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Sérgio F. A. Batista

Affectation dynamique des usagers sur les grands réseaux des transports considérant différents types de comportements des usagers

Devant le jury composé de :

Jorge LAVAL	Professeur (Georgia Tech)	Rapporteur
Francesco VITI	Professeur (Université du Luxembourg)	Rapporteur
Kay AXHAUSEN	Professeur (ETH, Zurich)	Examinateur
Margarida COELHO	Professeur (Université d'Aveiro)	Examinatrice
Christine SOLNON	Professeur (INSA, Université de Lyon)	Présidente du jury
Ludovic LECLERCQ	Directeur de Recherche (IFSTTAR, Univ.	Directeur de thèse
	Lyon)	

Thèse préparée au LICIT (Laboratoire d'Ingéniérie Circulation Transport)

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Declaration

I hereby declare that the contents of this dissertation are original and have not been submitted in whole or in part, for consideration for any other degree or qualification to this or another university. This research work was developed at *Laboratoire d'Ingénierie Circulation Transport (LICIT)* under the supervision of Prof. Ludovic Leclercq and sent for consideration to the Doctoral School *Mécanique-Energétique-Génie Civil-Acoustique (MEGA) - ED162* of the University of Lyon (France), for the Doctoral Degree in Civil Engineering. Part of this work was developed in collaboration with Prof. Nikolas Geroliminis from the École Polytechnique Fédérale de Lausanne (EPFL). All research works are properly referenced and available at the References section. Some chapters of this manuscript were submitted for publication in scientific journals and are properly referenced at the beginning of each chapter.

Preface

This journey started on the 30th of September 2015 when I took the plane to Lyon. This adventure of three years culminated in the final work presented in this thesis. Despite the road was not always easy throughout these 3 years, this research work was possible not only thanks to me, but also to several people that gave me important support and to whom I am very grateful.

I firstly would like to thank my girlfriend and family for their support and patient during these 3 years.

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Abstract

The population growth in urban areas represents an issue for transportation planning. This overload of urban transportation systems, leading to significant monetary costs and environmental issues. Policy measures are then needed to decrease the level of congestion and increase the efficiency of transportation systems. In a short term, traffic simulators might be a powerful tool that help to design innovative solutions. But, the classical traffic simulators are computationally demanding for large scale applications. Moreover, the set up of the simulation scenario is complex. An aggregated traffic modeling might be a good solution (Daganzo 2007; Geroliminis & Daganzo 2008). The city network is divided into regions where a welldefined Macroscopic Fundamental Diagram (MFD) regulates the traffic conditions inside each one. The MFD relates the average traffic flow and density inside a region. Despite the idea of aggregating the city network is simple, it brings several challenges that have not yet been addressed. Up to today, only Yildirimoglu & Geroliminis (2014) proposed a dynamic traffic assignment framework for regional networks and MFD models. This framework is based on the simple Multinomial Logit model and does not explicitly deal with trip length distributions. Moreover, their framework does not consider that users are different from each other and have different purposes and preferences for their travels.

The goal of this PhD dissertation is to twofold. First, the influence of the users behavior on the global network performance is investigated. This analysis focuses on the network mean speed and its internal and outflow capacities, comparing different models that account for different kinds of users behavior against the Deterministic and Stochastic User Equilibrium. Second, an innovative and complete dynamic traffic assignment framework for multi-regional MFD-based models is proposed. This framework is divided into several milestones and is based on the connections between the city and regional networks. In a first step, systematic scaling-up methods are proposed to gather the regional paths. In a second step, four methods are discussed to calculate the distributions of trip lengths that characterize these regional paths. In the third step, a network loading model that considers distributions of trip lengths that are explicitly calculated and the evolution of the regional mean speeds is proposed. Finally, this dynamic traffic assignment framework is extended to account for bounded rational and regret-averse users. This PhD is part of a European ERC project entitled MAGnUM: Multiscale and Multimodal Traffic Modeling Approach for Sustainable Management of Urban Mobility.

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Résumé

La croissance démographique dans les zones urbaines représente un problème pour la planification des transports. La surcharge des systèmes de transport urbains entraîne des coûts monétaires importants et des problèmes environnementaux. Des mesures politiques sont alors nécessaires pour réduire le niveau de congestion et accroître l'efficacité des systèmes de transport. À court terme, les simulateurs de trafic pourraient constituer un outil puissant pour la conception de solutions innovantes. Mais les simulateurs de trafic classiques sont exigeants sur le plan informatique pour les applications à grande échelle. De plus, la mise en place du scénario de simulation est complexe. Une modélisation de trafic agrégée pourrait être une bonne solution (Daganzo 2007; Geroliminis & Daganzo 2008). Le réseau routier des villes est divisé en régions, où un diagramme fondamental macroscopique bien défini (MFD) régule les conditions de circulation à l'intérieur de chacune. Le MFD concerne le débit et la densité de trafic moyens dans une région. Malgré que l'idée d'agréger le réseau de la ville soit simple, il soulève plusieurs défis qui n'ont pas encore été abordés. Jusqu'à aujourd'hui, seule Yildirimoglu & Geroliminis (2014) propose un cadre d'affectation dynamique du trafic pour les réseaux régionaux et les modèles MFD. Ce cadre est basé sur le modèle Logit multinomial et ne traite pas explicitement des distributions de longueurs de parcours. De plus, leur structure ne considère pas que les utilisateurs sont différents les uns des autres et ont des objectifs et des préférences différents pour leurs voyages.

L'objectif de cette thèse est double. Tout d'abord, l'influence du comportement des utilisateurs sur la performance globale du réseau routier d'une ville est étudiée. Cette analyse se concentre sur la vitesse moyenne du réseau et ses capacités internes et de sortie, en comparant différents modèles tenant compte des différents types de comportement des utilisateurs par rapport à l'équilibre utilisateur déterministe et stochastique. En second lieu, un cadre innovant et complet d'affectation dynamique du trafic pour les modèles multirégionaux basés sur le MFD est proposé. Ce cadre est divisé en plusieurs étapes et repose sur les connexions entre la ville et les réseaux régionaux. Dans un premier temps, des méthodes systématiques de mise à l'échelle sont proposées pour rassembler les voies régionales. Dans un deuxième temps, quatre méthodes sont discutées pour calculer les distributions de longueurs de parcours pour caractériser ces chemins régionaux. Dans la troisième étape, un modèle de chargement de réseau qui considère les distributions de longueurs de parcours explicitement calculées et l'évolution des vitesses moyennes régionales est proposé. Enfin, ce cadre d'affectation dynamique du trafic est étendu pour prendre en compte les usager qui ont une aversion au

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regret ou une rationalité imparfaite. Cette thèse s'inscrit dans le cadre d'un projet européen ERC intitulé MAGnUM: approche de modélisation du trafic multi-échelle et multimodal pour la gestion durable de la mobilité urbaine.

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Resumo

O crescimento populacional nas áreas urbanas representa um problema para planificação de sistemas de transportes. Um forte aumento da procura pode levar à sobrecarga dos sistemas de transporte e trazer grandes custos económicos e ambientais. Para diminuir o nível de congestionamento e aumentar a eficiência dos sistemas de transporte, são necessárias medidas politicas adequadas. A curto prazo, os simuladores de tráfego podem ser uma ferramenta poderosa para ajudar a projetar soluções inovadoras. Contudo, os simuladores de tráfego convencionais requerem um elevado poder computacional para aplicações a larga escala. Por outro lado, a configuração do cenário de simulação é complexa. Uma simulação agregada do tráfego aparenta ser uma boa solução (Daganzo 2007; Geroliminis & Daganzo 2008). A ideia consiste em dividir a rede urbana em regiões onde as condições de tráfego são aproximadamente homogéneas e reguladas através de um Diagrama Fundamental Macroscópico (MFD). A função MFD relaciona o fluxo e a densidade de tráfego que circula dentro de uma região. Apesar da ideia de agregar a rede urbana em regiões ser simples, ela traz vários desafios que ainda não foram estudados. Apesar da ideia de agregar a rede urbana ser simples, ela traz vários desafios que ainda não foram abordados. Até hoje, apenas Yildirimoglu & Geroliminis (2014) propôs uma metodologia de afetação dinâmica dos utilizadores em redes regionais e considerando os modelos MFD. Ela é baseada no modelo Logit Multinomial e não considera distribuições de distâncias de percurso calculadas explicitamente. Além disso, esta metodologia não considera que os utilizadores são diferentes uns dos outros e possuem diferentes objetivos e preferências para as suas viagens.

Esta tese de doutoramento visa responder a dois objetivos principais. Numa primeira parte, pretende-se investigar a influência do comportamento dos utilizadores na performance global da rede urbana. Esta analise focaliza-se na velocidade media dos veículos assim como nas capacidades internas e de escoamento da rede. Para tal, as performances dos modelos que consideram diferentes tipos de comportamento dos utilizadores são comparadas com as dos Equilíbrio Determinístico e Estocástico do Utilizador. Numa segunda parte, pretende-se propor um mecanismo completo e inovador de afetação dinâmica dos utilizadores em redes regionais, considerando os modelos MFD. Esta metodologia divide-se em diversas etapas e baseia-se na interface entre as redes urbana e regional. Primeiramente, são discutidos méto-dos sistemáticos para o calculo dos caminho regionais. Segundo, são propostos diversos métodos para calcular as distribuições de distancias de percurso dentro de cada região de cada caminho regional. Terceiro, é proposto um modelo de carregamento da rede que con-

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List of Symbols

City Network:	
а	Link of the city network.
l _a	Length of link a.
k	Route on the city network.
0	Origin node on the city network.
d	Destination node on the city network.
Ω^{od}	Route choice set of a city network and <i>od</i> pair.
S	Number of routes listed in Ω_k^{od} .
Га	Set of all links of the city network.
N _{links}	Number of links listed in Γ_a .
N _{nodes}	Number of nodes that define the city network.
Ξ	Set of all <i>od</i> pairs of the city network.
<i>q</i> _a	Flow of link a.
q_{al}^c	Flow capacity of link <i>a</i> and lane <i>l</i> .
N _{lanes}	Number of lanes of link a.
t _a	Free-flow travel time of link a.
Q_k	Flow of route k.
δ_{ka}	Dummy variable that equals 1 if route k uses link a.
TT_k^{od}	Travel time of route <i>k</i> of <i>od</i> pair.
σ_k^{od}	Standard deviation of the distribution of travel times of route k and
	od pair.
TC_k^{od}	Travel cost of route k of od pair.
т	User or traveler.
Т	Simulation time.
$\overline{TT_k}$	Average travel time per route.
Q _{out}	Network outflow.
Random Htility r	nodels.

