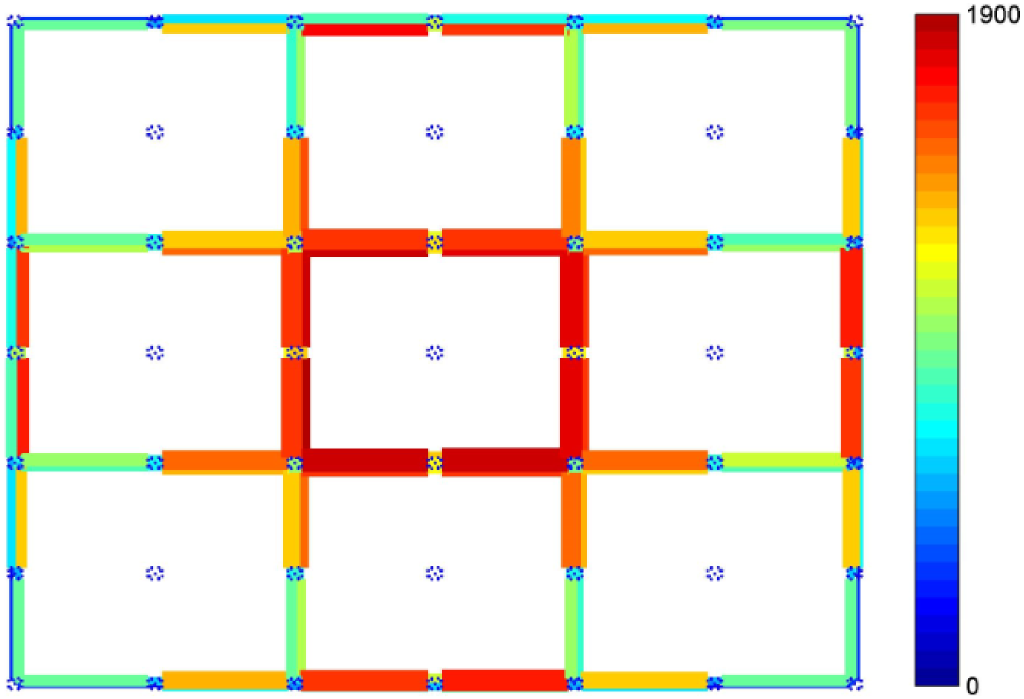

Traffic demand pattern generation for a grid network based on experiment design

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Abstract

In this paper, we present a preliminary approach for generating different traffic demand patterns to analyze the traffic performance of a grid network. The proposed methodology is based on the sampling strategy proposed in (Ge and Menendez, 2013), and combined with ideas from research on experiment design.

The proposed algorithm is illustrated using an abstract grid network with bidirectional streets. The purpose of this paper is to demonstrate how does this algorithm work for investigating the relationship between different spatial distributions of the demand (i.e., geographical position where the demand is generated/attracted) and the traffic performances. In this study, we have tried multiple magnitude of the total demand (i.e., quantity of the demand) in the network, but no variation of the temporal distribution (i.e., time when the demand is generated) is considered. Based on the evaluation of the analysis results, we are able to conclude the best and the worst traffic demand conditions in terms of traffic performance for the given grid network.

Keywords

Traffic demand pattern – Network – Experiment design – Traffic performance

1. Introduction

Traffic scenario generation plays an important role in transportation research. The generation of multiple traffic scenarios based on specific events (e.g., incidents, construction work), traffic demand patterns, and signal plans can be used in the short-term traffic forecasting, and support the traffic control systems to apply the optimal control strategy in advance. Furthermore, for a given traffic network, the traffic scenario generation can be employed in evaluating the performance of the network under different traffic conditions, and helps the transportation planner to explore the robustness of the network design.

Despite the importance of traffic scenario generation, to the best of the authors' knowledge, the topic has not advanced much in terms of practical applications. In many cases, the traffic scenarios are generated manually (e.g., Scott et al., 2006) by practitioners that may omit certain important cases. On the other hand, using the brute force approach to generate all possible scenarios can be very time consuming for both the scenario generation process and the subsequent analysis. Moreover, as some scenarios generated by an exhaustive search may only show minor differences between each other, the computation resources could be wasted in the assessment of those very similar scenarios. Therefore, the development of an optimal approach that generates a limited number of representative scenarios could be very valuable.

In this paper, we present an efficient approach to generate different traffic demand patterns to analyze the traffic performance of a grid network. The proposed methodology is based on the sampling strategy proposed in (Ge and Menendez, 2013), which is a recently developed approach for sampling parameters for sensitivity analysis. This method is combined with ideas from research on experiment design, in which powerful statistical techniques are used to screen the valuable experimental data from raw data.

