low demands fairly well, even if it ignores complex traffic dynamics. The results of both approaches also reveal that the TW network is most resilient to disruptions because of its flexibility and redundancy. The other two networks with movement restrictions (TWL and OW networks) are much more severely impacted when disruptions take place, especially when road users do not know about the disruption ahead of time.

The remainder of this paper is organized as follows. First, we describe the simplified and microsimulation approaches that were used to study how vehicles route themselves in a network both without and with disruptions. Then, we describe the results of a set of experiments that were used to quantify network resilience under link disruptions. Finally, some concluding remarks are provided.

METHODOLOGY

This section describes the networks used in this work, the two modeling approaches used to simulate traffic operation, and the evaluation metrics used to measure resilience after disruptive events in the network. The two modeling approaches vary vastly in the level of complexity at which traffic flow is modeled. However, as will be shown later, these methods produce similar results when the networks operate at relatively low demands. Thus, the simpler method can be used under low demand scenarios without the need to model detailed vehicle interactions.

Network set-up

Idealized square grid networks are considered with origins and destinations located at midblock locations. The most outside ring of the grid network is assumed to operate without any movement restrictions (i.e., no left turn prohibition or one-way street operation) to ensure all trips are able to reach their destinations when disruptions occur. In addition, it is also assumed that no traffic enters or exits the network from the most outside ring. Some additional tests reveal that the general results and trends obtained in this work stay the same without the restrictions.

Figure 1 provides an illustration of the network layout for a sample 5×5 network; however, note that the actual networks tested in this paper were 10×10 square grids. The dots in Figure 1 represent signalized intersections, while squares represent mid-block locations where the origins and destinations are located. The shaded area in the center of the network represents the portion of the network where movement restrictions (e.g., left turn prohibition or one-way street operation)

are applied and origins and destinations are placed. It is assumed that there are two travel lanes on each link. For the TW and TWL networks, one travel lane is assigned to each direction. In the OW network, both lanes serve the same direction and the direction alternates across blocks.

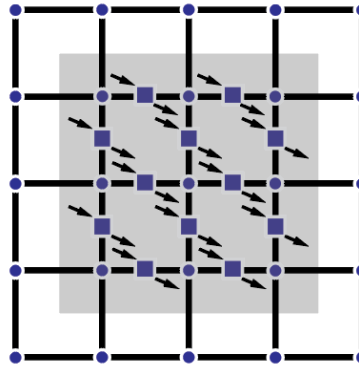


Figure 1 Network geometry

Disruptions in the network are represented by closure of half a block so that the connectivity of the network is not impacted and all vehicles are still able to make their trips. The road users are assumed to either learn of the disruption only when they arrive to the closed link (i.e., they have no prior knowledge of the disruption) or know about the disruption at the beginning of their trip (i.e., they have prior knowledge of the disruption). In either case, only one disruption (i.e., closure of exactly half a block) is allowed to take place in the network to keep the network routing problem tractable in the simplified approach. Each section is tested iteratively to compare the impacts of disruption in different parts of the network.

Simplified approach

The first modeling approach (termed the simplified approach) used in this work assumes that road users select their routes to minimize travel distance (primary goal) and number of turning maneuvers (secondary goal). This general routing behavior has previously been found reasonable under light traffic conditions (27). This method does not consider travel times on links or at nodes (intersections) and therefore cannot represent more congested conditions when travel delay severely impacts route choice. However, the simplicity in this approach facilitates tractable analysis of traffic distribution—allowing us to determine not only how vehicles distribute themselves across a network, but also why—and provides more insights into the differences in traffic operations across the network configurations.

This simplified analysis is performed for networks with and without link disruptions. To efficiently assign all traffic in the network, OD pairs with similar shortest path patterns are first grouped according to factors such as link orientation (horizontal or vertical link), relative location between the OD pair, and distance to the disrupted link. Then, some general shortest path rules are identified for each case, which is later used to assign traffic volumes to the links.

Note that such a case-by-case route analysis is only performed for the TW and TWL networks. Directional movement restrictions in OW networks result in a large number of potential routing scenarios. Even in a complete network without link disruptions, over ten cases exist under

combinations of relative location of OD points, travel direction of trip, and movement restrictions near the OD points. When link disruption is involved, the problem becomes difficult to be enumerated with a purely analytical approach. Therefore, Dijkstra's algorithm (28) is applied to the OW networks as an alternative.

Figure 2 illustrates the optimal paths for trips beginning on a horizontal link within a network that allows left turns (TW, first row) and a network that does not allow left turns (TWL, second row) at intersections. Squares in the figures represent the origins and stars represent destinations. Dashed lines are used when multiple shortest paths with the same minimum number of turns are available for the OD pair, in which case the trips are assumed to be split evenly among the alternative paths. Trips beginning on a vertical link can be categorized in a same way as in Figure 2 after a rotational shift. Note that multiple paths are often available between most OD pairs in the TW network, whereas in the TWL network only a single shortest path is available between all OD pairs. This lack of redundancy in available shortest paths suggests that the TWL network might be less resilient to disruptions than the other network configurations. Although not illustrated in the figure, in OW networks, multiple shortest paths are also generally available between an OD pair when they are more than two blocks away.

A similar approach is applied to traffic assignment in the TW and TWL networks when link disruptions take place. Figure 3 provides an illustration for traffic assignment when road users know about disruptions at the beginning of their trips (prior-knowledge case). Red lines in the figure indicate the location of the link disruption, green lines indicate the shortest path, and again dashed green lines indicate the possible existence of multiple routes with the same travel distance and number of turning maneuvers. Only one potential route is labeled when there are multiple alternative routes available to simplify the figures.