-	
U_k	Perceived utility of route k .
V_k	Deterministic utility of route k.
$\overline{V^{od}}$	Vector that contains all deterministic route utilities.

ϵ_k	Stochastic or error term of route k.
ϵ_{a}	Error term of link a.
\overrightarrow{Q}	Vector that contains all route flows of all od pairs listed in ξ .
Q^{od}	Total demand for <i>od</i> pair.
$P_k^{od}(V^{od}(\overrightarrow{Q}))$	Probability of choosing route k from Ω_k^{od} .
θ^{od}	Scale parameter of a Gumbel distribution for the Multinomial Logit
	model.
eta_{C} , γ_{C}	Free parameters of the C-Logit model.
$eta_{PSL}, oldsymbol{\gamma}_{PSL}$	Free parameters of the Path-Size Logit model.
β_{PSC}	Free parameter of the Path-size Correction Logit model.
σ_{kl}	Similarity coefficient between routes k and l .
$\gamma_{\it PCL}$	Free parameter of the Paired Combinatorial Logit model.
$lpha_{mk}$, μ_m	Inclusion parameters and Nesting coefficients of the Cross Nested Logit
	model.
Σ	$S \times S$ covariance matrix of the Multinomial Probit model.
F _{ML}	$N_I \times N_I$ link-path incidence matrix.
T_{ML}	$N_l \times N_l$ link variance matrix.
ζ^k_{ML}	Row vector of variables that follow a normal distribution with zero
	mean and unit variance.
$ u_{ML}^k$	Row vector of i.i.d. Gumbel distributed variables.
$arphi(\zeta^k_{ML})$	Density function of ζ_{ML}^k .
M_{ML}	Number of draws considered for the Mixed Logit model.
η_a , ζ_a	Scale and shape parameters of a gamma distribution for link a.
Μ	Number of samples for the Monte Carlo simulation approach.
t_k^i	Sample i of the travel time of route k .
t ⁱ a	Sample <i>i</i> of the travel time of link <i>a</i> .

Method of Successive Averages:

$lpha_j$	Descent step of the Method of Successive Averages.
j	Descent iteration of the Method of Successive Averages.
Gap	Relative gap function for the DUE and SUE.
$N(\lambda)$	Number of violations.
Φ	Pre-defined superior threshold for the number of violations.
N _{max}	Maximum number of allowed descent steps.

Q_k^*	Temporary flow of route k .
Q_k^{j+1}	Flow of route k at descent iteration $j + 1$.
Q_k^j	Flow of route <i>k</i> at descent iteration <i>j</i> .

Prospect Theory:

-

$X_k(t_k)$	Time prospect.
$v_k(t_k)$	Value function.
t_k	Deterministic travel time.
$\omega(p_k)$	Weighting function for gains and losses.
p_k	Probability that the perceived travel time is framed as a gain or a loss.
δ_k^{gain}	Dummy variable that equals 1 if t_k is framed as a gain or 0 otherwise.
δ_k^{loss}	Dummy variable that equals 1 if t_k is framed as a loss or 0 otherwise.
$lpha^{ extsf{PT}}$, $eta^{ extsf{PT}}$	Degrees of diminishing sensitivity for gains and losses, respectively.
λ^{PT}	Loss-aversion degree.
$\gamma^{ extsf{PT}}$, $\delta^{ extsf{PT}}$	Distortion in the perception of the probability p_k for gains or losses,
	respectively.
T_0^{od}	Reference point of <i>od</i> pair.

Bounded Rationality:

AL ^{od}	Aspiration level of <i>od</i> pair.
Δ^{od}	Tolerance or indifference band of <i>od</i> pair.
ω^{od}	Set of <i>satisficing</i> routes.
Υ^{od}	Users' strict preference order set.
A_R	Number of repetitions for the indifference preference order.
TT ^{UE}	Route travel time at the User Equilibrium (UE).

Regret Theory:

H_k^{od}	Perceived regret.
h_k^{od}	Average regret.
R(y)	Regret function.
δ^{od}	Regret-aversion parameter.

Value of Time and Value of Reliability:VOTValue of time.

| XXX

VOR Value of reliability.

Regional networks	and MFD models:
r	Region.
0	Origin region.
D	Destination region.
Ω^{OD}	Regional choice set of regional OD pair.
W	Set of regional OD pairs.
p	Regional path.
R	Number of regions that define <i>p</i> .
X	Set of regions that define the regional network.
Ψ	Set of regional paths.
$\overline{q_r}$	Average circulating flow inside the region r .
$\overline{k_r}$	Average density inside region r.
τ	Time period.
t	Time instant.
N_{v}	Number of circulating vehicles inside region r during time period τ .
tdi	Total distance of vehicles <i>i</i> inside region <i>r</i> .
t t _i	Total time spent by vehicle <i>i</i> inside region <i>r</i> .
δ_{iv}	Dummy variable that equals 1 if vehicle i travels inside region r .
L ^r _{net}	Total region length.
P _r	Travel production of region r.
n _r	Accumulation of vehicles inside region r.
V _r	Average speed of vehicles inside region r.
$Q_{in,r}(t)$	Inflow function.
$Q_{out,r}(t)$	Outflow function.
$\overline{L_r}$	Average trip length for all vehicles traveling inside region r .
L _{vr}	Trip length of vehicle i traveling inside region r .
t _{entry}	Entry time of vehicle <i>i</i> inside region <i>r</i> .
t _{exit}	Exit time of vehicle <i>i</i> inside region <i>r</i> .
Г	Set of trips.
N _{od}	Number of od pairs sampled on the city network, to define Γ .

Regional trip lengths:	
$\overline{L_p^{M_j}}$	Average regional trip length of regional path p calculated through method j (M_j).
Method 1:	
$\overline{L_i}$	Average regional trip length for the $i-$ th region.
l _{ik}	Length of the part of trip k that occurs in region <i>i</i> .
δ_{ik}	Dummy variable that equals 1 if trip k travels on region i .
Method 2:	
j	Next adjacent region to <i>i</i> .
L _{ij}	Distribution of regional trip lengths of region i that goes to j .
$\overline{L_{ij}}$	Average regional trip length to go from region <i>i</i> to <i>j</i> .
δ_{ijk}	Dummy variable that equals 1 if trip k travels on region i and goes to region j.
Λ	Set of adjacent regions to <i>i</i> .
γ	Parameter that equals 1 if p is composed by 2 or more regions.
Method 3: intern	al trips
$\overline{L_i}$	Average regional trip length for the region <i>i</i> .
$lpha_{ik}$	Dummy variable that equals 1 if k is an internal trip of region i .
Method 3: crossi	ng trips
h	Previous origin region.
L _{hij}	Distribution of regional trip lengths of region i , for trips coming from
	region <i>h</i> and going to region <i>j</i> .
L _{hij}	Average regional trip length to go from region h to j and crossing region i .
δ_{hijk}	Dummy variable that equals 1 if trip k comes from region h and goes
	to <i>j</i> by crossing region <i>i</i> .
Method 4:	
L_i^p	Distribution of regional trip lengths for p on region i
$\overline{L_i^p}$	Average regional trip length of <i>p</i> on region <i>i</i> .

δ^{p}_{ik}	Dummy variable that equals 1 if trip k travels on region i and both
	define regional path <i>p</i> .
Regional networ	k loading:
TT_p^{OD}	Perceived travel time for regional path p and regional OD pair.
L _{rp}	Trip length of regional path p inside region r .
$\overline{L_{rp}}$	Average trip length of regional path p inside region r .
δ_{rp}	Dummy variable that equals 1 if regional path p crosses region r .
U_p^{OD}	Perceived utility of regional path p of regional OD pair.
$\overline{v_r(n_r)}$	Average speed of region r.

Introduction

The populations of large urban areas are increasing in many countries around the world. On a daily life basis, people have to travel in these cities for different purposes (for examples, to go to work or to do some leisure activity). In many cities around the world, the demand is largely increasing and the transportation networks are not adapted to adequately respond to these situations. Thus, understanding urban mobility is becoming a key aspect in infrastructure planning. On one hand, the city networks are more congested, leading to larger travel delays and the consequent deterioration of the transportation network efficiency. On the other hand, the increase of the level of congestion has important environmental issues and brings several concerns for the public health, due to the pollution. In a short term, one solution is to improve the road traffic management. Traffic simulators are a key component to help designing and testing new strategies before being implemented into the field. However, their application to large cities is computationally demanding and they are often difficult to calibrate. Recently, an aggregated traffic modeling approach has become more in fashion and caught the attention from the scientific community after the seminal works of Daganzo (2007) and Geroliminis & Daganzo (2008). Their idea is to perform an aggregate traffic modeling, dividing the city network into regions where the traffic conditions are approximately homogeneous. The traffic states inside each region are regulated by a well-defined Macroscopic Fundamental Diagram (MFD), that relates the mean traffic flow and density. The concept of the MFD introduces new insights in modeling urban traffic at the city scale. The idea is to model traffic as exchange flows between regions instead of the traditional approaches where one needs to track the users' trajectory on the city network. This type of modeling offers a much lighter

1

computational effort and represents a new trend in the traffic flow theory community.

1.1 Introduction to MFD-based models

The first thoughts about an aggregated network traffic modeling were introduced by Godfrey (1969) and later revisited by Herman & Prigogine (1979). Several studies used simulations to relate average speed, flow and density at the network level (Mahmassani et al. 1984, 1987; Williams et al. 1987). In Fig. 1.1 is shown an example of a city network composed by a set of links represented by the gray lines. Each link of the city network has a physical length l_a . This network is delimited by a solid black line, defining a region r. This region r defines the regional network. The definitions of an average flow $(\overline{q_r})$ and an average density $(\overline{k_r})$, at the aggregated network level, are possible thanks to the definitions of Edie (1963):

$$\overline{q_r} = \frac{1}{L_{net}^r T} \sum_{i=1}^{N_v} t d_i \delta_{ir}$$
(1.1)

2

$$\overline{k_r} = \frac{1}{L_{net}^r T} \sum_{i=1}^{N_v} t t_i \delta_{ir}$$
(1.2)

where N_v is the number of vehicles circulating in the city network during time period τ ; td_i is total distance of vehicle *i* inside the city network *r*; tt_i is the total time spent by vehicle *i* inside city network *r*; δ_{iv} is a dummy variable that equals 1 if vehicle *i* travels on region *r* during time period τ ; and L_{net}^r is the total region length and is calculated as:

$$L_{net}^{r} = \sum_{a} I_{a} \delta_{ar}, \forall a \in \Gamma_{a}$$
(1.3)

where δ_{ar} is a dummy variable that equals 1 if link *a* belongs to region *r*, or 0 otherwise; and Γ_a is the set of all links of the city network.