The proposed algorithm is illustrated using an abstract grid network with bidirectional streets. The purpose is to demonstrate how does this algorithm work for investigating the relationship between different spatial distributions of the demand (i.e., geographical position where the demand is generated/attracted) and the traffic performances. In this study, we have tried multiple magnitude of the total demand (i.e., quantity of the demand) in the network, but no variation of the temporal distribution (i.e., time when the demand is generated) is considered. Based on the evaluation of the analysis results, we are able to conclude the best and the worst traffic demand conditions in terms of traffic performance for the given grid network.

The paper is organized as follows: an introduction of the methodology is given in Section 2; the application of the proposed pattern generation algorithm is illustrated with a case study in Section 3; the conclusions and suggestions for future work is included in Section 4.

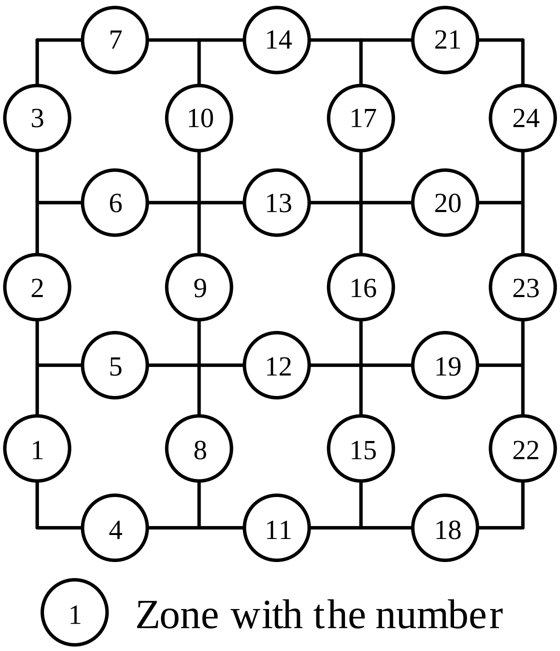
2. Methodology

In general, for a grid network with a certain type of topology, the generation of the traffic demand pattern comprises three elements:

1) Magnitude of the demand: the number of trips generated / attracted at a certain location of the network.
2) Spatial variation of the demand: the variation of the spatial locations for generating / attracting the trips.
3) Temporal variation of the demand: the variation of the time for generating / attracting the trips.

As the goal of this research is to investigate the general algorithm for generating different traffic demand patterns, it could be more feasible for us to start with a very simple case. For this reason, in this research we only consider an abstract 4-by-4 grid network with bidirectional streets. In addition, all the trips generated / attracted in the middle of the link (see Fig. 1). Moreover, we assume that there is no temporal variation of the demand generation, i.e., the demands are uniformly distributed in terms of time. We further assume that the trips between any two zones in the network can be either *T* or 0 (i.e., no trips).

Figure 1 The abstract 4-by-4 network considered in this research



It is obvious that for a n-by-n grid network, if all the trip zones are located in the middle of the link, there are $2n(n-1)$ zones in total (e.g., in Fig. 1, the total number of zones is 2*4*(4-1) = 24). If we consider zone i ($1 \leq i \leq 2n(n-1)$) as the trip start zone (i.e., origin), and zone j ($1 \leq j \leq 2n(n-1)$, $j \neq i$ as no internal trips are considered within a zone) as the trip end zone (i.e., destination), for these $2n(n-1)$ trip zones there are $N^* = 2n(n-1)*[2n(n-1)-1] = 4n^4-8n^3+2n^2+2n$ possible origin-destination (OD) pairs. In the 4-by-4 grid network illustrated in Fig. 1 the total number of OD pairs is 552.

As mentioned before, we have assumed that the trips between each OD pair can be either T or 0. For a given total magnitude of traffic demand in the network, i.e., $N \times T$ with $1 \leq N \leq N^*$, to generate the traffic demand patterns that yield the best or worst traffic performance of the network, we need to find the relevant combinations of N OD pairs (each of them has T trips while the other OD pairs have no trip).

Due to the high computational cost, an exhaust search or a fully randomized search (such as the Monte Carlo process for generating the samples) could be an unfeasible and tedious solution. For example, if the total magnitude of the traffic demand is $6T$, the number of possible combinations of any 6 different OD pairs out of the 552 OD pairs in the 4-by-4 network is around $3.8*10^{13}$. In this case, it could be too time consuming for a normal computer to enumerate and evaluate all possible combinations of OD pairs. Note that although this process can be accelerated by adopting the parallel computing techniques and/or taking the symmetric characteristics of the grid network into account, it is still a very time demanding work for a normal computer if considering the total number of possible combinations.

Therefore, a more efficient approach for searching the OD pair is needed. For this reason, we propose to borrow some ideas from the research of experiment design, where efficient sampling and searching algorithms are systematically studied and developed (e.g., Roupec and Popela, 2009). In this study we employ the searching approach as described in (Ge and Menendez, 2014), which was originally developed to solve the sampling problem for the sensitivity analysis of high dimensional and computationally expensive traffic simulation models. The algorithm we adopt in this paper is described in details as below.