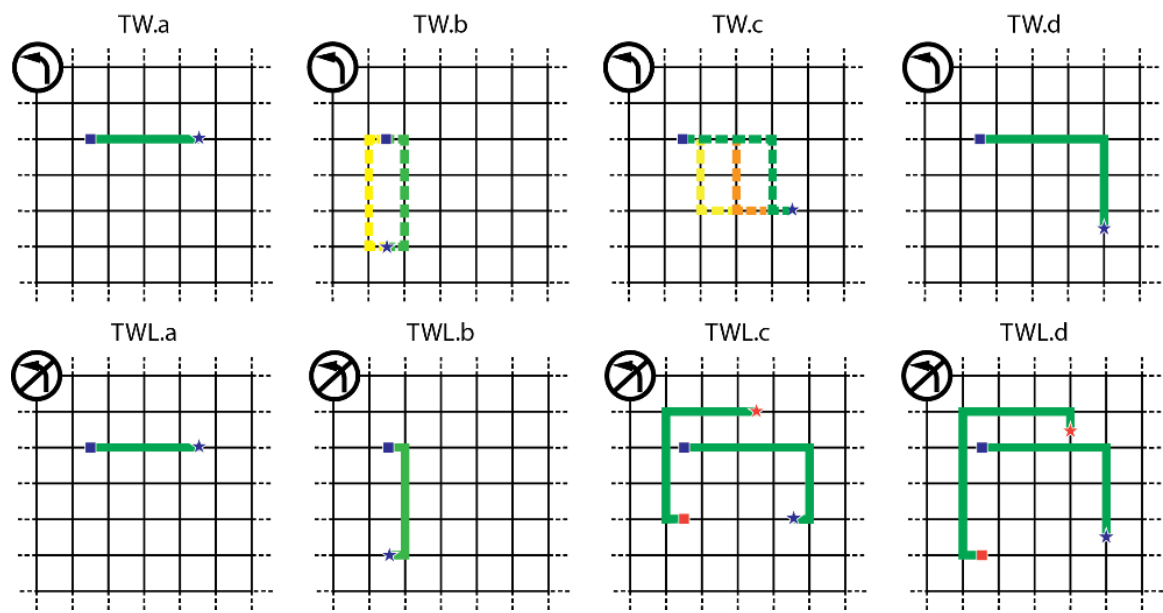


Figure 2 Traffic assignment for complete TW and TWL networks

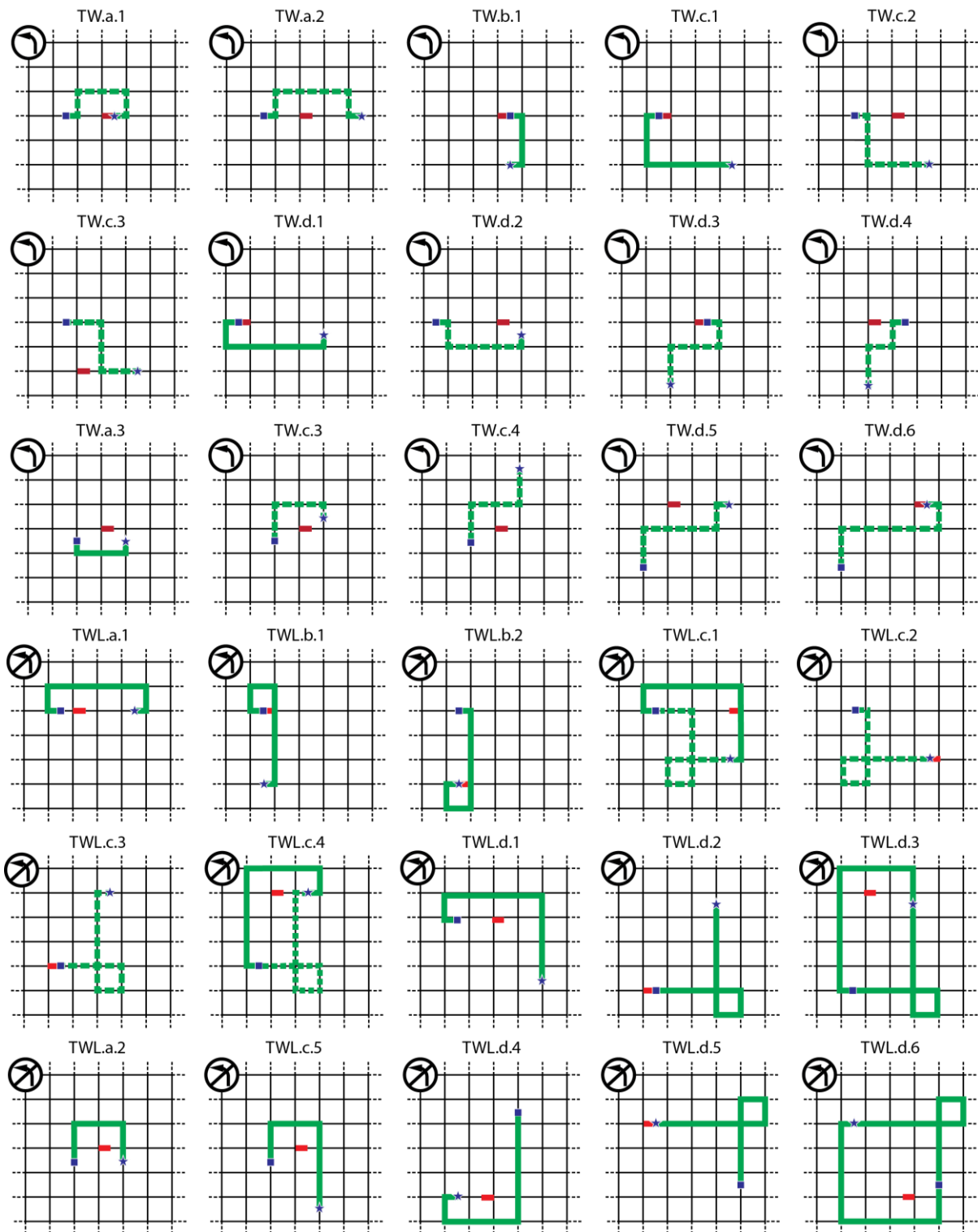


Figure 3 Traffic assignment for prior-knowledge link disruptions

The first three rows in Figure 3 present the cases for a TW network. It can be observed that link disruptions can increase the distance a vehicle must travel for just a small proportion of OD pairs: either those traveling from/to a node directly connected to the disrupted link (TW.c.1, TW.d.1, TW.d.3, TW.d.6) or those traveling between two nodes of vertical distance smaller than one block (TW.a.1, TW.a.2, TW.d.2 and TW.c.3). Other than these cases, disruptions only reduce the number of available shortest-distance/minimum turning-maneuver routes available (e.g., TW.b and TW.c) or increase the number of turning maneuvers without changing the travel distance (e.g., TW.d).

In contrast, the impacts of link disruptions are much more severe in the TWL network. The left-turn restrictions force vehicles to detour near the origin or destination location. In many cases, this detour requires three consecutive right turns around a block since left turns are prohibited. Some of the worst cases include TWL.c.1-4, TWL.d.2-3, and TWL.d.5-6, where the trip lengths under link disruptions are four blocks longer than the Manhattan distances between the OD pairs. Interestingly, for cases shown in TWL.c.1-4, several alternatives with the same travel distance becomes available when a link is disrupted. This might actually help distribute the traffic more evenly in the TWL network, although the impacted vehicles have to travel longer distances.

A similar traffic assignment logic was applied to disruptions without prior knowledge as well. In this case, the impacts of the disruptions become more severe as re-routing can only take place after vehicles arrive to the disrupted link. This is especially problematic in the TWL network due to the turning restrictions.

Microscopic simulation approach

The simplified approach provides initial insights into the potential routing scenarios. However, it applies a purely travel-distance-based traffic assignment and does not consider travel delays at intersections or the number of vehicles traveling on each link in the route choice process. Although travel distance and trip time should be roughly linearly related under light traffic, it is much more realistic to route road users based on the travel times using a route choice model that accounts for travel time directly, as well as unobserved preferences. Furthermore, the simplified analysis does not consider vehicle interactions or traffic dynamics at the intersections, which can be a primary source of delay in urban areas. Thus, further experiments are conducted in the microscopic traffic simulation environment Aimsun to verify the results from the simplified approach.

Aimsun explicitly models microscopic vehicle behaviors such as intersection delay, car-following, lane-changing, yielding, and routing to mimic more realistic scenarios. Each individual vehicle in Aimsun is tracked and travel times on a specific link are grouped by vehicle's turning movements at the downstream intersection. In such a way, travel times for various turning movements can be accurately captured in path cost evaluation. Shortest paths in Aimsun are calculated and updated using a Dijkstra Algorithm at constant time intervals. At the beginning of the simulation, an initial cost function evaluates the free-flow travel times on each link and creates an initial traffic assignment. After that, path costs on each link from previous simulation intervals are evaluated at constant time intervals through a dynamic cost function to update the traffic assignments. When a disruption occurs on a link, an arbitrarily large penalty is added to the cost function of the link either for vehicles that have already arrived to the closed link (for no-prior-