The traffic states at a given time t are given by the Macroscopic Fundamental Diagram (MFD). The MFD is a relationship that relates the aggregated flow $\overline{q_r}$ and aggregated density $\overline{k_r}$ (Fig. 1.1 (a)). Another formalism to describe the MFD is the relation between travel production P_r and the vehicles accumulation n_r (Fig. 1.1 (b)). The accumulation is the total number of vehicles circulating inside region r at a given time instant t. The travel production P_r and accumulation n_r are defined as:

$$P_r = \overline{q_r} \times L_{net}^r = \frac{1}{T} \sum_{i=1}^{N_v} t d_i \delta_{ir}$$
(1.4)

Dynamic traffic assignment for multi-regional transportation systems considering different kinds of users' behavior

1.1. Introduction to MFD-based models

3



Fig. 1.1 – City network delimited by one region, that defines a regional network. A link length I_a is highlighted.

$$n_r = \overline{k_r} \times L_{net}^r = \frac{1}{T} \sum_{i=1}^{N_v} t d_i \delta_{ir}$$
(1.5)

There is also a third formalism to describe the MFD, through the relationship between the average speed v_r and the accumulation n_r (Fig. 1.1 (c)). The average speed v_r is defined as:

$$v_{r}(n_{r}) = \frac{P_{r}(n_{r})}{n_{r}} = \frac{\sum_{i=1}^{N_{v}} t d_{i} \delta_{ir}}{\sum_{i=1}^{N_{v}} t d_{i} \delta_{ir}}$$
(1.6)



Fig. 1.2 – (a) Mean Flow MFD. (b) Production-MFD. (c) Speed-MFD.

The existence of the MFD relationship is initially proved by Geroliminis & Daganzo (2008), using traffic data from Yokohama city (Japan), and later by other field experiments (e.g. Geroliminis & Sun 2011a,b; Ambühl & Menendez 2016; Derrmann et al. 2017; Loder et al. 2017) as well as by simulation data (e.g. Geroliminis & Daganzo 2008; Ji et al. 2010; Gonzales et al. 2011). The MFD relationship exists for homogeneously congested regions. But, in real
cities, traffic is often heterogeneously distributed. This is one of the reasons why the MFD relationship is not always well-defined (see e.g. Buisson & Ladier 2009; Gayah & Daganzo 2011; Leclercq et al. 2015). The location of fixed sensors to measure traffic flow is very important and methodologies for finding optimal sensor locations have been investigated in the literature (e.g. Viti & Corman 2012; Viti et al. 2014; Zockaie et al. 2018).

Aggregated traffic models based on MFD have been firstly introduced by the seminal works of Daganzo (2007) and Geroliminis & Daganzo (2008). Under slowly varying demand and uniformly distributed congestion, Daganzo (2007) proposes that the traffic dynamics inside a single region r is governed by the following conservation equation:

$$\frac{dn_r(t)}{dt} = Q_{in,r}(t) - Q_{out,r}(t), t > 0$$
(1.7)

where $Q_{in,r}(t)$ is the inflow function; and $Q_{out,r}(t)$ is the outflow function.

Depending on the assumptions made on $Q_{out,r}(t)$, one can distinguish two MFD-models in the literature: the accumulation-based (Daganzo 2007; Geroliminis & Daganzo 2008); and the trip-based (Arnott 2013; Fosgerau 2015; Lamotte & Geroliminis 2016; Mariotte et al. 2017; Leclercq et al. 2017; Mariotte & Leclercq 2018).

In the accumulation-based model, the outflow function $Q_{out,r}(t)$ is defined as the ratio between the production-MFD $P_r(n_r(t))$ and the average trip length $\overline{L_r}$:

$$Q_{out,r} \approx \frac{P_r(n_r(t))}{\overline{L_r}} \tag{1.8}$$

where $\overline{L_r}$ is the average trip length for all vehicles crossing the same region. This transformation has been firstly introduced in Daganzo (2007) and comes from the application of the Little's formula, which requires steady state conditions. This explains why slow varying demand and supply is part of this model assumption.

In the trip-based model (Arnott 2013; Fosgerau 2015; Lamotte & Geroliminis 2016; Mariotte et al. 2017; Leclercq et al. 2017; Mariotte & Leclercq 2018), the MFD dynamics is centered on the vehicle trip length L_{vr} :

$$L_{vr} = \int_{t_{entry}}^{t_{exit}} V_r(n(s)) ds$$
(1.9)

where t_{entry} and t_{exit} are the entry and exit times of the vehicle v in region r, respectively; $t_{travel} = t_{exit} - t_{entry}$ is the travel time of vehicle v inside region r; and $V_r(n(s))$ is the speed-MFD. Assuming that the trip length L_{vr} is independent of t and that both t_{travel} and n(t)are continuous functions and differentiable at t, from Eq. 1.9 and under a fluid regime, it

is possible to obtain a relation for the outflow $Q_{out}(t)$ (Arnott 2013; Mariotte et al. 2017; Mariotte & Leclercq 2018):

$$Q_{out,r}(t) = Q_{in,r}(t - t_{travel}) \frac{V_r(n_r(t))}{V_r(n_r(t - t_{travel}))}$$
(1.10)

Note that Eq. 1.10 is valid for all vehicles having the same trip length L_{vr} . The numerical solution of the trip-based model are discussed in Mariotte et al. (2017).

The MFD-based models have been extended to a multi-region system by Geroliminis (2009) and Geroliminis (2015). For this, one needs to scale up a city (or microscopic) network into a regional (or macroscopic) network. In Fig. 1.3 (a) is shown an example of a city network. The idea is to divide the city network into regions where the traffic conditions are approximately homogeneous. This set of regions defines the regional network. In Fig. 1.3 (b) is shown the city network divided into seven regions. The corresponding regional network is shown in Fig. 1.3 (c). Each region has an intrinsic MFD function. These regions should be connected. For their definition, one can use different techniques described in the literature (Saeedmanesh & Geroliminis 2016, 2017; Lopez et al. 2017; Casadei et al. 2018). In this thesis, the city network partitioning (i.e. the definition of the regions' borders) is assumed to be well-defined and given as an input parameter.

In the multi-regional system, one models the flow exchanges between regions as indicated by the gray arrows in Fig. 1.3 (c). For this purpose, one can consider the accumulationor trip-based MFD models. To perform the MFD-based simulation, one needs to assign the aggregated demand on the regional network. It is then essential to develop a regional dynamic traffic assignment framework for multi-regional systems MFD-based models. The scaling of city into regional networks plays a central role in this framework. Instead of referring to origin and destination nodes, one refers to regional Origin and Destination. In Fig. 1.3 (b) is shown two trips that define a regional path. A regional path is defined as the ordered sequence of crossed regions from the Origin to the Destination. This notion of regional path is introduced by Yildirimoglu & Geroliminis (2014). As one can observe in Fig. 1.3 (b), one trip defines only one regional path. However, a regional path can be defined by several trips (see e.g. the green trips in Fig. 1.3 (b)). Thus, each regional path is characterized by trip length distributions inside each region it crosses, instead of a fixed length. As an example, one can observe in Fig. 1.3 (b) that the lengths of the green trips inside the gray region are different. On the other hand, in the city network, two trips are correlated if they share links in common. Two regional paths are correlated if they cross the same region and the correlation is captured through the MFD dynamics. In Fig. 1.3 (b) is shown an example where both the blue and

green regional paths cross the gray region. Due to the MFD dynamics, a vehicle that enters the gray region and travels on the green regional path, will automatically affect all the other vehicles traveling on all regional paths that cross this same region.



Fig. 1.3 – (a) City network with three routes. Two of these routes are correlated as shown by the red links. The city network partition is also represented. (b) Partition of the city network where there are represented the corresponding blue and green regional paths. (c) MFD multi-regional network that corresponds to the partition of the city network shown in (b).

1.2 Traffic assignment framework

The core of the new urban mobility trends is focused on the users and their ability to access multi-modal networks. Understanding users choices is crucial to comprehend urban mobility patterns in a city. This is very challenging since each user is different from each other. Users are heterogeneous and have different types of behavior towards their route choices. Moreover, users get informed about the network traffic states thanks to the use of new smart-phone applications and may adapt their choices according to their level of information. For example, on a rainy day, one can decide to take the subway or public transport instead of the car, to avoid traffic congestion. But, the comfort of choosing the public transport is inferior to the one of the private car. On the other hand, different users might value their trip travel times differently. A user that is going to work in the morning does not want to be late and gives more importance to the options that give more reliable travel times. On the contrary, someone that is going for shopping or to do some leisure activity might be more relaxed about the travel time and might choose options that seem to be more comfortable.



Fig. 1.4 - Flowchart that summarizes the traffic assignment procedure.

Traffic assignment algorithms are designed to model users' choices considering their trip preferences, purposes and behavior. The term traffic assignment defines the calculation of path flow distributions for all od pairs depending on the network traffic states. It transforms the global demand (i.e. the od matrix) into the local demand (i.e. link flow demand) that is going to trigger the lead of congestion depending on the available capacities and traffic control. Depending on the model considered to model the users' choices, one achieves different network loading equilibrium.