The search of the best and worst demand pattern with N ($1 < N < N^*$) OD pairs starts with generating all possible combinations of N^*-1 OD pairs from the full set of N^* OD pairs. In the first step, there are only N^* possible combinations that can be enumerated. Then the algorithm will evaluate the traffic performance of each combination that contains N^*-1 OD pairs, and find one combination (i.e., B_{N^*-1}) that yields the best traffic performance, and one combination (i.e., W_{N^*-1}) that yields the worst traffic performance. Then in the second step, the search starts with generating the possible combinations containing N^*-2 OD pairs out of B_{N^*-1} and W_{N^*-1}, and find the best OD pairs combination $B_{N^*\text{-}2}$ and worst OD pairs combination $W_{N^*\text{-}2}$. This process is repeated until only N OD pairs (i.e., B_N or W_N) are left, and they are considered as the best or worst combination. Since in Step k ($1 \leq k \leq N^*\text{-}N$) the number of possible combinations enumerated is only $N^*\text{-}k+1$, the total number of possible combination is quite limited. In the aforementioned example, to search for the combination of 6 OD pairs, only 152607 combinations (much less than $3.8*10^{13}$) are generated and evaluated if using this algorithm.

Furthermore, since the computational cost for the above algorithm is quite cheap, to make the algorithm more robust, we can afford to search multiple combinations of the best or worst OD pairs rather than one single combination. In the first step, we will pick the M (e.g., 10) best or worst combinations containing N^*-1 OD pairs from the whole set, namely, $B_{N^*\text{-}1}^m$ and $W_{N^*\text{-}1}^m$ ($1 \leq m \leq M$). In the following steps the aforementioned iteration process is performed based on $B_{N^*\text{-}1}^m$ and $W_{N^*\text{-}1}^m$. In the end, we can obtain M combinations that contain N potentially best or worst OD pairs. In this process, it is possible to use a simple and computationally cheap traffic assignment algorithm (e.g., assign all the trips of a certain OD pair to the shortest path) in the iterations to derive $B_{N^*\text{-}1}^m$ and $W_{N^*\text{-}1}^m$ (m=1, ..., M). Afterwards we can apply a more accurate but more computationally expensive traffic assignment algorithm such as the dynamic traffic assignment based on $B_{N^*\text{-}1}^m$ and $W_{N^*\text{-}1}^m$ to refine the results. In this way, it is expected to enhance the accuracy for generating the best and worst traffic demand patterns. We will illustrate the proposed algorithm with a case study in the next section.

3. Case study and results

3.1 Network design

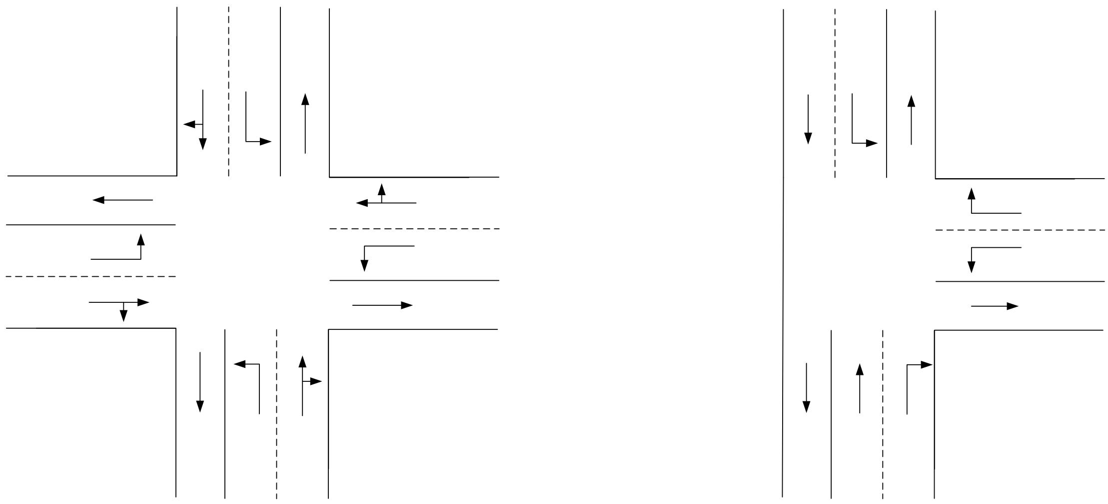
As already mentioned, the 4-by-4 grid network with bidirectional streets (see Fig. 1) is used in the case study. We assume that the capacity of the link is 1800 veh/h for each direction, and each link is 100 m long. Furthermore, the trips between one OD pair for is assumed to be 40 trips/h, i.e., T = 40 in this case study.

The layout of the intersections is shown in Fig. 2. There are two types of intersections:

- 4-leg intersection (Fig. 2a) inside the network. Noted that for the incoming traffic, the right turn and the through traffic are grouped in one lane, while the other lane is dedicated for left turners.
- 3-leg intersection (Fig. 2b) in the peripheral links of the grid network. Noted that in the 3-leg intersection the left and right turn, as well as the through traffic are all separated in different lanes.

