TOWARDS A SYSTEMATIC EXPLORATION OF THE INFLUENCE OF ROUTE CHOICES ON A NETWORK LEVEL OF PERFORMANCE

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July 25, 2014
ABSTRACT

The aim of this paper is to quantify the impact of local demand distribution on the global network behaviour. More precisely, we are interested in identifying how route choices influence the level of performance of a network. A mesoscopic traffic flow simulator is chosen as an experimental platform to perform this analysis on an idealized urban center network. To simplify the exploration, route choice alternatives are clustered in homogeneous groups with respect to the percentage of overlapping. A large set of flow distributions among routes is evaluated and different scenarios are then simulated leading to two main results. First, we are able to define the fluid/congested boundary on the network and its sensitivity to parameters is evaluated. Then, route choice effects on the network level of performance are quantified using the Network Macroscopic Fundamental Diagram which provides an aggregate vision of network behaviour. Moreover, spatial distributions of traffic conditions are also investigated because heterogeneities are a well-known source of network under-performances.
1. INTRODUCTION

Dynamic modelling of large urban traffic networks is very challenging. Indeed, the complexity results from the combined effects of the three components of an urban traffic network: supply, demand and traffic controls. The local supply is defined by the time-dependent capacity per link. It can be modified by traffic controls and altered by some local events. The local demand corresponds to incoming trips on a specific link. It dynamically results from the global demand (trips from origins to destinations) and the route choice process. Congestion happens when the local demand exceeds the local supply creating spatial and temporal heterogeneities at the network level.

Recent works have exhibited from empirical data in downtown Yokohama (see Geroliminis and Daganzo, 2008) a well-defined relation between space-mean flow and density. The existence of such a Network Macroscopic Fundamental Diagram (NMFD) is really appealing because it provides a simple indicator of a network level of performance. Indeed, for a given traffic state, the mean spatial speed can be known giving access to travel time estimation. If the network is homogeneously loaded, the NMFD shape will only depend on supply and traffic control. In this case, several works have been conducted leading to analytical methods for NMFD estimation taken into account for network topology and control settings (e.g. Geroliminis and Daganzo, 2008; Geroliminis and Buyaci, 2012; Leclercq and Geroliminis, 2013). Moreover, for congested network configuration, the NMFD allows to quantify the deviation from theoretical capacity at a network level. Therefore, it allows characterizing the decrease of performance of the network (capacity drop) caused by heterogeneities resulting either to uneven distribution of local demand or supply.

Concerning the demand impact, originally, the NMFD was found not to be influenced by the OD matrix and route choices, (see Geroliminis and Daganzo, 2008). However, recent studies show that networks with an uneven (in space) or inconsistent (in time) distribution of congestion may exhibit traffic states that do not fill as a unimodal and well-defined curve. Changes seem only to be significant when the network operates near its global maximum capacity. Moreover, Geroliminis and Sun (2011) show that spatial distribution of vehicle density within a reservoir significantly influences the NMFD scattering and several studies (e.g. Cassidy et al, 2011; Gayah and Daganzo, 2011; Saberi and Mahmassani, 2012) deal with the effects of inhomogeneity of densities over a network. Recently, Knoop and Hoogendoorn (2013) introduced the Generalized Fundamental Diagram to take into account the spatial inhomogeneity of densities that is considered as an input of the mathematical analysis. Moreover, further works on a simple parallel network have highlighted how route choices distributions modify the NMFD shape, e.g. Leclercq and Geroliminis, 2013. In Mahmassani and Peeta (1993), overall user cost and network performance under time dependent system optimum and user equilibrium assignement patterns are examined through numerical experiments performed on a test network under various loading levels. All these works focus on the influence of network traffic distribution on the network performance estimated from the NMFD. However, few studies investigate the cause of heterogeneous network traffic states and thus make the direct connection between the network loading (distribution of the demand) and the network performance.