The concept of traffic assignment dates back to the seminal works of Wardrop (1952). The Deterministic User Equilibrium is based on the 1^{st} principle of Wardrop, where each user aims to minimize his/her own travel time. Users are assumed to have a perfect information about the network travel times and traffic states. But, this is not true since travel times are stochastic by nature, due to the variability of the traffic conditions. For this reason, the Random Utility models have been used to account for the distributions of travel times. This leads to the Stochastic User Equilibrium (Daganzo & Sheffi 1977; Daganzo 1982), where users also aim to minimize their own travel times. But, their perception of travel times is not perfect. These two network equilibria have been criticized in the literature since they are based on the strong assumption that users always aim to minimize their own travel times. In fact, as shown by survey data (Zhu & Levinson 2015), users do not always choose the route with the minimal travel time. On the other hand, each user is different from each other. That is, each user has his/her own travel preferences and purposes. In order to take into account these two factors, several alternative frameworks have been discussed in the literature. Simon (1957, 1966, 1990, 1991) introduced the concept of bounded rationality that was firstly adapted to departure time choice by Mahmassani & Chang (1987). The authors also discussed the first ideas of the bounded rational behavior applied to route choice. In this framework, users aim to choose routes that satisfy their own criterion for the travel time, i.e. routes that have a travel time below a certain threshold. Prospect Theory introduced by Kahneman & Tversky (1979) and Tversky & Kahneman (1992) to the economic field, considers that users are risk-averse or risk-seeking depending on the evaluation of the time prospect against a reference point. Moreover, users are more sensible to losses than gains (i.e. the loss effect). Avineri (2006) introduced the network equilibrium considering Prospect Theory. Alternatively, some authors also consider the application of Regret Theory to route choice (Chorus 2014; Li & Huang 2016), to model the regret-aversion behavior. Other studies also discuss network equilibria that consider heterogeneous users. That is, each user is a different individual and might value the travel times differently (Lu et al. 2008) or have different preferences for the reliability of their travel times (Jackson & Jucker 1982; Jiang et al. 2011).

In Fig. 1.4 is represented a flowchart that summarizes the most common procedure to calculate the network equilibrium. The demand level and pattern is given as an input parameter. The first step of the procedure consists in identifying a route choice set for each od pair, where the users will be assigned according to a route choice model. As previously discussed, there are different route choice models that account for different types of users' behavior as well as heterogeneous demands (i.e. each user is a different individual and has his/her own preferences and purposes for their travels). In the second step, one proceeds to the network loading, where users are assigned to the different routes in the choice set, according to the choice model that is selected. The users travels are modeled through a traffic simulator, that accounts for dynamic network effects. This allows to update the distribution of route travel times and to update the users choices accordingly. This process is repeated until the network loading equilibrium is achieved. In Fig. 1.4, one can directly return to the choice model or to the choice set generation steps. A network equilibrium is achieved when no user can find another route different than his/her current one that shows an improvement on his/her own criterion for the choice. This criterion can be, for example, the route travel time and/or travel cost. The equilibrium condition is maintained as long as the travel demand does not change.

1.3 Research Objectives

The goals of this thesis are twofold. In the first part of this thesis the influence of different kinds of the users' behavior on a city network performance is investigated. For this purpose, the risk-seeking and risk-aversion behavior (modeled by Prospect Theory), bounded rationality and regret-aversion (modeled by Regret Theory) users behavior are considered. The Deterministic and Stochastic User Equilibrium are set as reference. The tests are performed on a Manhattan network and a mesoscopic Lighthill-Whitham-Richards (LWR) traffic model is used to determine travel times that account for congestion and spillback effects. The network performance is evaluated through the resulting Macroscopic Fundamental Diagram (or MFD) and network outflow capacity. In the second part of the thesis, a regional dynamic traffic assignment framework for multi-regional systems MFD-based models is discussed. This framework consists of: (i) the definition of the regional choice set; (ii) the characterization of the regional paths through distributions of trip lengths; and (iii) the definition of the regional network equilibrium that account for distributions of trip lengths that are explicitly calculated. The extension of this regional dynamic traffic assignment framework for MFD models to account for different kinds of users behavior is also discussed.

1.4 Main Contributions

The main contributions of this thesis are summarized in this section. The influence of different kinds of users behavior in the internal and outflow capacities as well as the mean speed of a city network is investigated in the first part of the thesis. For this, the risk-aversion and riskseeking (modeled by Prospect Theory) as well as regret-aversion (modeled by Regret Theory) behaviors and bounded rational users are considered. The Deterministic and Stochastic User Equilibrium are set as the references to evaluate the network performance. A framework that considers the implementation of Prospect Theory and distributions of travel times has been implemented. In a network settings with few alternatives, users tend to behave more as perfect rationalizers and the network performance increases compared to the Stochastic User Equilibrium. A framework that accounts for bounded rational users with indifferent and strict preferences as well as the uncertainty of travel times has also been proposed. The increase of the users' indifference for their route choice allows them to choose paths with longer travel times. When users are completely indifferent for their route choice, they are equally assigned on all routes connecting an od pair. The internal and outflow capacities of the city network decrease when users have indifferent preferences. The users strict preferences decrease the internal mean speed of the network, but its internal and outflow capacities increase compared to the references. The regret-aversion behavior increases the network performance as the level of users regret increase, compared to the Stochastic User Equilibrium.

In the second part of the thesis, a dynamic traffic assignment framework for MFD-based models is proposed. It consists of three building blocks. The first step consists in the calculation of the regional paths based on a set of trips in the city network and on its partitioning. Three methods are discussed. Two of them are based on exhaustive searches on the city network and require a sufficient graph coverage for their calibration. These two methods are computationally expensive for large scale networks. A third method based on shortest-path calculations directly in the regional network is proposed. It gives regional paths sets with a very good level of similarity as the other two methods and is computationally lighter. Second, four methods are proposed to calculate distributions of trip lengths to characterize the regional paths. These four methods are based on a set of trips in the city network and on the definition of its partitioning. The difference between them relies on the level of information that is considered to filter the trips and aggregate their trip lengths. The method that filters the trips by the regional path they define is shown to better represent the heterogeneity of the trip lengths inside the regions that a regional path crosses. The definition of trip lengths clearly influences the simulated traffic states by the trip-based MFD model. A methodology

to update the trip lengths for regional Origin-Destination matrices that vary in time is also proposed. The estimated trip lengths through this methodology shows a good agreement with the ones that are recalculated based on the new Origin-Destination matrix. Third, based on distributions of trip lengths and on the evolution of regional mean speeds, four definitions of the regional network equilibrium are investigated. As demonstrated, these two factors cannot be neglected in the calculation of the regional network equilibrium. An extension of this regional dynamic traffic assignment framework to account for different kinds of users behavior, such as bounded rationality and indifferent preferences as well as regret-aversion, is discussed.

The proposed regional dynamic traffic assignment framework in this thesis is the first one to explore the connections between the city network topology and the aggregation to the regional network. Systematic scaling-up methods are proposed to gather the regional paths and calculate the distributions of trip lengths to characterize them. The network loading model that is proposed accounts for distributions of trip lengths that are explicitly calculated as well as the evolution of the regional mean speeds. It does not assume any prior distribution of travel times. Instead, the distributions of trip lengths and evolution of the mean speeds are considered and Monte Carlo simulations are used to calculate the regional network equilibrium. The correlation between regional paths is taken into account by the evolution of the mean speeds that are considered in the network equilibrium calculation. This framework also accounts for different kinds of users behavior, such utility minimizers, bounded rational and regret-averse users.

1.5 Thesis outline

This thesis is organized in 8 chapters, where 6 of these chapters are organized into two parts. In Fig. 1.5 a schematic road map of the thesis is presented.

Chapter 1 is the introduction part of the thesis and includes the background, research objectives, main contributions and thesis outline.

The goal of Part I of this thesis is to investigate the influence of different kinds of users behavior on the global network performance, compared against the DUE and SUE. The goal is to assess the sensibility of the network global functioning to the local users choices. In this first part, a Manhattan test network is considered and a mesoscopic Lighthill-Whitham-Richards (LWR) model is used to determine dynamic route travel times. This is addressed in the following chapters:

• In Chapter 2, a literature review about traffic assignment models is provided. This includes a literature review about choice set generation models and assignment models.

Dynamic traffic assignment for multi-regional transportation systems considering different kinds of users' behavior

1.5. Thesis outline

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Fig. 1.5 – Thesis Outline.

The latter includes Random Utility models, Fuzzy Logic, Prospect Theory, Bounded Rationality, Regret Theory, Value of Time and Value of Reliability. Simple static implementations on toy networks of some Random Utility models are also illustrated.

• In Chapter 3, the influence of the users' risk-aversion and risk-seeking behavior, modeled by the implementation of Prospect Theory, on the network performance and individual route flows is investigated. This chapter represents a stand alone research paper including abstract, introduction, methodology, results and conclusions.

Batista, S. F. A. and Leclercq, L. (in prep.), Influence of the users risk-aversion and risk-seeking behavior on a traffic network performance: a simulation study. Submitted to the Journal Transportation Letters: The International Journal of Transportation Research.

• In Chapter 4, the influence of the users' bounded rationality, considering the users' indifferent and strict preferences for their route choices, on the network performance and individual route flows is investigated. This chapter represents a stand alone research paper including abstract, introduction, methodology, results and conclusions.

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Batista, S. F. A., Zhao, C.-L. and Leclercq, L. (2018), Effects of users' bounded rationality on a traffic network performance: a simulation study. Journal of Advanced Transportation, Article ID 9876598, 20 pages.

In Section I the overview of the Part I of the thesis is presented. First, additional results considering the influence of users regret-aversion behavior on a Manhattan network are discussed. Second, the influence of the different kinds of users behavior investigated in this Part I on the network mean speed as well as its internal and outflow capacities are summarized.

The goal of Part II of this thesis is to propose a full Dynamic Traffic Assignment framework for multi-regional systems MFD-based models. In the following three chapters, the proposed methods and methodologies are tested on the 6^{th} Lyon (France) district network divided into eight regions. This framework is addressed in detail in the following chapters:

• In Chapter 5, three approaches to calculate regional paths and define the regional choice set are investigated. This chapter represents a stand alone conference research paper including abstract, introduction, methodology, results and conclusions.

Batista, S. F. A. and Leclercq, L. (2018), Introduction of multi-regional MFD-based models with route choices: the definition of regional paths. Accepted to the PLURIS 2018 - 8th LUSO-BRAZILIAN CONGRESS for Urban, Regional, Integrated and Sustainable Planning.

 In Chapter 6, four approaches to calculate regional trip lengths distributions for the regional paths, given the definition of the regional network topology and a set of trips on the city network, are discussed. A framework to update the trip lengths for different regional OD matrices is introduced. Trip-based MFD simulations are performed to show the impact of different trip length distributions calculated through the four methods on the evolution of the traffic states. This chapter represents a stand alone research paper including abstract, introduction, methodology, results and conclusions.