knowledge disruptions) or for all vehicles when they enter the network (for prior-knowledge disruptions), so that the vehicles will divert from the link.

Each vehicle entering the network has several potential routing options and the C-logit model (29) is implemented to mimic a user equilibrium selection process in which each vehicle uses the route that minimizes its own travel time. The C-logit model is a variation of logit model and includes an extra term to account for link overlap. By explicitly accounting for this overlap, the C-logit model helps overcome oscillation and instability present in conventional logit models applied to dense grids. For the experiments in this paper, a maximum of three potential routing options are considered for trips between any OD pair. The costs of travel on all routes are updated every three minutes based on the experienced travel times on the links in the past six minutes.

In addition to more realistic routing, the simulation can also describe more realistic traffic dynamics at intersections. Traffic signals were placed at all intersections in the simulated traffic network. All signals were assumed to operate with a fixed cycle length of 60 seconds: north-south and east-west movements share the available green time equally (27 seconds for each green phase followed by 3 seconds of yellow and all-red times) and offsets between adjacent traffic signals were assumed to be zero. Although coordination along individual arterials has been proven to improve traffic operation along a corridor, a recent study found that the benefits were limited when administered at network-wide on grid networks (30), as operation improvement to one favorable direction brought by coordination can be offset by the operation degradation in conflicting directions. Therefore, such a zero-offset setting in the networks should provide generalizable insights.

Network performance evaluation metrics

In both modeling approaches, the operation of a network is measured using the resulting maximum volume on a lane, the standard deviation of lane volumes across the network, and the mean travel distance. Maximum volume on a lane is measured from the most heavily used lane inside the entire network after the disruption occurs. The lane may be on a busy link in the undisrupted network, or a link not so busy but taking over a high proportion of detour traffic after the disruption. This metric measures the most constraining condition after disruption happens, and might provide an indication of congestion building in the network. Standard deviation of lane volumes is measured across all lanes across the network, and serves as a metric for the distribution of traffic. A smaller standard deviation of lane volumes indicates a more evenly distributed network, which is generally more ideal in urban network operation as it results in higher overall network efficiency (31). The mean travel distance measures how efficiently vehicles can reach destinations. Note that the number of trips is a constant in the experiments; thus, a longer mean travel distance is equivalent to higher mean volumes on the links.