In this paper, we will focus on the impact of local demand distributions on the network traffic conditions in order to improve the description of heterogeneities resulting from the network structure and the global demand profile. More precisely, we are interested in identifying how route choices influence the level of performance of the network. The aim is then to establish
a methodology to characterize route choice impacts on the NMFD and on the global network performance indicators. In order to better identify which component of route choices has the larger impact, route selection will be studied apart from flow distribution. Since fine meshed network leads to a large number of potential route choices, a clustering method to reduce the problem size by defining homogeneous sets of route selections with identical properties will be proposed.

As route choices are difficult to observe in practice for dense urban networks and are thus hard to capture, we follow a simulation-based approach to carry out the analysis. The outline of the paper is the following. In Section 2, the global framework of the study is presented detailing the network and the analysis designs. The proposed clustering method for route sets generation is also presented. Then, Section 3 and 4 are concerned with the results of the simulations of different scenarios. The network level of performance is examined at different scales using several indicators. First, the fluid/congested boundary and its sensitivity to parameters are analysed. Second, the impact of route choices is studied more in detail through the NMFD and the potential exhibited capacity drop. Last, spatial heterogeneities are quantified using standard deviation of macroscopic traffic conditions. Finally, Section 4 presents conclusions and an outlook on further researches.

2. NETWORK DESIGN AND ROUTE CHOICE MODELLING

In this study, we consider an idealized network mimicking an urban center. Heterogeneities are studied both analytically and by simulation. The simulations are performed using the even based mesoscopic model proposed by (Leclercq and Becarie, 2012) which is fully consistent with the LWR model (see Lighthill and Whitham, 1955; Richards, 1956) at a macroscopic scale for a single-class triangular fundamental diagram. Moreover, this model provides passing times for all vehicles at all link boundaries so that vehicle trajectories within all links can be estimated. In order to complete the analysis design, supply and demand are defined in the following.

2.1 Idealized network design and supply description

The network is represented by a lattice-like road network with 12 origins and 12 destinations. Only North and West to South and East directions are considered to reduce the problem size. The 84 links of the network represent one-way road sections (see the flow directions represented by arrows on Figure 1) while the 60 nodes represent intersections. Each road section $i$ has the same length $l_i = 300m$. The fundamental diagram parameters are a free flow speed $v = 50km/h$, a jam density $k_{jam} = 200 veh/km$ and a capacity $C = 0.3676 veh/s$. Intersections are controlled by two phases traffic signals with a fixed cycle equal to 1mn, identical for green and red times with no offset. Let us note that some symmetry properties are inherent to this network design. Moreover, the network is not loaded at the beginning of simulations.

2.2 Demand description and Route Choices modelling

Global demand

As described above, the studied network is composed of a set of 144 origin-destinations and for each OD pair a uniform distribution through destinations occurs. Two parameters are then introduced to define the demand: the input flow $Q_{in}$ and $\alpha \in [0,1]$ which allows to increment the
Lighthill, Herman and Greenshields

In order to ensure that the origins links are not saturated, we impose

\[ Q_{in}(1 + 5\alpha) < C \]  \hspace{1cm} (1)

where \( C \) is the link capacity.

**Local demand**

The next step is the route choice description. It is well known that predicting which route a given traveller would take when going from one origin to one destination, is a key step in traffic forecasting models. The route choice depends, on the one hand, on the attributes of the available routes, such as travel time, number of traffic lights etc. On the other hand, characteristics and preferences of the traveller also influence the choice. All these aspects of the route choices problem make it particularly complex, especially for large networks representing dense urban areas. Usually, two approaches can be considered for route choices description. They can either be provided by a model based on equilibrium principle (user equilibrium or system optimum), or using an implicit/explicit expression for choices as for dynamic traffic assignment models. Reviews of route choice models are available in the literature in Bovy and Stern (1990), Ben-Akiva and Bierlaire (2003) for discrete choice methods and in Szeto and Wong, 2012 for traffic assignment. In this paper, we will not question the equilibrium principle or traffic assignment models but instead define a framework to estimate the impact of a high variety of potential choices. Thus, a two-step process will define route choices: i) paths selection and ii) flow distribution over paths.