It should be noted that the links in the network only have one lane per direction, while an extra lane is added in intersections in order to separate or combine the traffic.

Figure 2 The layout of the intersection in the grid network.

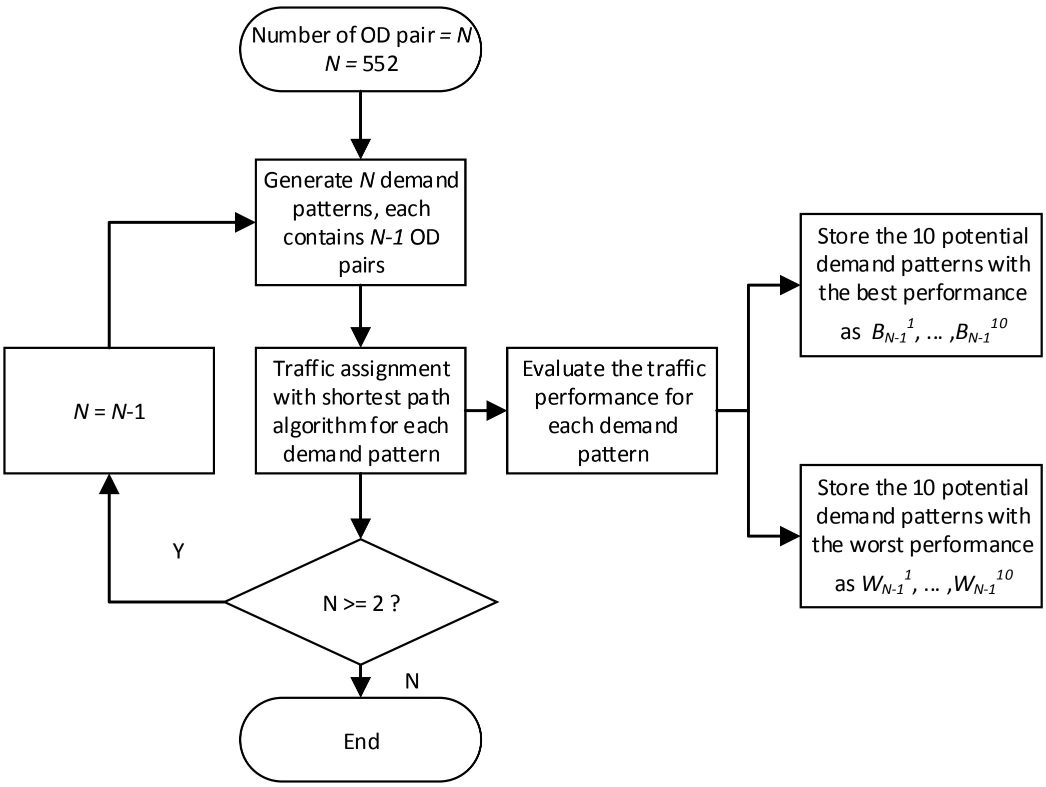


(a) layout of the 4-leg intersection (b) layout of the 3-leg intersection

3.2 Traffic assignment model

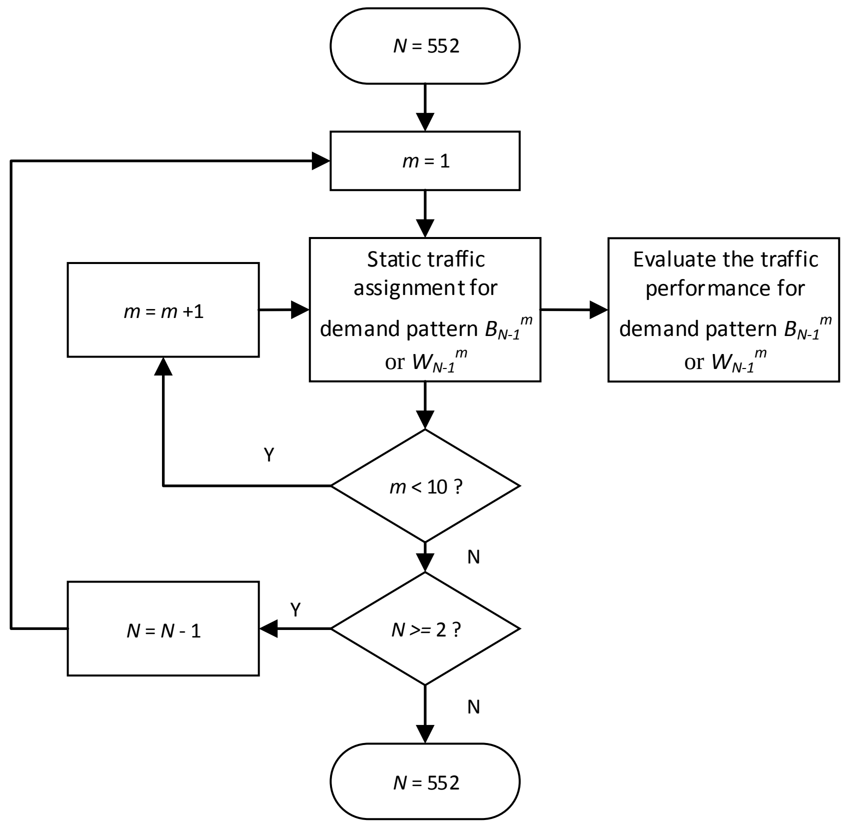
As described in Section 2, to make the demand pattern generation more accurate, we separate the computation process into two consecutive phases: demand pattern generation (Fig. 3) and demand pattern evaluation (Fig. 4).