Batista, S. F. A., Leclercq, L. and Geroliminis, N. (in prep.), Trip length estimation for the aggregated network models: scaling microscopic trips into regions. Submitted to Transportation Research Part B: Methodological.

• In Chapter 7, a framework to solve for the network equilibrium, taking into account distributions of trip lengths that are explicitly calculated, is discussed. Four utility functions are proposed. Each of them yields a different network equilibrium. This chapter represents a stand alone research paper including abstract, introduction, methodology, results and conclusions.

Batista, S. F. A. and Leclercq, L. (in prep.), A dynamic traffic assignment framework for MFD multi-regional models. Submitted to Transportation Science.

In Section II, the overview of the second part of the thesis is presented. An extension of the proposed Dynamic Traffic Assignment framework to account for bounded rational as well as regret-averse users is discussed. Preliminary MFD simulation results are discussed. The regional network includes the city of Villeurbarnne and the 3^{rd} and 6^{th} districts of Lyon (France).

Chapter 8 is the conclusion of this thesis, summarizing the main contributions and highlighting the future research directions.

1.6 List of publications and communications

https://orcid.org/0000-0002-5388-7253

R⁶ https://www.researchgate.net/profile/Sergio_Batista3

Peer-reviewed papers:

- Batista, S. F. A. and Leclercq, L. (in prep.), Influence of the users risk-aversion and risk-seeking behavior on a traffic network performance. Submitted to the Journal Transportation Letters: The International Journal of Transportation Research.
- Batista, S. F. A., Zhao, C.-L. and Leclercq, L. (2018), Effects of users' bounded rationality on a traffic network performance: a simulation study. Journal of Advanced Transportation, Article ID 9876598, 20 pages (https://dx.doi.org/10.1155/2018/ 9876598).
- Batista, S. F. A., Leclercq, L. and Geroliminis, N. (in prep.), Trip length estimation for the aggregated network models: scaling microscopic trips into regions. Submitted to Transportation Research Part B.
- Batista, S. F. A. and Leclercq, L. (in prep.), Regional dynamic traffic assignment framework for MFD multi-reservoirs models. Submitted to Transportation Science.

- Batista, S. F. A. & Leclercq, L. (2018), Introduction of multi-regional MFD-based models with route choices: the definition of regional paths, PLURIS 2018 - 8th LUSO-BRAZILIAN CONGRESS for Urban, Regional, Integrated and Sustainable Planning, Coimbra, Portugal.
- Batista, S. F. A. & Leclercq, L. (2018), *Regional dynamic traffic assignment framework for multi-reservoir MFD models*, hEART2018 Symposium, Athens, Greece.
- Batista, S. & Leclercq, L. (2018), *Users' behavior and dynamic network loading*, The 7th International Symposium on Dynamic Traffic Assignment, Hong Kong.
- Batista, S. & Leclercq, L. (2017), A dynamic traffic assignment model based on the Prospect User Equilibrium, ICEUBI2017 – International Congress on Engineering – A Vision for the Future, Covilhã, Portugal.
- Batista, S., Leclercq, L. & Geroliminis, N. (2017), *Trip length estimation for the macro-scopic traffic simulation: scaling microscopic into macroscopic networks*, Transportation Research Board 97th Annual Meeting, Washington DC, USA.
- Batista, S., Leclercq, L. & Geroliminis, N. (2017), *Trip lengths and the macroscopic traffic simulation: an interface between the microscopic and macroscopic networks*, hEART2017 Symposium, Haifa, Israel.
- Batista, S., Mariotte G. & Leclercq, L. (2016), *The physics of traffic in urban areas at a macroscopic scale*, FISICA2016, Braga, Portugal.

Conference talks:

- Batista, S. & Leclercq, L. (2018), Introduction of multi-regional MFD-based models with route choices: the definition of regional paths, PLURIS 2018 8th LUSO-BRAZILIAN CONGRESS for Urban, Regional, Integrated and Sustainable Planning, Coimbra, Portugal.
- Batista, S. & Leclercq, L. (2018), *Regional dynamic traffic assignment framework for multi-reservoir MFD models*, hEART2018 Symposium, Athens, Greece.
- Batista, S. & Leclercq, L. (2018), *Users' behavior and dynamic network loading*, The 7th International Symposium on Dynamic Traffic Assignment, Hong Kong.
- Batista, S. & Leclercq, L. (2018), *Macroscopic trip lengths: an essential ingredient for the MFD-based simulation*, GET2018, Fátima, Portugal.

- Batista, S. & Leclercq, L. (2017), A dynamic traffic assignment model based on the Prospect User Equilibrium, ICEUBI2017 – International Congress on Engineering – A Vision for the Future, Covilhã, Portugal.
- Batista, S., Leclercq, L. & Geroliminis, N. (2017), *Trip lengths and the macroscopic traffic simulation: an interface between the microscopic and macroscopic networks*, hEART2017 Symposium, Haifa, Israel.
- Batista, S. & Leclercq, L. (2017), *Macroscopic Dynamic Traffic Assignment*, GET2017, Fátima, Portugal.
- Batista, S., Mariotte G. & Leclercq, L. (2016), *The physics of traffic in urban areas at a macroscopic scale*, FISICA2016, Braga, Portugal.
- Batista, S. & Leclercq, L. (2016), *Choix des usagers et modélisation dynamique agrégée des réseaux multi-modaux*, Mobilcités 2016, Vaulx-en-Velin, France.

Conference poster presentations:

- Batista, S., Leclercq, L. & Geroliminis, N. (2017), *Trip length estimation for the macro-scopic traffic simulation: scaling microscopic into macroscopic networks*, Transportation Research Board 97th Annual Meeting, Washington DC, USA.
- Batista, S. & Leclercq, L. (2016), *Route choice modeling combining link cost uncertainties and individual users preferences*, Journées des Doctorants du départment COSYS de l'IFSTTAR, Paris, France.

Seminars and Scientific talks:

- Batista, S. & Leclercq, L. (2018), *Regional dynamic traffic assignment framework for multi-regions: MFD-based models*, Scientific seminar of LICIT, Lyon, France.
- Batista, S. (2018), Users' behavior and heterogeneity and dynamic network loading, ERC MAGnUM meeting, Vaulx-en-Velin, France.
- Batista, S. (2018), *Users' behavior and dynamic network loading*, ERC MAGnUM meeting, Vaulx-en-Velin, France.
- Batista, S. (2017), A dynamic traffic assignment model based on the Prospect User Equilibrium, ERC MAGnUM meeting, Vaulx-en-Velin, France.

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- Batista, S. (2017), *Multi-scale dynamic traffic assignment*, Yearly ERC MAGnUM meeting, Lyon, France.
- Batista, S. (2017), *A review of choice models and traffic simulation*, ERC MAGnUM meeting, Vaulx-en-Velin, France.
- Batista, S., Mariotte, G. & Leclercq, L. (2017), *Macroscopic Traffic Simulation & Dynamic Traffic Assignment*, Seminar at the University of Coimbra (CITTA), Coimbra, Portugal.
- Batista, S. (2016), *Choice models: Random Utility and Bounded Rationality*, Yearly ERC MAGnUM meeting, Lyon, France.
- Batista, S. (2016), *A multimodal route choice model based on individual user utilities*, Scientific seminar of LICIT, Lyon, France.
- Batista, S. (2016), *Embedded route and mode choice modelling approach*, ERC MAGnUM meeting, Vaulx-en-Velin, France.
- Batista, S. & Mariotte, G. (2015), *State of the Art on Macroscopic Traffic Modeling*, Scientific seminar of LICIT, Lyon, France.
- Batista, S. & Mariotte, G. (2015), *First layout of the MFD simulator*, ERC MAGnUM meeting, Vaulx-en-Velin, France.

Oral presentations to the general public:

• Batista, S. & Leclercq, L. (2017), *Macroscopic Traffic Simulation*, Welcome meeting for international researchers organized by Espace Ulys of the University of Lyon.

Part I

Influence of users' behavior on network performance



Traffic Assignment: a literature review

This chapter introduces a literature review about the traffic assignment components. In Sect. 2.2, the route choice set generation models are introduced. In Sect. 2.3, the Deterministic and Stochastic User Equilibrium of the network loading are discussed. To account for the uncertainty of travel times, two approaches based on Random Utility models and Fuzzy Logic are discussed. In Sect. 2.4, there are discussed the application of two examples of some Random Utility models, in two toy networks. In Sect. 2.5, a literature review about other models that account for different kinds of users' behavior and heterogeneity is introduced. In Sect. 2.6, the existence and uniqueness of the Dynamic User Equilibrium are outlined.

2.1 Introduction

The city network (see Fig. 2.1 (a)) is composed by a set of directed links. Each user of the network has a specific origin and target destination as well as different purposes and preferences for his/her own travels. The origin (o) and destination (d) of users correspond to nodes in the city network as shown in Fig. 2.1 (a). As the medieval proverb says "All Roads Lead to Rome", meaning that there are an infinite number of possible routes connecting one od pair. Fig. 2.1 (b) depicts a simple example of one od pair connected by two routes. Nevertheless, to assign users on a city network, one needs to identify a plausible number of routes to define the route choice set Ω^{od} . In Sect. 2.2, a literature review about different models to calculate Ω^{od} is provided. The next challenge is to model the users' route choices according to their different preferences and purposes. A literature review about static traffic assignment models is discussed in Sect. 2.4 and Sect. 2.5. The extension to the dynamic context and a statement on how the contributions of this thesis go beyond the literature review is discussed in Sect. 2.6.



Fig. 2.1 - (a) City network with three routes. (b) Example of a graph that represents two routes connecting one od pair.

2.2 Choice set generation

The first step of a traffic assignment framework is the definition of the route choice set. For notation purposes, let Ω^{od} be the route choice set, for the city network origin-destination (od) pairs, defined as:

$$\Omega^{od} = \{r_k\}, \forall k = 1, \dots, S \land \forall (o, d) \in \Xi$$
(2.1)

where S is total number of feasible routes connecting a given od pair of the city network; and Ξ is the set of all od pairs of the city network.