A total of 3430 potential paths are available to link the set of 144 origin-destinations composing the studied network; some of them are explicitly represented in Figure 1. First let us note that resulting from network design assumptions, all these paths have the same length. As a

![FIGURE 1: Simulations are performed with an urban center represented by a lattice-like unidirectional road network. The arrows represent flow directions.](image-url)
consequence, the free flow travel time is identical for all paths so that they can be clustered according to the level of overlapping. Moreover, in simulations, routes are assigned to vehicles once they enter the network.

**Step 1: Clustering method for paths description**
A crucial property when considering the route set is the correlation between the different alternatives. Several models have been proposed to take this component into account: Cascetta et al. (1996) for the C-Logit model, Ben-Akiva and Bierlaire (1999) for the Path Size Logit (PSL) model, Vovsha and Bekhor (1998) for the Link-Nested Logit model. In this study, we choose to derive the route set definition from the C-Logit model. This model explicitly addresses the correlation among alternatives (like the two available routes from $O_b$ to $D_b$ in Figure 1). The basic idea is to treat the interdependency of the routes through a commonality factor. Thus, highly overlapped paths have a larger factor and therefore smaller utility with respect to similar paths. For each alternative path $p_k$ of a given OD pair, the common factor $CF_k$ is proportional to the degree of overlapping of path $p_k$ with other alternative paths. It is computed as follows:

$$CF_k = \beta \ln \sum_{l} \left( \frac{L_{lk}}{L_l} \right)^{\gamma}$$

where $L_{lk}$ is the length of sections shared by paths $l$ and $k$, while $L_l$ and $L_k$ are the length of paths $l$ and $k$ respectively. Note $CF_k$ that defines the proximity of alternatives independently of the flux on each road, which is appealing if we want to study fluid/congested boundary dissociating the two states. In this work, we assume $\beta = 1 = \gamma$ and compute $CF_k$ for each path $k$ of a given OD pair. Figure 2 shows the results for two distinct OD pairs. In order to develop a clustering method for route set generation, we decide to target five clusters of paths characterized by their $CF_k$ value as plotted in Figure 2. Therefore, for a given OD pair, clusters definition then corresponds to a uniform splitting of the interval defined by the minimum and maximum values of $CF_k$. More precisely the $G_1$ cluster contains two paths with no sections shared and for $i = 2$ to 5, cluster $G_i$ contains alternative paths with more and more shared sections. Note that the distribution of $CF_k$ is specific for each OD as illustrated in Figure 2. Note also that under these assumptions, two clusters have specific characteristics: $G_1$ only contains the two most independent paths while $G_5$ contains those which are the most correlated.

**Step 2: Sample choice for each cluster of paths**
Due to the definition of paths clusters, several routes are available in a given one. In order to perform simulations, we impose a maximum of 5 roads for each OD pair. For each cluster $G_i$, the selected paths are denoted from $R_1$ to $R_5$ with decreasing values of the commonality factor, $R_1$ corresponding to the maximum. The selection method is illustrated in Figure 2: for each OD pair, $CF_k$ values for each alternative path $p_k$ is plotted in blue, the 5 clusters boundary is also plotted while the selected paths $R_j$ in each cluster are drawn in red. The impact of this particular sampling method will be further questioned.

Once the paths are assigned to each OD pair, the following step consists in distributing the inflow of vehicles across the 5 potential paths. The aim of this study is to evaluate a large variability of such a path flow distribution. For this, we consider a discrete approximation of a normal distribution depending on two parameters $p$ and $\sigma$. This allows for instance to simulate a uniform distribution over all paths or on the opposite to favour one of the 5 potential paths setting the maximum on it.

To summarize the design analysis and the demand definition, Table 1 present the
parameters involved in this analysis and the range of values explored in the different scenarios.