Figure 3 Process for demand pattern generation.



In the first computation phase for demand pattern generation, the program will search for the 10 demand patterns (i.e., combinations of OD pairs) that potentially have the best and worst performance under certain total demand $N*T$ (N = 1, …, 551). In this phase, we use the shortest path algorithm for the traffic assignment. This algorithm applies the Dijkstra's algorithm (for details see Dijkstra, 1959) to determine one single route from the origin zone to the destination zone that yields the shortest travel distance. Then it assigns all the trips of that OD pair to this route. In the intersection, different green times are given to the left turners (2.5s) and right turners (22.5s). As a result, when two routes have the same travel distance, the traffic assignment will prefer to choose the route with less left turns. It should be noted that the shortest path traffic assignment is chosen because of its efficiency in computation, and the main purpose of this study is to demonstrate the application of the proposed algorithm for demand pattern generation. In other cases if higher accuracy of the traffic assignment is required, a more realistic traffic assignment algorithm may be considered, although the process for generating the demand pattern should remain the same.

Figure 4 Process for the demand pattern evaluation.



In the second phase for evaluating the traffic demand patterns, we use the static traffic assignment model that follows the approach described in (LeBlanc et al., 1975) using the Frank-Wolfe (FW) algorithm (Frank and Wolfe, 1956). The traffic from multiple OD pairs is assigned to different routes through an iterative process, and the assignment will stop when the user's equilibrium (Wardrop, 1952) is reached. We apply this algorithm on each of the best and worst demand patterns that are found in the first computation phase, and evaluate the corresponding performances (see the indicators in Section 3.3). Again, the reason for using the static assignment model here is due to its acceptable accuracy and relatively low computational cost (Ortigosa and Menendez, 2014). For other studies, the practitioners are free to choose more accurate traffic assignment models (Bar-Gera, 2010; Dial, 2006) based on their needs, though the evaluation process presented in Fig. 4 should remain the same.

3.3 Performance indicator

In the first computation phase for generating the potential traffic demand patterns, we include 7 indicators to assess the traffic performance by a certain combination of the OD pairs. These indicators are shown in Table 1.

Table 1 Indicators used for evaluating the traffic performance in the first computation phase.

Rank	Name	Description
1	Max flow at intersection	Maximum flow of the through and turning maneuvers at the intersection
2	Max flow at link	Maximum flow travels on the link
3	Max left turn flow at intersection	Maximum flow of the left turning maneuvers at the intersection
4	Max through flow at intersection	Maximum flow of the through maneuvers at the intersection
5	Total travel distance	The total distance travelled on links
6	Average flow at links	The mean of the flow among links that have non-zero flow
7	Standard deviation of flow at links	The standard deviation of the flow among links that have non-zero flow

The first and second indicators are used to described the maximum flow at different locations of the network, the third and fourth indicator are used to describe the traffic demand of certain driving manoeuvres at the intersection, and the last 3 indicators are used to describe the dispersion of the flow on the links. Moreover, we pick the 10 best or worst potential demand patterns according to the priority of the indicators. For example, if two demand patterns have the same number of maximum flow at the intersection and links, then the one with more left turning maneuvers will be considered in the W set as it is expected to have greater potential of causing congestion than the other demand pattern.

In the second computation phase for evaluating the performance of the chosen demand patterns, we have chosen 3 indicators for describing the traffic performance (see Table 2) of the network. The first two indicators are the same as those used in the first computation phase. The third indicator is used to describe the total travel time in the network, i.e., the sum of the travel time on links and intersections. The travel time on links is calculated using the BPR function (Bureau of Public Road, 1964):

$$TT_{i,j} = TT_{i,j}^{\ 0}(1 + a(V_{i,j} / C_{i,j})^b)$$

where $TT_{i,j}$ is the travel time of link (i, j), $TT_{i,j}^0$ is the travel time with free flow on link (i, j), and $V_{i,j}$ and $C_{i,j}$ are respectively the traffic volume and capacity of the link (i, j). In our study the parameters a and b are set to 0.15 and 4 respectively. The travel time at intersections used the improved delay formulation based on the HCM-2010 formulation (Highway Capacity Manual, 2010). For details about the delay formulation, the interested readers are suggested to refer to (Ortigosa and Menendez, 2014).