To calculate the routes, the Dijkstra algorithm is the most known for shortest-path calculations. But, it requires a large computational time to find shortest-paths in large city networks. The A* algorithm is to be preferred for large scale implementations, since it has an heuristics that guides the search method towards the destination node. The guidance function f(n) at node *n* to go to the next node is:

$$f(n) = g(n) + h(n)$$
 (2.2)

where g(n) is the total path cost from the origin node to n; and h(n) is the heuristics that estimates the lowest cost path from n to the destination node. Note that if h(n) = 0, the A* reduces to the Dijkstra algorithm.

In the literature there are other models discussed to calculate the routes. The K-shortest path algorithm (Eppstein 1998; Hadjiconstantinou & Christofides 1999; van der Zijpp & Catalano 2005) computes the K-less expensive routes for one od pair. The link elimination (Azevedo et al. 1993) consists of two steps: the route search; and the route elimination. The first computed route corresponds to the shortest-path for the od pair. The links defining this route are partly or all eliminated from the city network and a new shortest-path is calculated. The spirit of the link penalty (de la Barra et al. 1993; Rupahil et al. 1995; Park & Rilett 1997) is similar. The costs of partly or all links that define the calculated routes, are increased instead of being eliminated from the city network. The labeling approach was introduced by Ben-Akiva et al. (1984). Labels are set according to the users' preferences and each one is linked to a different route. The maximum number of routes that compose the choice set are defined by the number of labels considered. A branch-and-bound algorithm is discussed by Prato & Bekhor (2006), to explicitly solve a constrained enumeration problem of routes. It increases the heterogeneity of the choice set compared to the previously discussed algorithms, while keeping the computational costs low. This is done during the branching step, where a set

2.3. Static network loading equilibrium: the Deterministic and Stochastic User Equilibrium

of logical thresholds are defined. A set of links is sampled and only the ones that satisfy the set of thresholds are added to the final tree. One should define the following thresholds: a directional threshold, that excludes the connections between the links that will take the user closer to the origin rather than the destination; a temporal threshold, that will eliminate paths with excessive travel time; a loop threshold, to avoid paths containing large detours; a similarity threshold, to remove highly overlapping paths from the final tree; and a constraint threshold, that removes unrealistic routes which the users would not consider attractive. The bounding step will connect the sampled links. The simulation approach consists in sampling the generalized costs at the link level and perform a shortest path search. The procedure is repeated until the number of desired routes is reached. The procedure stops when the number of desired routes is reached. The generalized costs are modeled through probability distributions. Ramming (2002) and Bliemer et al. (2007) consider a normal distribution. While, Nielsen et al. (2002), Bierlaire & Frejinger (2005) and Prato & Bekhor (2006) consider a truncated normal distribution. Sheffi (1985) proposes to truncate the normal distributions for negative values of the generalized costs. This skews the generalized cost distributions. Instead, Nielsen (1997) argues that considering a gamma distribution is more adequate. The spirit of the doubly stochastic approach (Nielsen 2000) is similar, but both link generalized costs and attributes are simulated. A review about these models is provided by Prato (2009). More recently, Flötteröd & Bierlaire (2013) discusses an approach to sample paths using the Metropolis-Hastings algorithm.

In this thesis, the K-shortest path and the A^{*} algorithm are considered. It is also assumed that the path set Ω^{od} is known.

2.3 Static network loading equilibrium: the Deterministic and Stochastic User Equilibrium

The concept of traffic assignment was introduced by Wardrop (1952). In his paper, he proposed two equilibrium principles:

- User Equilibrium: each user of the network chooses the route that minimizes his/her travel time.
- *System Optimum*: all users of the network will choose the routes that will minimize the total travel time of the system. In this case, users have to cooperate with each other to minimize the total travel cost of the network.

The User Equilibrium is also referred in the literature as the Wardrop first principle. The latter corresponds to the Deterministic User Equilibrium (DUE). Under DUE conditions, no user can increase his or her own travel time by unilaterally change routes. Mathematically, this network loading equilibrium can be calculated by solving the following optimization problem (Beckmann et al. 1956):

$$\min z(q_a) = \sum_a \int_0^{q_a} t_a(x_a) dx_a, \forall a \in \Gamma_a$$
(2.3)

subject to:

$$q_{a} = \sum_{k} Q_{k} \delta_{ka}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.4)

$$\sum_{k} Q_{k} = Q^{od}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.5)

$$q_a \ge 0, a \in \Gamma_a \tag{2.6}$$

$$Q_k \ge 0, k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.7)

where Γ_a is the set of all *a* links of the network; q_a is the flow of link *a*; Q_k is the flow of route *k*; Q^{od} is the total demand of the od pair; $t_a(q_a)$ is the travel time of link *a*; and δ_{ka} is a dummy variable that equals 1 if route *k* travels on link *a*, or 0 otherwise. Note that Eq. 2.5 ensures the flow conservation; and Eq. 2.6 and Eq. 2.7 ensures the non-negativity of the link and route flows, respectively.

The system of equations 2.3 to 2.7 is the fixed-point formulation of the DUE (Sheffi 1985). A classical approach to solve this problem is based on the Method of Successive Averages (Sheffi 1985). To ensure good convergence properties of the MSA, one should properly define the descent step α_j , where *j* is the descent iteration. For this, the following two conditions should be satisfied (Sheffi 1985):

$$\sum_{j=1}^{\infty} \alpha_j = \infty \tag{2.8}$$

$$\lim_{j \to \infty} \alpha_j \to 0 \tag{2.9}$$

One definition of α_j that satisfies both of the previous conditions is: $\alpha_j = \frac{1}{j}$. In the

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literature, there are discussed other definitions of α_j (Polyak 1990; Liu et al. 2007; Taale 2008; Chen et al. 2011a).

The DUE assumes that users are perfectly rational, selfish and fully informed about all possible routes and their travel times. However, routes travel times are not deterministic in nature since the traffic states change across time. On the other hand, it is not realistic to assume that users have a perfect rationality. In fact, they perceive route travel times with uncertainty. To treat the uncertainty of travel times, there are two approaches discussed in the literature. The most commonly used is based on the Random Utility (RU) models (McFadden 1978), where the uncertainty is modeled as a distribution of route travel times. The RU models are introduced in Sect. 2.3.1. On the other hand, Fuzzy Logic (FL) treats the uncertainty of route travel times as fuzzy numbers and is introduced in Sect. 2.3.2.

2.3.1 Random Utility models

In RU models (McFadden 1978), the uncertainty of route travel times is modeled through a stochastic term ϵ_k , $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. In the literature, this term is also referred to as error term. The network equilibrium corresponds to the Stochastic User Equilibrium (SUE) introduced by Daganzo & Sheffi (1977) and Daganzo (1982). The utility function of route k is:

$$U_k(\overrightarrow{Q}) = V_k(\overrightarrow{Q}) + \epsilon_k, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.10)

where U_k is the perceived utility of route k; V_k is the deterministic route utility; and $\vec{Q} = (Q_1^{od}, \ldots, Q_k^{od}, \ldots, Q_N^{od}), \forall (o, d) \in \Xi$ is a row vector of all route flows for all od pairs listed in Ξ . This utility function is valid for an homogeneous demand of users sharing the same od pair.

A route flow pattern is under SUE conditions if and only if it satisfies the following condition:

$$Q_k^{od} = Q^{od} P_k^{od}(V^{od}(\overrightarrow{Q})), \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.11)

where $V^{od}(\overrightarrow{Q})$ is the deterministic route travel time; Q^{od} is the total demand of the *od* pair; and $P_k^{od}(V^{od}(\overrightarrow{Q}))$ is the probability of choosing route *k* from the route choice set Ω^{od} , that is calculated as: 2.3. Static network loading equilibrium: the Deterministic and Stochastic User Equilibrium

$$P_{k} = P_{k}^{od}(V^{od}(\overrightarrow{Q})) = Pr(U_{k} < U_{j}, \forall j \in \Omega^{od} \land j \neq k \land \forall (o, d) \in \Xi | V^{od}(\overrightarrow{Q})),$$

$$\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi \quad (2.12)$$

Considering Eq. 2.11, Daganzo (1982) formulated the unconstrained minimization model for the SUE:

$$\min z(\overrightarrow{Q}) = -\sum_{o} \sum_{d} Q^{od} S^{od} (V^{od}(\overrightarrow{Q})) + \sum_{a \in \Gamma_a} q_a t_a(q_a) - \sum_{a \in \Gamma_a} \int_{0}^{q_a} t_a(x_a) dx_a$$
(2.13)

where $S^{od}(V^{od}(\overrightarrow{Q}))$ is defined as:

$$S^{od}(V^{od}(\overrightarrow{Q})) = E\left(\min_{k\in\Omega^{od}} U_k(V^{od}(\overrightarrow{Q}))\right), \forall (o,d) \in \Xi$$
(2.14)

and,

$$q_{a} = \sum_{k} Q_{k} \delta_{ka}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.15)

$$Q_{k} = \sum_{a} q_{a} \delta_{ak}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.16)

where δ_{ak} is a dummy variable that equals 1 if link *a* belongs to route *k*; or, 0 otherwise.

This unconstrained minimization model can also be transformed in a fixed point problem (Sheffi 1985) and solved using the classical Method of Successive Averages (MSA).

The error terms ϵ_k are unobserved. Therefore, the modeler has to make assumptions about the statistical distributions. The simplest RU model is the Multinomial Logit (Dial 1971). It assumes that ϵ_k are independent and identically distributed (i.i.d.) Gumbel variables, with a scale parameter θ . The family of Logit models is described in Sect. 2.3.1.1. The Probit model (Daganzo & Sheffi 1977) assumes that error terms are multi-normal variate distributed variables. It is presented in Sect. 2.3.1.2. The Mixed Logit model (Bolduc & Ben-Akiva 1991; Bekhor et al. 2002; Frejinger & Bierlaire 2007) makes use of the simple structure of the Multinomial Logit model. It assumes that the error terms are defined by the sum of two terms: one that is normally distributed; and another one that is Gumbel distributed. It is described in Sect. 2.3.1.3. An alternative approach to avoid the computational costs of computing the Probit model is to use Monte Carlo simulations as discussed in Sheffi (1985).

This approach is described in Sect. 2.3.1.4.