![FIGURE 2: Histogram of normalized Commonality Factors for $\beta = 1 = \gamma$ for different OD pairs. In red, $CF_k$ values corresponding to selected paths.](image)

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$Q_{in}$</th>
<th>$G_i$</th>
<th>$p$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0,1]</td>
<td>[0, $Q_{max}$]</td>
<td>$i \in 1, 2, 3, 4, 5$</td>
<td>[0,1]</td>
<td>[0.01; 10]</td>
</tr>
</tbody>
</table>

**TABLE 1: Parameters of the study**

In the next sections, different scenarios are analysed using both analytic and numerical computations. Two distinct analyses are performed to quantify the network level of performance. First, the fluid/congested boundary for the network and its sensitivity to parameters is presented in Section 3. This allows characterizing the global network behaviour from a rough and binary point of view. Indeed, we focus on dynamic loadings. When the local demand on each link does not exceed its capacity, traffic dynamics only correspond to the queue evolutions within links. No spillbacks occur and the whole network remains in free-flow conditions. Otherwise, congestion will appear in any link where the local demand exceeds capacity and will propagate within the network. The network can then be considered as congested or at least partly congested.

Then, once congestion has appeared, in order to better evaluate the impact at the network level, two complementary studies are presented. In Section 4, route choices effect is investigated more in detail through numerical simulations given access to the NMFD and the potential exhibited capacity drop. Last, spatial heterogeneities are quantified by studying the distribution of traffic conditions.
3. ANALYSIS OF THE NETWORK FLUID/CONGESTED BOUNDARY

3.1 Methodology
A simple way to characterize the network performance is to determine the binary state of the network (free-flow or congested). Interestingly, this can be done without resorting to simulations. Indeed, the network fluid/congested boundary can be analytically computed following the mathematical formalism described in Bierlaire (2002) that we briefly recall. We refer to Section 2 for a detailed description of the studied network. Let us denote by \( q \) the origin-destination flows associated to each of the 144 considered OD pairs and by \( u \) the link flows for each link. With the notations already introduced, each OD pair \( k \) is linked by the set of \( p_k \) alternatives paths. The link-path incidence matrix \( L \), only depends on the network topology and is defined by \( L_{kl} = 1 \) if link \( k \) belongs to path \( l \), 0 otherwise. Thus, the problem can be rewritten under the matrix form:

\[
L C q = u
\]  

Solving (3) allows determining with low computational cost the network fluid/congested boundary. Indeed, as explained in section 2, a simulation input is defined by the \( n \)-uplet of parameters \((\alpha, Q_{in}, G_i, p, \sigma)\) where \(\alpha\) and \(Q_{in}\) are related to the demand, \(G_i\) corresponds to the cluster of paths for a given OD while \(p\) and \(\sigma\) are related to the flow distribution over paths for each OD pairs. Exploring the range of each parameter, system (3) is solved. If the results are such that there is at least one saturated link \( u_j \leq C \), \( C \) being the link capacity, the \( n \)-uplet is assigned as “congested”. Indeed, if a congestion appears at some point, it will naturally spillback over at least a part of the network.

3.2 Results
Following this methodology, several tests are performed to study the fluid/congested boundary as network performance indicator. Figure 3 shows the evolution of the fluid/congested boundary depending on the demand: \( Q_{in} \) (x-axis) versus \( \alpha \) (y-axis), for three values of \( \sigma \): a small one, \( \sigma = 0.1 \), meaning that the maximal inflow is mainly concentrated on one path, a large one \( \sigma = 9.1 \) simulating the case of a uniform inflow distribution and an intermediate one \( \sigma = 0.5 \).

For this test case, the central path described through the parameter \( p \) corresponds to the path \( R_3 \) denoted for each cluster. Note that when \( \sigma \) is large, \( p \) has no influence. The range of values for \((\alpha, Q_{in})\) corresponding to the fluid network configuration respectively congested configuration is plotted in black, respectively in grey. Let us recall that \( Q_{in} \) parameter is constrained by the value of \( \alpha \) as detailed in Section 1 eq.(1). Therefore, the range of values cannot be entirely explored leading to this specific shape.