RESULTS

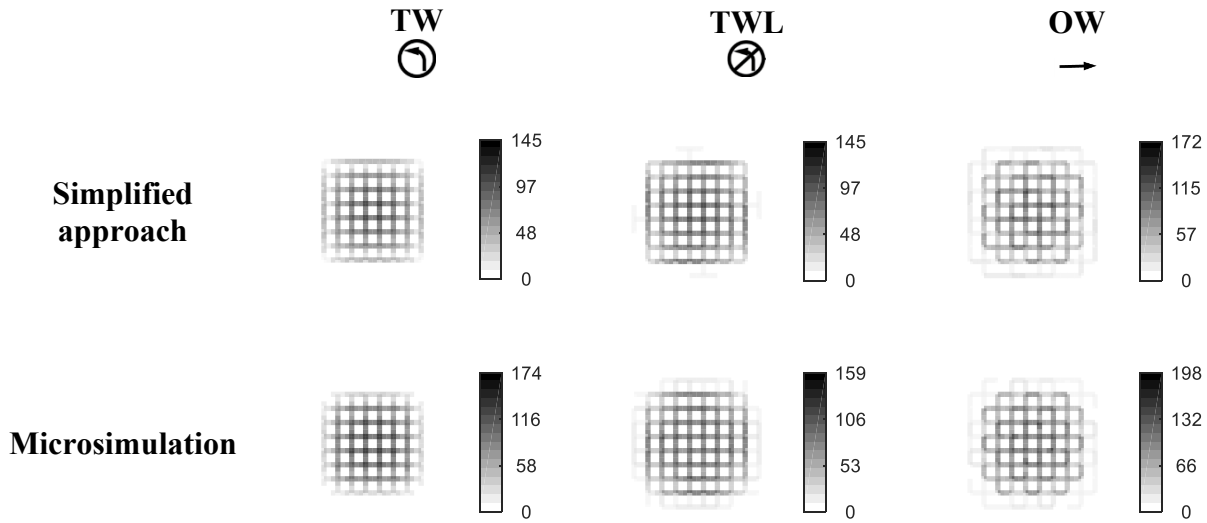
This section provides the results of the experiments performed using the simplified approach and microsimulation method. The first two subsections consider a completely homogeneous demand pattern with 2000 trips inside the network (0.16 trip between each OD pair). The results from the two approaches are compared with each other in the first two subsections to assess how well the simplified approach captures the features present in the much more realistic, but computationally

intensive, microsimulation approach. The last subsection examines the network operation with inhomogeneous demand pattern using the simplified approach.

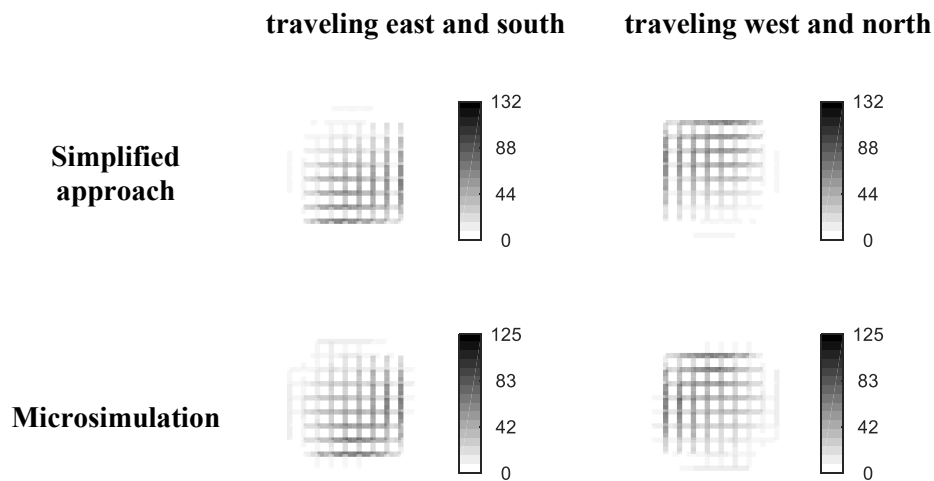
Network operation without link disruptions

Figure 4 illustrates the traffic assignment results in undisrupted networks using both the simplified approach and microsimulation. The shade on each link in Figure 4a represents the total volume on that link (two lanes combined). Overall, results from the two approaches match quite well. In the TW network, the volumes on the sections gradually decrease when they are further away from the network center. The transition is smooth due to the numerous alternative routes available between most OD pairs. In the TWL network, the traffic volumes decrease in only one direction: each row of horizontal links has almost identical volumes with a peak in the middle, and this is also true for every column of vertical links. This is because trips between any specific OD pair in a TWL network have only one unique shortest path (as illustrated in Figure 2), and the volume on a horizontal link is almost solely dependent on its location along the vertical axis. Also, there are some trips using the most outside ring because of the turning restriction inside the TWL network. The traffic pattern in the OW network appears to be a combination of the other two network types. In some cases, trips in the OW network have alternative shortest paths available, which results in a rougher transition compared to the TW network. Also, the movement restriction results in more trips using the outside-most ring.