Table 2 Indicators used for evaluating the traffic performance in the second computation phase.

Name	Description
Max flow at intersection	Maximum flow of the through and turning maneuvers at the intersection
Max flow at link	Maximum flow travels on the link
Total travel time in network	The total travel time on links and intersections

3.4 Results

3.4.1 Traffic performance

The traffic performance in terms of the maximum flow at intersections, maximum flow at links, and the total travel time in the network for the different traffic demand patterns are plotted in Fig. 5.

Fig. 5a and Fig. 5b show the maximum flow at intersections and links with different number of OD pairs in the combination for the worst and best cases. It should be noted that in both cases, there are some small oscillations at some places along the maximum flow curve. This is due to the randomness in the demand pattern generation, and the use of two different traffic assignment models in the pattern generation and evaluation phases phase (see Section 3.3). Nevertheless, the comparison between the worst case and best case shows that due to the different choices of OD pairs in the combination, there is significant difference of the maximum flow even when they have the same total demand. The biggest absolute difference in this case happens when almost half of the total OD pairs have trips. This indicates that when almost half of the OD matrix is empty, the different spatial distributions of the demand can bring high variations to the maximum flow at both intersections and links.

Figure 5 The traffic performance for the worst demand patterns and best demand patterns

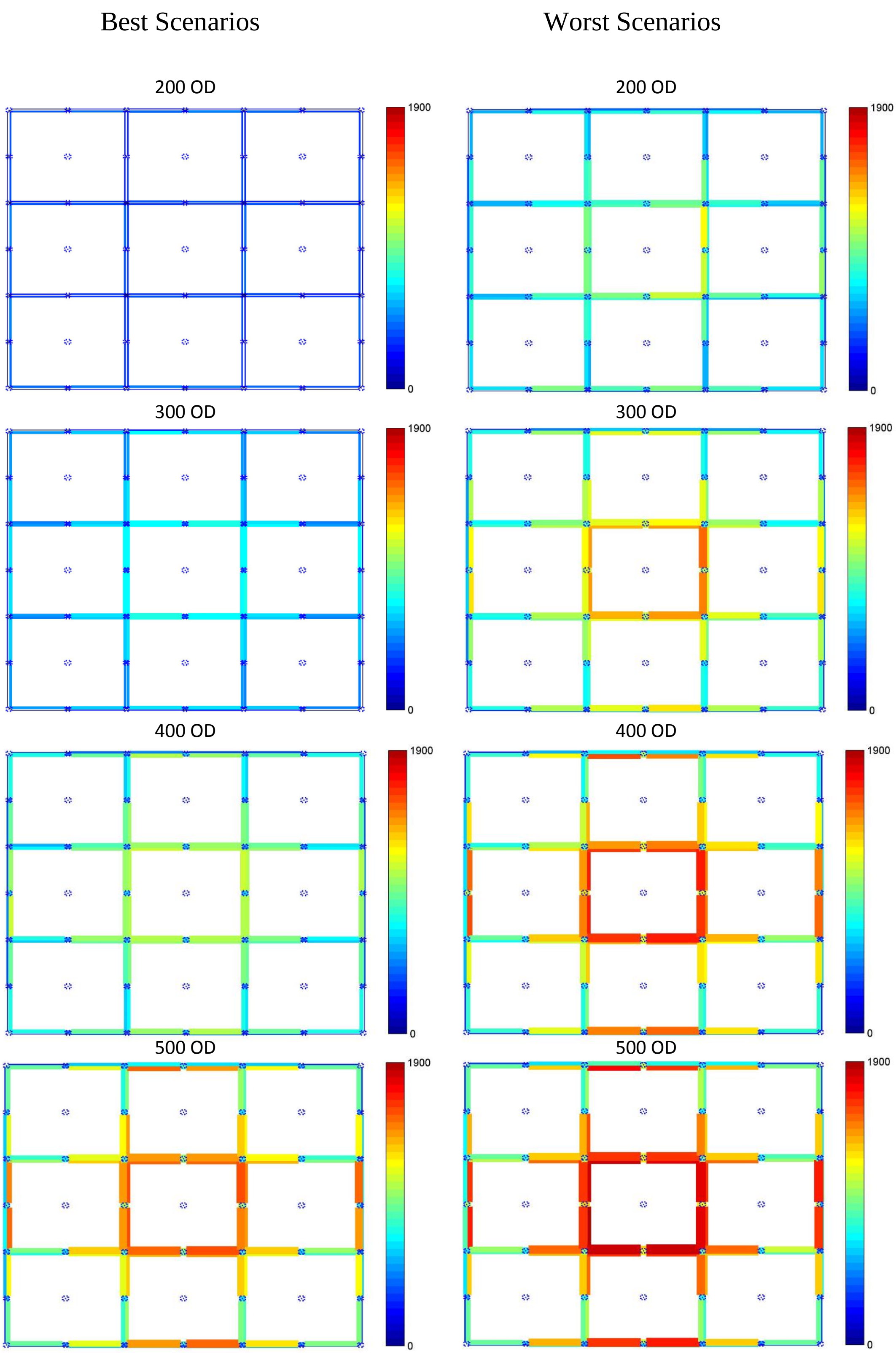
Fig. 5c shows the total travel time in the network due to the worst and best demand patterns. It also indicates that in most cases, depending on the spatial distribution of the demand patterns, there can be a significant variation of the total travel time in the network. On the other hand, it shows that when the number of OD pairs is less than 100 in the combination, the difference of the total travel time between the worst case and best case is not very significant. This is because when the total demand is low, regardless of the spatial distribution of demand, there will be no congestion in the network, and the travel time is just the travel time of free flow. When the total demand is beyond a certain value (e.g., 4000 trips/h in this case), the demand pattern in the worst case starts to produce congestion at intersections, while there is still no congestion in the best case, the difference of the total travel time will become more and more significant. This further indicates that for a given network, the choice of the spatial distribution of the demand can actually influence the network's capacity in dealing with the congestion. For example, in this case study, the network starts to have congestion when the total demand is 4000 trips/h with the worst demand pattern, while for the best demand pattern the congestion only starts when the total demand is over 12000 trips/h. In the next section, we will present some characteristics of the demand patterns generated for this abstract grid network.