Several conclusions can be deduced from Figure 3. First of all, it has to be noted that the shape of the fluid/congested boundary does not depend on either clusters’ id or \( \sigma \) value. Next, for a given clusters’ id (that is for a given line), comparing the three columns, the impact of \( \sigma \) parameter can be studied. It is clear that the higher \( \sigma \) is (that is the most the flow is distributed over the selected paths for the given cluster) the lower the network is congested. For instance, for cluster \( G_2 \), the percentage corresponding to fluid network configuration grows from 40% for...
FIGURE 3: Fluid/congested boundary evolution depending on the demand. In columns, different values of \( \sigma \) and in lines, the level of overlapping from cluster \( G_1 \) to \( G_5 \).

\( \sigma = 0.1 \) to 56% for \( \sigma = 9.1 \). Then, for a given \( \sigma \) (that is for a given column), the clusters’ id analysis can be performed. Results on Figure 3 show that the higher the value of \( CF_k \) is (that is for a high clusters’ id), the larger is the fluid zone. For instance, for \( \sigma = 0.1 \), the percentage corresponding to fluid network configuration grows from 30% for cluster \( G_1 \) to 86% for cluster \( G_5 \). That means that the more the paths overlap between each OD pair when \( CF_k \) value is high, the lower the network is congested. This is a non-intuitive conclusion since usually, when considering a single OD pair, low overlapping intuitively means a better (in the sense of
uniformly) distribution over the different routes. Indeed, higher overlapping values will increase the shared portions of routes with higher flows and thus a higher probability for congestion. However, we are interested here in the whole network performance and have to consider all OD pairs. That is why in order to improve our analysis, we will study more in detail what the clustering method using the $CF_k$ coefficient means at the network level. For each cluster of paths and for each link of the network, we plot in Figure 4 the number of paths crossing over this link normalized versus the total number of paths of each cluster. We can observe for instance that due to the particular structure of the studied network a low “commonality factor” values for each OD pair (see first subplot) favours the peripheral links. Then, comparing the subplots in Figure 4, the level of global overlapping is increasing from cluster $G_1$ to cluster $G_5$ and we clearly observe that considering close alternatives for routes at the single OD level may paradoxically lead to a whole set of routes that weakly overlap. Figure 5 clearly shows that the lowest $CF_k$ value is (see cluster $G_1$) means that more than 50% of the network links carry very few paths (less than 10). For higher $CF_k$ the links carry more paths with a more homogeneous distribution. This means that the repartition of paths over the network is more well balanced when $CF_k$ inverse.

In the second test, the value of $\sigma$ is assumed to be high enough to have a uniform flow distribution over the paths and no effect of the $p$ value. Computations are performed for different numbers of paths: 1, 2 or 5 paths in each cluster, again chosen from the maximal $CF_k$ value in each cluster. The fluid/congested boundary depending on the demand parameters is plotted in Figure 6 for clusters $G_2$ to $G_4$ which are less specific. The main conclusion is that the higher the number of paths is, the lower congestion can be observed. However, the most noticeable gain is obtained when the number of paths increases from 1 to 2.

When this number is higher than 5 no changes can be identified. Last, we perform a test to study the impact of the choice for the sample of five paths in a given cluster. We try different options, for instance 5 paths with an increasing $CF_k$ value for each cluster, 5 paths equally distributed among a cluster. The results obtained show that there is no significant effect.

Combining the results of these tests, this study shows that the more homogeneously the flow is distributed over the network, the better the network performance. In our study, homogeneity conditions result both from high level of overlapping and a uniform flow distribution through the different paths.

4. REFINED ANALYSIS OF THE LOCAL DEMAND DISTRIBUTION ON THE NETWORK PERFORMANCE

In this section, we will resort to refined indicators to assess the network performance. Some are inspired by the concept of the NMFD (network traffic evolution, capacity drop,...), others correspond to classical representations of heterogeneities (density standard deviation, ...).