It should also be mentioned that the maximum volumes on a section are close in the TW and TWL networks only because the traffic on both lanes are combined in the heatmaps. There is a significant difference when the travel lanes (i.e., directional traffic volumes) are considered separately. In the TW network, the maximum lane volume occurs in the network center and the two lanes on that section have similar volumes. In the TWL network, however, the maximum lane volume occurs on sections near the network peripheries and in a very imbalanced way, as shown in Figure 4b. The pattern is caused by the movement restrictions in the network. Since left turns are prohibited in the network, west-to-east traffic is more concentrated in the south part of the network, and similar patterns are observed with other movements as well.



a) volumes on each section (two lanes combined) in undisrupted networks



b) directional volumes in undisrupted TWL network

Figure 4 Traffic assignment results in undisrupted networks

Although the two modeling approaches show highly consistent patterns in traffic distribution, some differences should be acknowledged. In the TW and OW networks, the traffic assignment from microsimulation shows a heavier use of the central portions compared to the simplified approach. This occurs for several reasons. First, vehicles in the microsimulation have only three alternative paths included in route choice. Second, because of the low demands inside the network, assigning more vehicles to a relatively busy path does not necessarily increase its travel time. As a result, vehicles in microsimulation tend to gravitate towards the links in the highly accessible central part of the network. In the TWL network, only one shortest path exists for most OD pairs, so the traffic assignment results from the two approaches are closer.

As a summary, Table 1 provides the three evaluation metrics described in the previous section. From both modeling approaches, the mean travel distance averaged across all trips in the TWL network is slightly less than one block longer than the one in TW network. Meanwhile, the mean travel distance in the OW network is greater than two blocks longer than the TW network because of the movement restrictions and resulting travel circuitry in this type of network. These findings are consistent with previous studies (22, 24). Note that the mean travel distances are always longer in Aimsun, as these travel distance values include the distance to traverse intersections, which is ignored in the simplified approach.

Table 1 Summary for network operation without disruptions

a) simplified approach

	Max. volume	Std. volume	Mean travel distance (blocks)
TW 	72.33	26.07	5.06
TWL 	131.90	35.94	5.95
OW 	86.01	28.16	7.24

b) microsimulation

	Max. volume	Std. volume	Mean travel distance (blocks)
TW 	94.40	26.62	5.14
TWL 	125.40	33.48	6.06
OW 	98.30	25.91	7.37

From both modeling approaches, the TWL network has the highest directional volume on a single link and the highest standard deviation of directional volumes inside the network. In other words, the TWL network appears to provide the least even traffic distribution as a consequence of the asymmetric traffic patterns revealed in Figure 4b. The TW and OW networks have relatively close values on these two metrics, but their maximum directional volumes are higher from the Aimsun results, especially in the TW network.

Network operation under link disruptions

Results from the previous subsection provide baselines of the traffic operation in the networks without any disruptions. The three network configurations are now tested with disruption impacting regular operation. Disruptions on individual sections in the network are tested in an iterative fashion where one and only one section is closed to traffic in each test. Table 2 summarizes the operational metrics measured from the disrupted networks (Table 2a and 2c) and their relative differences compared to undisrupted networks (Table 2b and 2d). For both sets of tables, the mean and standard deviation values (in parentheses) are aggregated over all the disruptions that occur to each individual section inside the networks.

Table 2 Summary for network operation under disruptions in simplified analysis**a) operation under disruptions from simplified approach**

		Max. volume	Std. volume	Mean travel distance (blocks)
NPK	TW 	82.65 (9.47)	26.66 (0.53)	5.11 (0.02)
	TWL 	147.77 (21.10)	36.95 (1.11)	6.13 (0.08)
	OW 	107.18 (23.48)	29.08 (0.86)	7.39 (0.08)
PK	TW 	83.19 (8.56)	26.68 (0.37)	5.08 (0.01)
	TWL 	142.79 (17.01)	35.71 (0.87)	6.04 (0.04)
	OW 	100.50 (10.56)	28.67 (0.37)	7.30 (0.04)

b) relative differences compared to undisrupted networks from simplified approach

		Max. volume	Std. volume	Mean travel distance (blocks)
NPK	TW 	14.26% (13.1%)	2.3% (2.0%)	0.04 (0.02)
	TWL 	12.04% (16.1%)	2.8% (3.1%)	0.19 (0.08)
	OW 	24.61% (27.3%)	3.2% (3.0%)	0.14 (0.08)
PK	TW 	15.00% (11.83%)	2.3% (1.4%)	0.01 (0.01)
	TWL 	8.26% (12.9%)	-0.7% (2.4%)	0.10 (0.04)
	OW 	16.84% (12.3%)	1.8% (1.3%)	0.06 (0.04)

c) operation under disruptions from Aimsun

		Max. volume	Std. volume	Mean travel distance (blocks)
NPK	TW 	98.56 (8.19)	26.80 (0.57)	5.21 (0.02)
	TWL 	138.46 (10.33)	33.85 (0.70)	6.21 (0.04)
	OW 	111.60 (19.74)	26.44 (1.68)	7.48 (0.06)
PK	TW 	103.24 (12.42)	27.17 (0.54)	5.16 (0.01)
	TWL 	133.80 (13.95)	33.37 (0.81)	6.17 (0.04)
	OW 	109.45 (11.44)	27.20 (0.94)	7.43 (0.04)

d) relative differences compared to undisrupted networks from Aimsun

		Max. volume	Std. volume	Mean travel distance (blocks)
NPK	TW 	4.40% (8.68%)	0.67% (2.15%)	0.07 (0.02)
	TWL 	10.42% (8.23%)	1.09% (2.10%)	0.15 (0.04)
	OW 	13.53% (20.08%)	2.05% (6.48%)	0.11 (0.06)
PK	TW 	9.36% (13.16%)	2.05% (2.04%)	0.02 (0.01)
	TWL 	6.70% (11.13%)	-0.34% (2.43%)	0.11 (0.04)
	OW 	11.34% (11.64%)	5.00% (3.62%)	0.06 (0.04)

Table 2a and 2b provide the results obtained from the simplified approach. In both cases, the TW network appears to be the least impacted by the disruptions. The TW network experiences the lowest absolute and relative differences for mean travel distances. For example, the mean trip distances in the TW network barely change under disruptions when prior knowledge is available to road users, which is attributed to the existence of multiple shortest paths for most OD pairs in this network configuration. Even when prior knowledge is unavailable and road users begin their detours after reaching the intersection, the TW network still shows limited increases in travel distances because of its flexibility and redundancy.