2.3.1.1 Family of Logit models

The Multinomial Logit (Dial 1971) is the simplest random utility model to implement. It assumes that the route error terms, ϵ_k , are i.i.d. Gumbel distributed with a scale parameter θ . This model has the advantage of having a closed form and the probability of choosing route k from the choice set Ω^{od} is:

$$P_{k} = \frac{\exp(-\theta U_{k})}{\sum_{i=1}^{S} \exp(-\theta U_{i})}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.17)

The application of the Multinomial Logit model has several limitations. First, the Multinomial Logit model lacks the ability to capture the correlation between overlapping routes (i.e. routes that share a link or a sequence of links in common). Second, it requires a proper scaling θ parameter, that has to be estimated or manually adjusted. Moreover, the i.i.d. assumption implies that all routes connecting the same od pair have a similar variance of the route travel time distributions. Chen et al. (2012) investigated this problem and discussed that introducing a global θ per each od pair partially solves the problem of dealing with heterogeneous variances between the different routes. Thus, the θ parameter is scaled to the od level (i.e. θ^{od}). The ideal scenario would be to have a flexible formulation of the Multinomial Logit model able to deal with a heterogeneous perception of the variances for all routes. But, it violates the i.i.d. assumption. The scale parameter θ^{od} is calculated as:

$$\theta^{od} = \sqrt{\frac{\pi^2}{6 \text{Var}(\epsilon_k)}} \tag{2.18}$$

where $Var(\epsilon_k)$ represents the variance of route k. Note that, all routes connecting the same od pair should have the same variance.

To relax the i.i.d. assumption, that leads to the Independent and Irrelevant Alternative (IIA) property, several alternative models have been discussed. Some authors proposed to introduce a correction factor within the deterministic part of the utility function (Cascetta et al. 1996; Ben-Akiva & Bierlaire 1999; Ramming 2002; Bovy et al. 2008). Other approaches belonging to the Generalized Extreme Value (GEV) family, such as the Nested Logit models, have also been widely used in the literature as an alternative to the Multinomial Logit model (Chu 1989; Vovsha 1997; Prashker & Bekhor 1998, 2000). A review about these models is provided by Prato (2009).

2.3.1.2 Probit model

The Probit model was introduced to route choice by Daganzo & Sheffi (1977). It assumes that the error terms ϵ_k are multi-normal variate (MNV) distributed, i.e. $\epsilon_k \sim MNV(0, \Sigma)$ where Σ represents the $S \times S$ covariance matrix defined as:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1S} \\ \sigma_{12} & \sigma_2^2 & \dots & \sigma_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1S} & \sigma_{2S} & \dots & \sigma_S^2 \end{bmatrix}$$
(2.19)

where the diagonal elements represent the variances of the *S* routes listed in Ω^{od} ; and the other elements represent the covariances between the other routes listed in Ω^{od} . This flexible definition of the variance-covariance matrix allows the Probit model to capture the correlation between overlapping routes.

The probability P_k of choosing route k from the route choice set Ω^{od} is:

$$P_{k} = \int_{V_{k}-V_{j}}^{\infty} (2\pi)^{-\frac{N-1}{2}} (\det A_{k})^{\frac{1}{2}} \exp\left[-\frac{1}{2}Y_{kj}^{T}A_{k}^{-1}Y_{kj}\right] dY_{kj}, \forall j = 1, \dots, S \land j \neq k \land \forall k \in \Omega^{od}$$
$$\land \forall (o, d) \in \Xi \quad (2.20)$$

 Y_{kj} is a $(S-1) \times 1$ vector that represents the error differences between the *k*-route and all the other *S*-1 routes listed in Ω^{od} ; and A_k is the $(S-1) \times (S-1)$ covariance matrix directly obtained from Σ , using an auxiliary $S \times (S-1) B_k$ matrix:

$$A_k = B_k^T \Sigma B_k \tag{2.21}$$

and,

$$B_{k} = [\delta_{lm}] \text{, where } \delta_{lm} = \begin{cases} -1, \text{ if } l = m\\ 1, \text{ for } l = k\\ 0, \text{ otherwise} \end{cases}$$
(2.22)

The Probit model does not have a closed form to calculate the probabilities P_k (Eq. 2.20). Therefore, one needs to integrate the multi-normal variate distribution over all possible routes listed in Ω^{od} . This largely increases the computational cost required. Simulation techniques

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have been discussed to estimate these integrals. Daganzo & Sheffi (1977) proposed to use the Clark's approximation. Lerman & Manski (1981) proposed the method of Simulated Maximum Likelihood (SML). McFadden (1989) proposed the Method of Simulated Moments (MSM). Stern (1992) proposed one of the most famous simulator, that separates the error term into two components: one that is normally distributed with zero mean and diagonal covariance; and other that has a covariance matrix as small as possible. The Geweke-Hajivassilou-Keane (GHK) (Borsch-Supan & Hajivassiliou 1993) makes use of the Monte Carlo simulations to numerically solve the integrals. Bolduc (1999) discussed the estimation of the Probit model using a simulated maximum likelihood through the implementation of the GHK simulator (Borsch-Supan & Hajivassiliou 1993). The reader is reported to the paper of Bolduc (1999) for the mathematical formulation of this approach. Bhat (2011) discusses an approach based on a maximum composite marginal likelihood (MACML) to calculate the MNV integrals.

The advantage of the Probit model is that it allows a flexible definition of the variancecovariance matrix, that is able to capture the correlation between overlapping routes. However, it has only been applied to small networks (e.g. Yai et al. 1997) due to the computational power required to solve the MNV integrals.

2.3.1.3 Mixed Logit model

The Mixed Logit (ML) model (Bolduc & Ben-Akiva 1991; Bekhor et al. 2002; Frejinger & Bierlaire 2007) considers that the error terms ϵ_k are defined by the sum of two terms:

$$\epsilon_{k} = F_{ML} T_{ML} \zeta_{ML}^{k} + \nu_{ML}^{k}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.23)

where F_{ML} is a $N_{links} \times N_{links}$ link-path incidence matrix and N_{links} the number of links that define Γ_a ; T_{ML} is a $N_{links} \times N_{links}$ link variance matrix; ζ_{ML}^k is a $N_{links} \times 1$ vector of variables that follow a normal distribution of zero mean and unit variance; and ν_{ML}^k is a vector of $S \times 1$ of i.i.d. variables that follow a Gumbel distribution.

The link-path incidence and the link variance matrices are obtained, respectively, as (Bekhor et al. 2002):

$$F_{ML} = \delta_{ak} = \begin{cases} 1 & \text{if } a \in k \\ 0 & \text{otherwise} \end{cases}, \forall a \in \Gamma_a$$
(2.24)

$$T_{ML} = \operatorname{diag}(\sigma_1, \dots, \sigma_a, \dots, \sigma_{N_{links}}), \forall a \in \Gamma_a$$
(2.25)

Bekhor et al. (2002) proposed that the link variance is proportional to its length. But, if

the error distributions at the link level are known, the derivation of the diagonal elements of T_{ML} is directly calculated.

The probability of choosing route k from Ω^{od} is calculated by integrating the density function of ζ_{ML}^{k} over all its possible values:

$$P_{k} = \int_{\zeta_{ML}} \Lambda(k \setminus \zeta_{ML}) \prod_{m=1}^{M_{ML}} \varphi(\zeta_{ML}^{m}) d\zeta_{ML}^{m}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.26)

where $\varphi(\zeta_{ML}^k)$ is the normal density function of ζ_{ML}^k . This integration can be solved numerically as follows (Bekhor et al. 2002):

$$P_{k} = \frac{1}{M_{ML}} \sum_{d=1}^{M_{ML}} \Lambda\left(k \setminus \zeta_{ML}^{d}\right), \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$

$$(2.27)$$

where ζ_{ML}^d is a term that represents a draw *d* from the distribution of ζ_{ML} ; and M_{ML} is the number of draws. As it is exemplified by Ramming (2002) an adequate number of draws should be considered (~1000).

This model is also referred in the literature as the Hybrid Logit or Logit Kernel.

2.3.1.4 Probit model solved by Monte Carlo simulations

The Probit model can also be solved through Monte Carlo simulations (Sheffi 1985). The idea is that instead of keeping track of the analytical tractability of the travel time distributions at the route level, one considers them at the link level. For this, it is assumed that the link travel time utilities are additive, to calculate the route travel time. Sheffi (1985) proposes to discretize the distributions of travel times at the link level into M samples and locally solve Deterministic User Equilibrium (DUE) problems. Let t_k^i be a sample i of the travel time of route k and M be the total number of samples. Let also t_a^i be a sample i of the travel time of link $a, \forall a \in \Gamma_a$. The sample t_k^i is calculated as:

$$U_{ki}^{od} = t_k^i = \sum_{a \in \Gamma_a} t_a^i \delta_{ak}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi \land \forall i = 1, \dots, M$$
(2.28)

where δ_{ak} is a dummy variable that equals 1 if link *a* defines route *k*, or 0 otherwise.

For each sample *i* of the route travel times, compute t_k^i (Eq. 2.28) and assign users based on an all-or-nothing procedure to the route with the minimal perceived utility (or minimal travel time). The new temporary route flows for the MSA, $Q_k^{od,*}$, are updated by averaging all the local DUE solutions. These route flows, $Q_k^{od,*}$, are used to update the new route flows, $Q_k^{od,j+1}$, at iteration j + 1 as:

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$$Q_k^{od,j+1} = Q_k^{od,j} + \alpha_j \{Q_k^{od,*} - Q_k^{od,j}\}, \forall k \in \Omega^{od} \land \forall (o,d) \in \Xi$$

$$(2.29)$$

where $Q_k^{od,j}$ represent the route flows at iteration j of the MSA.

As convergence criteria for the MSA, one can adopt the three formulations discussed in Sbayti et al. (2007):

• the relative Gap (Sbayti et al. 2007):

$$Gap = \frac{\sum_{o} \sum_{d} \sum_{k \in \Omega^{od}} Q_k^{od} (V_k^{od} - C)}{\sum_{o} \sum_{d} Q^{od} C}$$
(2.30)

where $C = \min(V_k^{od})$, $\forall k \in \Omega^{od}$. The *Gap* function represents the difference between the route travel times and the travel times at equilibrium. Under DUE conditions, the Gap is equal to 0. The latter means that all users have chosen the routes with the minimum travel times. Under SUE conditions, the *Gap* is slightly larger than 0, however small. This happens due to the uncertainty in the users' perception of the travel times.

- the number of violations N(λ) (Sbayti et al. 2007), that represent the number of cases where |Q_k^{j+1} Q_k^j| is superior to a pre-defined path threshold Φ, for each od pair. The convergence is achieved when N(λ) ≤ Φ.
- a maximum number of j iterations N_{max} .