4.1 Different indicators to assess the network performance

Using the Edie’s generalized definitions (Edie, 1963) and assuming all vehicles trajectories are available, for each link $i$, the average flow $Q_i$ and density $K_i$ in the time step $[t + \Delta t]$ are given by

$$Q_i = \frac{\sum_k d_k}{l_i \Delta t}, \quad K_i = \frac{\sum_k t_k}{l_i \Delta t}$$

(4)

where $d_k$ is the distance travelled by vehicle $k$ in the considered zone (corresponding to link $i$
And time interval \([t + \Delta t]\) and \(t_k\) respectively its time spent in the zone. Let us note that \(\Delta t\) should be of the order of several signal timing to provide accurate mean estimations. These definitions allow determining two indicators series: on the one hand, the average network flow \(Q\), density \(K\) and speed \(V\) defined as follows:

\[
Q = \frac{\sum l_i Q_i}{\sum l_i}, \quad K = \frac{\sum l_i K_i}{\sum l_i}, \quad V = \frac{Q}{K}
\]

The time evolution of \(Q\) and \(K\) provide a synthetic vision of the network global behaviour. For simplicity, \((Q, K)\) plots are provided for successive time periods.

On the other hand, the standard deviation of the density across the network is used as an indicator of spatial distribution of network conditions.

Moreover, simulations duration is chosen large enough in order to ensure that the network reaches in a steady state. This has been monitored by computing the cumulative curves for the
total in-and-outflows. When the difference between these curves (that corresponds to the total accumulation within the network) is constant, the network is considered as in a steady state. Note that when the network is congested the difference can never be constant because oscillatory patterns are observed. In that case, we consider that the network is in a quasi-steady state when the magnitude of the variations is small enough.

**FIGURE 5 :** Percentage of links that carry at least x paths (repartition function)

**FIGURE 6 :** Fluid/congested boundary evolution for different number of paths with uniform inflow distribution for different levels of overlapping, cluster $G_2$ to $G_4$.

### 4.2 Results

The first test aims at evaluating the $(Q, K)$ plots sensitivity to the level of overlapping representing through the paths clusters in our analysis. Two cases are plotted in Figure 7 for a fixed demand corresponding to $\alpha = 0.15 = Q_{in}$. In the upper subplot a), $\sigma = 10$ corresponds to a uniform distribution whereas in the bottom subplot b) $\sigma = 0.1$. Figure 7 clearly shows that the NMFD shape depends on the degree of overlapping of paths: for instance on a) for clusters $G_3$ to $G_5$, the network remains in free-flow condition whereas for clusters $G_1$ and $G_2$ it switches to
congestion. Comparing the two plots, we can observe the impact of $\sigma$ since cluster $G_3$ now experiments congestion in b). Moreover, these plots give access to an estimation of the network capacity drop represented by the difference between solid and dot lines for each cluster.

Let us note that the reference for capacity is assumed to be the maximal obtained with one of the clusters for a given simulation. Comparing cluster $G_2$ and $G_3$ in a) and b), we clearly observe that the more the inflow is distributed, the lower the capacity drop is and the better the network performance. For instance, for cluster $G_2$, the absolute capacity drop is equal to 0.029 veh/s (13\%) for high $\sigma$ in a) and to 0.068 veh/s (30\%) for low $\sigma$ in b). Last, we can observe that in both cases (different values of $\sigma$), according to the cluster’s id, the network can be in a high instable intermediate state (see for instance, cluster $G_2$ in subplot a) and cluster $G_3$ in subplot b)) and that the variability decreases when congestion is well established.