The TWL network shows very different patterns. In both disruption cases, the TWL network undergoes the most severe increases in mean travel distances among the three network configurations due to the lack of redundancy and the difficulty in re-routing. This is especially problematic when prior knowledge is not available, since the road users will have to reach the disruptions before they detour. In most cases, these detours require several consecutive right turns around a block because of the turning restrictions.

The OW network has the highest increases in maximum lane volume (and a large increase in standard deviation of link volumes) under no-prior-knowledge disruptions, indicating a high concentration of detour traffic after disruptions occur on some links. Among the three network configurations, trips in the OW network still have the highest mean travel distance in both disruption cases. However, the TWL network exhibits the highest increase in mean travel distance, since a part of the impacted traffic in the OW network can switch to alternatives without extra travel distances.

Table 2c and 2d provide the results obtained from Aimsun, which are on the same order of magnitude and have the same relative rankings compared to the results from the simplified approach. Taking a closer look at the metrics and their relative changes compared to the base cases, the Aimsun results suggest lower relative increases in maximum lane volume and standard deviation of lane volumes, especially inside the TW and OW networks. The reason is twofold:

- As explained earlier, vehicles are assigned in a more aggregated manner in Aimsun. This is because the traffic assignment in Aimsun is based on travel times on links, and the low demands allow the more accessible central areas attract more traffic without increases in travel time. Therefore, the maximum lane volume and standard deviation of lane volumes in the networks without disruptions are relatively high in Aimsun.
- When disruption takes place in the network, there is an acute travel time increase on links near the disruption. The change will be reflected in vehicle routing and the impacted vehicles tend to use alternative routes with lower travel times, rather than spreading evenly among alternative routes with the same trip distance. As a result, more detour traffic will be assigned to relatively lightly used links, which limits the increase on the maximum lane volume and better distributes the traffic.

To further study the impacts of disruptions on each individual section in the networks, Figure 5 provides heatmaps illustrating the evaluation metrics after a disruption occurs on that specific link. A darker shade on a section indicates a higher value of the metric, or in other words, more severe operation deterioration. The numbers next to the color scale provide the values of the metrics and their relative differences compared to networks without disruptions (in parentheses). For maximum lane volume and standard deviation of lane volumes, percentage changes are presented; for mean travel distance, absolute changes are presented as this might be more intuitive.

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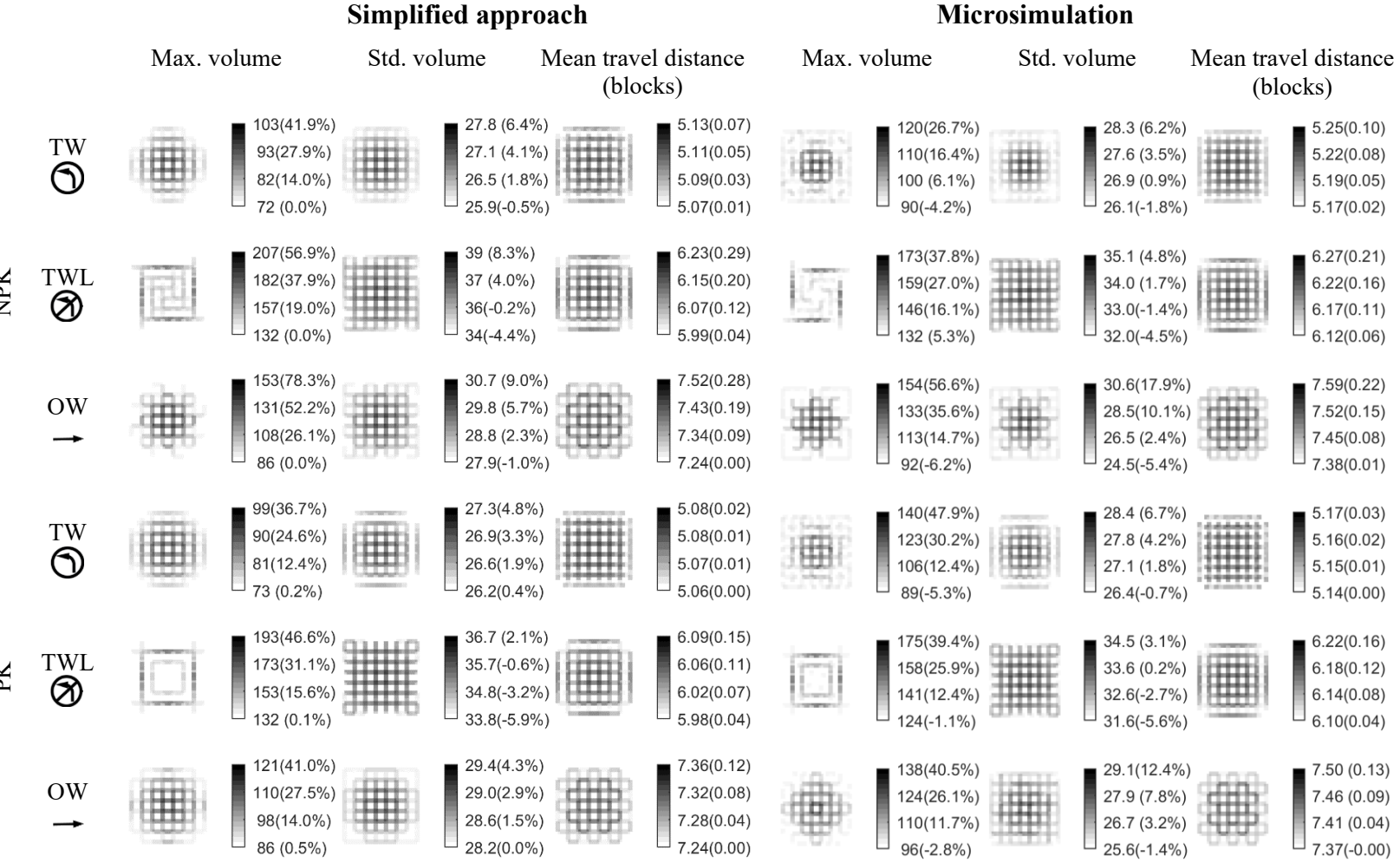