3.4.2 Characteristics of the demand patterns

To explore the general characteristics of the different demand patterns, we first plot the flow distributions on links in the best and worst scenarios with different number of OD pairs. Fig. 6 shows the flow distributions for the best scenarios (i.e., the 4 sub-plots on the left side) and worst scenarios (i.e., the 4 sub-plots on the right side). The number of OD pairs contained in the corresponding patterns are 200, 300, 400, and 500 respectively (from top to bottom in Fig. 6). Moreover, the colour and the width of the link represents the volume of the traffic flow: a wide and red link means that link has a high traffic volume, while a narrow and blue link means that the traffic volume of the corresponding link is low.

In both best and worst scenarios, along with the increase of the number of OD pairs (i.e., the total demand of the network), the flow grows faster in the internal links (e.g., the links with zones 9, 12, 13, and 16, see Fig. 1) than those peripheral links. If cross compare the flow distribution between the best and worst scenarios with the same number of OD pairs, it is obvious that the links in the worst scenarios always have higher variation of the flow than the links in the best scenarios. In addition, the spatial distribution of the flow in the best scenarios present significantly better symmetry than the flow in worst scenarios. This indicates that in the worst scenarios, the demand is more likely to be asymmetrically distributed in this symmetric grid network. On the other hand, the demand in the best scenarios is expected to have symmetric distribution, and this is especially true then the total demand is low.

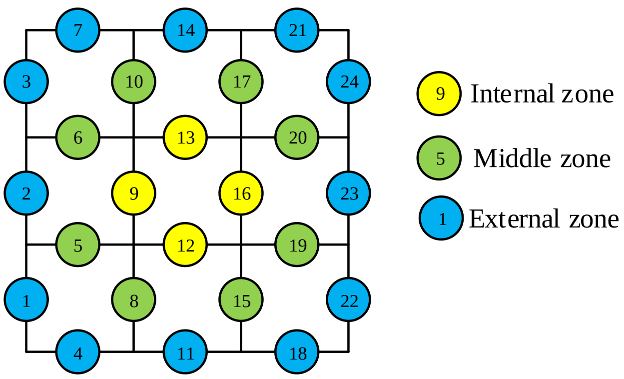
Figure 6 Flow distribution under different demand patterns and number of OD pairs



To further compare the spatial distribution of the demand patterns in the best and worst scenarios, we group the 24 zones in the work into 3 categories according to their locations (see Fig. 7):

- Internal zones: 9, 12, 13, and 16;
- Middle zones: 5, 6, 8, 10, 15, 17, 19, and 20;
- External zones: 1, 2, 3, 4, 7, 11, 14, 18, 21, 22, 23, and 24.