All previous tests have been performed attributing the same cluster’s id to the whole set of OD pairs. In the following test, the impact of this assumption is studied. Then, Figure 8 presents the NMFD obtained for two different distributions of clusters’ id over the OD as plotted on the left of the figure. On the upper subplot, the two border clusters are mixed while on the bottom one-mixed clusters correspond to more medium value of $CF_k$. First, the NMFD resulting from this clusters distribution seems to be the mean of the two original ones: for instance mixing clusters $G_1$ and $G_5$ leads to a congested configuration but with less capacity drop. However, the combination corresponding for instance to cluster $G_1$ for West origins combined with cluster $G_5$ for North origins (green line) is not equivalent in terms of network performance to the reverse one (magenta line). Especially, the $G_1 - G_5$ mixed solution (green line) corresponds to a higher congested configuration whereas the $G_5 - 1$ one is unstable with a larger range of oscillations. We can deduce that not only the level of overlapping plays an important role on the network level of performance but also its distribution between the OD.
A third test is conducted to study more locally the network performance. We then define 4 distinct subnetworks as illustrated in Figure 9 upper left corner and we plot the corresponding NMFD for each subnetwork, cluster by cluster. In this test, even if the same cluster’s id is assigned to the whole set of OD pairs, Figure 9 shows that the behaviour of the network is not spatially homogeneous depending on the level of overlapping. For instance, simulations for cluster $G_1$ and $G_2$ let appear either congested or free-flow steady state with respect to the subnetwork. We shall recall that simulations for these clusters on the global network are associated to congestion, see Figure 7. Not surprisingly, subnetworks 2 and 3 appear more congested for low $CF_k$ values than the two others quarters. This is because low $CF_k$ values make the peripheral links more attractive. Congestion then appears close to the entries where several demand inputs aggregates.

Last, in order to study heterogeneities more in detail, Figure 10 represents the standard deviation of the density over the whole network depending on the demand for three values of $\sigma$. First, looking at the effect of the level of overlapping comparing the different lines for a given $\sigma$, it has to be noted that the less global overlapping is, the most homogeneous the network is. We recall that low global overlapping means high $CF_k$ values for each OD pair in our case study (see Figure 4). Moreover, Figure 10 allows determining the range of parameters leading to the most heterogeneous zones. Indeed, it clearly appears that around the boundary of the admissible domain (in terms of constraint on the demand see Eq 1) especially for low $\sigma$ value et low clusters’id, the density on the network is highly heterogeneous with a standard deviation reaching its maximal value. This effect is dispersing when the local level of overlapping (for each OD pair) is increasing (comparing in the first column, cluster $G_1$ to $G_3$). The last point concerns the influence of $\sigma$ parameter: looking more especially at clusters $G_3$ to $G_5$, we see that the larger $\sigma$ is, the lower are heterogeneities. To conclude, the optimal solution in terms of homogeneous network seems to be when the paths are most correlated and the inflow uniformly distributed.
FIGURE 9: NMFD corresponding to 4 different subnetworks. The demand is defined by $Q_{in} = 0.15 = \alpha$ and $\sigma = 10$ such that the inflow is uniformly distributed.

FIGURE 10: Density standard deviation depending on the demand. In columns, different values of $\sigma$ and in lines, the level of overlapping from cluster $G_1$ to $G_5$. 
5. CONCLUSIONS

In this paper, an analysis of the effect of the local demand distribution on the network traffic conditions has been carried out, focusing on how route choices influence the level of performance of the network. In order to study route choices impact, a clustering method based on the level of paths’ overlapping has been proposed to generate homogeneous sets of paths. In this work, we also proposed a method to determine with low computational cost, the fluid/congested boundary and its sensitivity to route choice have also been studied. Two levels of analysis have been performed: i) the global network behaviour through fluid/congested boundary and ii) dynamic network indicator as the NMFD and spatial distribution of densities. The different evaluated scenarios confirm that network performance is highly affected by route choice, both by paths selection and flow distribution.

An important result here is that path overlapping at the network level cannot be directly assessed through the study of paths overlapping for each OD pair. Indeed, we observe in this study a counter-intuitive fact, i.e. low overlapping (low $C_{F_k}$) for each OD leads to the highest overlapping between paths at the network level. The question of characterizing the level of overlapping at the network level is very challenging, especially if we want to consider both the influence of paths overlapping and paths flow distributions. The authors are currently investigating this question.

These preliminary results and the associated framework look promising. Our goal is now to improve the analysis design and perform an extensive sensitivity analysis in order to determine the most influent parameters related to route choices and demand with respect to the global network performance.

ACKNOWLEDGMENT

This work has been supported by the ADEME project CYTEDINE.

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