Figure 5 Network operation after disruptions

The first three columns in Figure 5 show the results obtained from the simplified approach. The TW network shows similar patterns for maximum lane volumes under both prior-knowledge and no-prior-knowledge disruptions; however, both the TWL and OW networks behave quite differently when prior knowledge about the disruption is available to road users. In the TWL network, the maximum lane volume does not increase when disruptions take place on most links in the prior-knowledge case, since a few lanes carry high volumes and only a small proportion of detour traffic would use these busy lanes. For the same reason, the standard deviation of lane volumes in the TWL network even decreases for prior-knowledge disruptions on a high proportion of links. For no-prior-knowledge disruptions on many of the periphery links in the OW network, the maximum lane volume stays the same as the network without disruptions, indicating that more vehicles are taking local detours if they are not aware of the disruptions ahead of time.

The standard deviation of lane volumes tends to be higher under no-prior-knowledge disruptions in all network configurations. It should be noted that this metric may reduce when disruptions take place on links near the periphery of TWL networks, as these links generally carry heavy directional volumes and splitting the traffic among alternative routes may help to better balance the distribution of traffic.

The patterns of mean travel distances are similar in the two disruption cases for all network configurations. However, the increase magnitudes are much higher in the TWL and the OW networks under no-prior-knowledge disruptions, indicating longer detours when road users are unaware of the disruption ahead of time. In comparison, the TW network has close mean travel distances in the two disruption cases, showing a strong flexibility and redundancy.

The last three columns in Figure 5 show the results obtained from Aimsun. In general, these patterns are similar to the ones from the simplified approach. The two methods provide similar rankings for the impacts when disruption occurs on a specific link and similar trends under both prior-knowledge and no-prior-knowledge disruptions. A relatively large difference between the two approaches occur in the TW network, where the central part of the network appears to be more sensitive to disruptions when analyzed in Aimsun. Again, the difference is caused by the different traffic assignment strategies as the traffic in the TW network in Aimsun is not as evenly distributed as in the simplified approach.

Overall, the results from the simplified approach and microsimulation show similar patterns and the simplified approach appears to well replicate traffic behaviors under light traffic conditions. Therefore, the latter is used for further experiments with inhomogeneous demands as it is simpler and requires less computation power.

Network operation with inhomogeneous demands

The previous results focused on network operations when demands were homogeneous. However, demands are typically inhomogeneous during the critical operation periods, such as AM and PM peaks. In this subsection, the networks are examined under inhomogeneous demand patterns.

Based on analyses using the simplified approach, Figure 6 provides the impacts of disruptions with heavy external – internal (AM peak) and heavy internal – external (PM peak) traffic demands. Within each case, 2000 trips are generated in the networks, but the demand between any OD pair is scaled according to their locations inside the network. In the heavy external – internal scenario, nodes near the borders of the networks generate twice and attract two thirds

1 as much traffic as nodes near the network centers. In the heavy internal – external scenario, the
2 demand distribution is reversed.

3 As illustrated in Figure 6, even with the two entirely different demand scenarios, all
4 networks show rather consistent patterns in terms of impact severity when disruption takes place
5 on a specific link. Even though the magnitudes of the metrics can differ, the patterns for the most
6 critical links and the differences between prior-knowledge and no-prior-knowledge disruptions
7 stay the same as under homogeneous traffic demands. Therefore, the observations from this paper
8 are believed to be robust to different demand scenarios.