Figure 7 The abstract 4-by-4 network considered in this research



Accordingly, all trips in the network can be grouped into 9 types according to the locations of the origin zone and the destination zone:

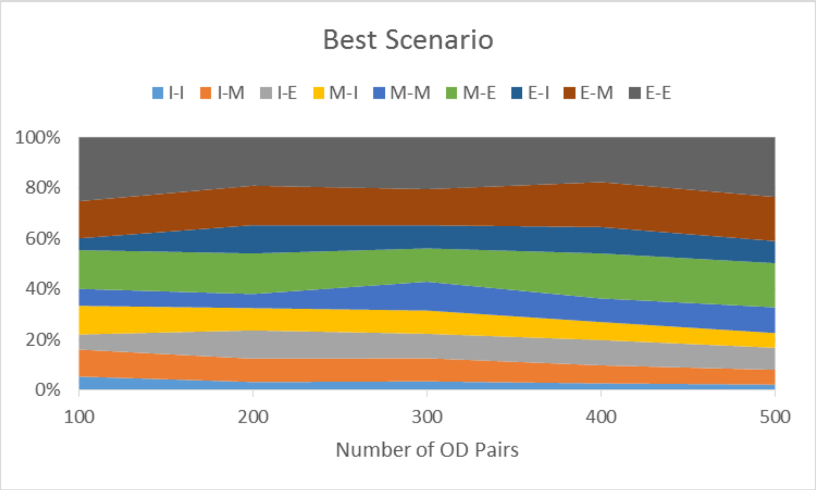
- From internal zone to internal zone (I-I)
- From internal zone to middle zone (I-M)
- From internal zone to external zone (I-E)
- From middle zone to internal zone (M-I)
- From middle zone to middle zone (M-M)
- From middle zone to external zone (M-E)
- From external zone to internal zone (E-I)
- From external zone to middle zone (E-M)
- From external zone to external zone (E-E)

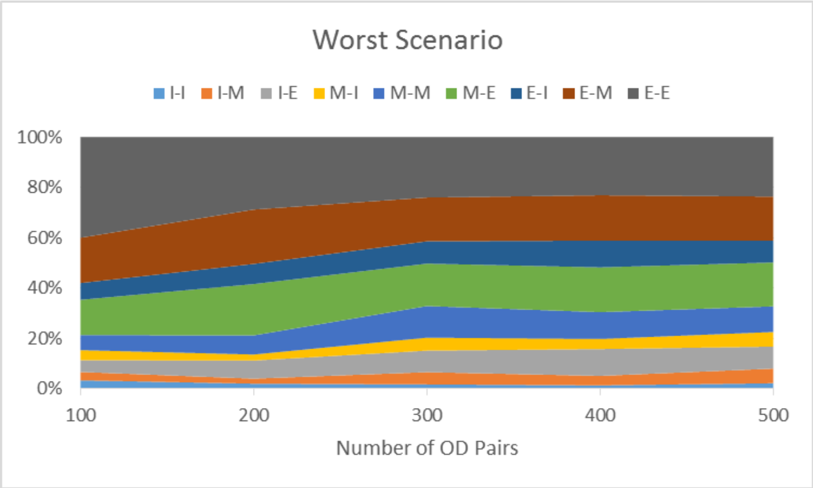
Note that different trip types have different number of zones, thus the maximum number of trips in each trip type can be totally different (e.g., in this case study, the E-E trip has a maximum of 5280 trips, while the I-I trip only has 480 trips at most). Therefore, it may make no sense to compare the absolute number of different types of trips in the same scenario. Instead, we can cross compare the share of different trip types in the best and worst scenarios. For example, the share of the I-I trip is calculated as:

$Share_{I\text{-}I}$ = Number of I-I trips / total number of trips

The share of different types of trips in the best scenario and worst scenario are illustrated in Fig. 7. Overall, the best scenarios always have relatively higher share of the I-I, I-M, and M-I trips than the worst scenarios, while the share of the E-M, E-E, M-E trips in the worst scenarios are comparatively higher. It indicates that the best demand patterns have more trips in the internal links than the worst demand patterns; on the other hand, the worst demand patterns have more trips generated and ended in the external links than the best demand patterns.

Figure 8 Share of the different types of trips





4. Conclusions

In this paper we present an efficient approach for generating traffic demand patterns for a grid network. This approach is developed based on the ideas from experiment design. It is expected to overcome the drawback from manually generating the demand pattern (e.g., incomplete enumerating of possible demand patterns), as well as the extremely high computational cost if using the approaches of exhaust search.

We illustrate the application of this approach through a case study. It includes an abstract 4-by-4 network with bidirectional links and 552 OD pairs. The proposed approach is used to generate the traffic demand patterns in terms of best and worst traffic performance. We evaluate the maximum flow at intersections and links, and the total travel time of the network. The findings show that the variations in the spatial distributions of the demand may cause big variations in the traffic performance. It further highlights the importance for the research of demand pattern generation, as the use of an incomplete set of demand patterns for the network design and evaluation may bring cascading effects, e.g., overestimating the capacity of the network if only the best demand pattern is used.

Moreover, the demand pattern generation approach proposed in this study is a general approach, and it is not based on any specific traffic model or type of network. The traffic assignment models and presented in this paper are just used for demonstration purposes, and they are not necessarily required in other studies. In fact, the practitioners are free to choose their own models as well the performance indicators considering the affordable computation cost, although the core process for the demand pattern generation should remain the same.

The future research could be devoted to introduce the variations of the magnitude and temporal distribution in the demand pattern generation, and further enhance the efficiency of the algorithm.

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