9

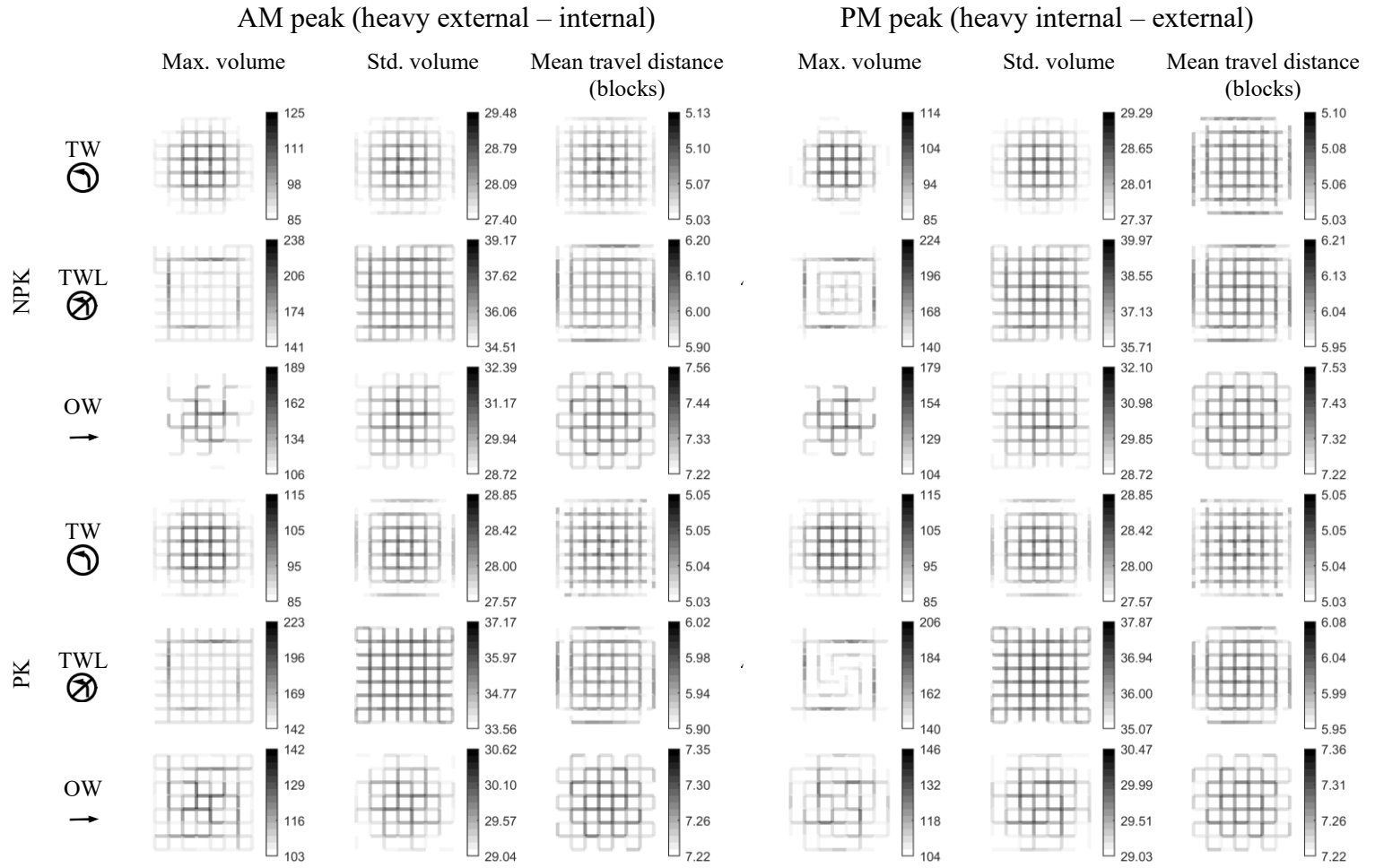


Figure 6 Network operation after disruptions with inhomogeneous demands

CONCLUDING REMARKS

This paper compares the impacts of link disruptions on the operation of three network configurations—two-way (TW), two-way without left turns (TWL) and one-way (OW)—under low demand scenarios. Two cases are considered for each network: when drivers do and do not have prior knowledge about the disruption. Although the experiments are performed only under light traffic conditions, the results help identify the sensitive links inside the network and shed light on where congestion might begin when a disruption occurs under heavier demand conditions.

Two modeling approaches are implemented to study the impacts of disruptions. The first is a simplified approach that assigns traffic based on minimizing travel distance and number of turning maneuvers between OD pairs. Typical routing scenarios were manually derived for the TW and TWL networks in the simplified approach to provide more insights into the traffic patterns. The second is a more realistic microsimulation method that better accounts for vehicle travel times, intersection delays and other features. Overall, the experiment results obtained from the two approaches match well, which suggests that the simplified approach is capable of assessing the impacts of link disruptions under light to moderate traffic conditions. Even if the traffic network gets more realistic or disruptions take place in multiple locations of the network, the simplified approach, with the aid of a shortest-path algorithm, can still serve as a lightweight approach to efficiently simulate traffic behaviors under low to medium demands.

When no disruption occurs, the TW network exhibits the most even traffic distribution with the lowest mean travel distance. In comparison, the TWL network exhibits the most unbalanced traffic distribution due to the strong directional demand patterns near the borders while the OW network shows the highest travel distance because of the circuitry inside.

Comparing the performance of the difference network configurations under link disruptions, the TW network is found to be the most resilient to the disruptions due to its flexibility and redundancy. The mean trip distance in the TW network remains relatively stable when disruptions occur since there are usually several shortest-path routing alternatives inside the network. In addition, the TW network exhibits the lowest maximum link volume as well as standard deviation of link volumes, showing an even distribution of traffic. Although the TWL and OW networks are believed to provide higher network capacities, vehicles impacted by disruptions in these two networks have to travel longer distances in a more concentrated manner because of the movement restrictions. Under light traffic conditions, the additional capacities in the two networks do not offset these increased travel distances since they go unused. The impacts would be much smaller in the TWL and OW networks if the road users have prior knowledge about the disruptions, as the detour would occur earlier and more evenly. For this reason, it is crucial to differentiate the information environments when studying disruptions in urban areas. This also indicates that provision of information can help alleviate the severity of disruptions.

It should also be noted that the TWL network differs from the other two network types as it is most impacted by disruptions near borders, where the directional demands are the highest. The TW and OW networks, on the other hand, are the most sensitive to disruptions in central areas. All these observations can be replicated with different demand patterns and are believed robust and general.

Based on the observations in the paper, future work is being conducted to study the network operation under higher traffic demands. Additionally, the impact of partial information provision

strategies—such as targeted information about the disruption to a subset of OD pairs or to vehicles traveling on links near the disruptions—should be studied.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Zhengyao Yu and Vikash V. Gayah; analysis and interpretation of results: Zhengyao Yu and Vikash V. Gayah; draft manuscript preparation: Zhengyao Yu and Vikash V. Gayah. Both authors reviewed the results and approved the final version of the manuscript.

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