Sheffi (1985) proposes that the link travel time distributions are normally distributed and to truncate the negative link travel times. But, this skews the link travel times distributions and may lead to erroneous results. Instead, Nielsen (1997) proposes to consider a gamma distribution. Throughout this thesis, it is assumed that the link travel time distributions follow a gamma distribution, with scale η_a and shape ζ_a parameters.

The procedure of the Monte Carlo simulations to solve for the network SUE and considering the MSA algorithm is summarized in Algorithm 1. Note that, this algorithm is also valid to solve a DUE assignment, where one just needs to set $\epsilon_a = 0$, $\forall a \in \Gamma_a$. Throughout this thesis, this is the adopted procedure to model the distributions of travel times, unless explicitly stated otherwise.

2.3.2 Fuzzy Logic

Fuzzy logic differs from Random Utility (RU) models by the way that it deals with uncertainty in the users' perception. Fuzzy logic was initially proposed by Zadeh (1965) and later 2.3. Static network loading equilibrium: the Deterministic and Stochastic User Equilibrium

Sample M link travel times t_a^i , considering a scale (η_a) and shape (ζ_a) parameters of a gamma distribution.

Initialize the descent step $\alpha_j = 1$. Initialize the route flows $Q_k^{od,j=1} = 0$.

Set the MSA stopping criterion *tol*, the maximum number of violations Φ and the maximum number of descent step iterations N_{max} .

Perform a loading of the network $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$.

while $Gap \ge tol \text{ or } N(\lambda) \ge \Phi \text{ or } j \le N_{max}$ do

Set $Q_k^{od,j} = Q_k^{od,j+1}$. for *I=1* to *M* do Compute $t_k^i, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$ (Eq. 2.28). For each od pair, assign users based on an all-or-nothing assignment to the route with the minimal travel time. end Update the new route flows $Q_k^{od,*}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$, based on an averaging of the users choices over all samples.

Update the route flows:

 $Q_k^{od,j+1} = Q_k^{od,j} + \alpha_j \{Q_k^{od,*} - Q_k^{od,j}\}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi.$ Update α_i , the Gap values (Eq. 2.30) and the number of violations $N(\lambda)$. Set i = i + 1.

end

Save the route flows: Q_k^{j+1} , $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. **Algorithm 1:** Pseudo-code algorithm to solve a SUE or DUE assignment, based on Monte Carlo simulations.

adapted to route choice modeling by Teodorović & Kikuchi (1990). It considers that users decisions involve imprecision and vagueness and users act as perfect rationalizers. Avineri (2012) provides a small review about fuzzy logic applied to route choice.

Two classes of fuzzy logic models applied to route choice have been discussed in the literature: fuzzy-rule based (Teodorović & Kikuchi 1990); and fuzzy-costs based (Henn 2005).

The first class of fuzzy models considers fuzzy rules and fuzzy control tools (Lotan & Koutsopoulos 1993; Koutsopoulos et al. 1994; Lotan 1997; Peeta & Yu 2002). Fuzzy rules can be described as linguistic rules, such as for example: "If travel time on route 1 is low and on route 2 is intermediate, then the user will for sure choose route 1". This approach can lead to undesirable results as it is stressed out by Henn (2005). In particular, the authors showed that fuzzy tools should not be handled anyhow.

The second class of fuzzy models (Bierlaire et al. 1993; Henn 2000; Henn & Ottomanelli 2003; Cantarella & Fedele 2003; Dell'Orco & Kikuchi 2004; Henn 2005; Henn & Ottomanelli 2006) considers that users do not have a perfect knowledge about the route travel times. In this case, some utility attributes are modeled as fuzzy numbers to take into account the imprecision and uncertainty. In the seminal works of Henn (2000); Henn & Ottomanelli

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(2003); Henn (2005); Henn & Ottomanelli (2006), route choice and flow assignment using fuzzy-costs are performed on test networks. But, the application of fuzzy logic to route choice lies in the proper definition of the membership function as it is highlighted by Henn (2005). The author also criticizes that several authors use a triangular-shape membership function, without providing a more accurate definition. Henn (2005) further investigated the concept of *fuzzy costs* and distinguished three different semantics, namely imprecision, uncertainty and degree of preference. Henn (2005) and Henn & Ottomanelli (2006) suggested a modeling approach that considers these three levels of fuzziness. The concept of fuzzy user equilibrium applied to traffic assignment is discussed by some authors (e.g., Wang & Liao (1999); Chang & Chen (2000)).

Other authors discuss modeling approaches that couple fuzzy logic with possibility theory (Dell'Orco & Kikuchi 2004). Possibility theory was introduced by Zadeh (1978) as an alternative to probability theory. Kikuchi & Chakroborty (2006) provides a review about the role of possibility theory in transportation problems. Its concept, computation procedures as well as utilities are discussed when handling incomplete information (Kikuchi & Chakroborty 2006). The idea behind this theory is the preservation of uncertainty in the users decision-making process. While probability theory is based on additivity axioms, possibility theory is based on max-axioms. Dell'Orco & Kikuchi (2004) discussed an example where possibility theory is used to infer about users choices and where route travel times are modeled as fuzzy numbers. The authors also show an application example of their approach on a three route test network.

Quattrone & Vitetta (2011) discusses a fuzzy utility model that can be applied to real networks. The users choices are evaluated using the concept of possibility instead of probability. These possibilities are then converted into choice percentages following Klir (1990). Fuzzy Logit and C-Logit models are discussed and calibrated based on data measurements by Quattrone & Vitetta (2011).

2.4 Application examples of Random Utility models

In this section, it is analyzed the implementation of the Multinomial Logit, the Mixed Logit, the Probit and the Probit model solved by Monte Carlo simulations in two toy networks. Two test scenarios are setup and discussed. The goal is to illustrate the different concepts and show the similarities and differences between the four models.

Test scenario 1

The goal of this first test is to show the limitations of the Multinomial Logit in dealing with correlated routes, compared against the other three models. For this, a route flow

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independent utility function is set:

$$U_{k}(\overrightarrow{Q}) = \sum_{a \in \Gamma_{a}} (t_{a} + \epsilon_{a}) \delta_{ak}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.31)

where t_a is the free-flow travel time of link a; δ_{ak} is a dummy variable that equals 1 if route k travels on link a, or 0 otherwise.

A network composed by one od pair and three routes (Fig. 2.2) is considered. Two variants of this network are considered: one without link overlapping between the routes (variant 1 - Fig. 2.2, top panel); and one with link overlapping between routes 1 and 2 (variant 2 - Fig. 2.2, bottom panel). For variant 1, the route choice set is: $\Omega^{od} = \{(1); (2); (3)\}$. For this variant, the following set of link travel times, t_a , are considered: $t_1 = 18$; $t_3 = 16$; and a variable link travel time for t_2 range between 10 and 22 increasing step size by 1 unit. For variant 2, the route choice set is $\Omega^{od} = \{(1,3); (1,4); (2)\}$. And, the following set of link travel times are considered: $t_1 = 10$; $t_3 = 8$; $t_4 = 7$; and a variable travel time for $t_2 \in [10 : 1 : 22]$. It is considered that ϵ_a are gamma distributed with a mean equal to t_a , $\forall a \in \Gamma_a$ and a similar variance for $\sigma_a = 16$, $\forall a \in \Gamma_a$. The parameters of the gamma distribution are updated as $\eta_a = \sigma_a$, $\forall a \in \Gamma_a$ for the scale parameter and $\zeta_a = \frac{t_a}{\sigma_a}$, $\forall a \in \Gamma_a$ for the shape parameter. A total of M = 10000 samples are fixed. For the convergence criteria, the number of violations is set to 0, the $tol = 10^{-3}$ and $N_{max} = 100$.



Fig. 2.2 – Network 1. *Left:* Variant with independent routes. *Right:* Variant with overlapping between route 1 and 2 (link 1).

The assignment results at equilibrium are shown in Fig. 2.3, for an increasing travel time of link 2. As one can observe, the Multinomial Logit gives similar assignment results as the other three models only for variant 1. This is because for the terms ϵ_a are sampled independently and the path utilities are not correlated. The Mixed Logit, Probit and the Probit model solved by Monte Carlo simulations give similar assignment results for both variants 1 and 2, because their formulations allow to capture the correlation between overlapping routes. In the case of the Probit model, the correlation is captured through the flexible definition of the variance-covariance matrix. The Mixed Logit assumes that one term of ϵ_k follows a normal distribution with zero mean and unitary variance. This term is defined at the link level and converted to

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Fig. 2.3 – Route flows at equilibrium with respect to an increase of the link 2 free-flow travel time. The results are shown for the Multinomial Logit, Mixed Logit, Probit and Probit model solved by Monte Carlo simulations. *Right:* Network 1 - variant 1. *Left:* Network 1 - variant 2.

the path level by a path-incidence matrix. The good fitting of the Probit model solved by Monte Carlo simulations with both the Probit and Mixed Logit validates this approach to solve for the SUE.

Test scenario 2

The goal of the second test scenario is to compare the assignment results of the Probit model when solved by directly integrating the MNV travel time distributions and when solved by Monte Carlo simulations. A flow independent utility function is defined:

$$U_{k}(\overrightarrow{Q}) = \sum_{a \in \Gamma_{a}} (t_{a} + q_{a} + \epsilon_{a}) \delta_{ak}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$

$$(2.32)$$

where q_a is the flow of link *a* that is calculated as follows:

$$q_a = \sum_{a \in \Gamma_a} Q_k \delta_{ak} \tag{2.33}$$

The Braess network shown in Fig. 2.4 is considered. The route choice set is: $\Omega^{od} = \{(1,4); (2,5); (1,3,5)\}$. The following set of link travel times are considered: $t_1 = 5$; $t_2 = 50$; $t_3 = 10$; $t_4 = 50$; $t_5 = 5$. All link travel times are normally distributed with zero mean and variance 2. A total number of M = 10000 samples are considered. For the convergence criteria, the number of violations is set to 0, the $tol = 10^{-3}$ and $N_{max} = 100$. Three demand levels are set up: $Q^{od} = 50, 100, 200$.



Fig. 2.4 – Braess network.

The assignment results at equilibrium, for both Probit formulations, are listed in Table 2.1. One can observe that the route flow provided by both Probit formulations are close but not equal, for the different values of the total demand Q^{od} . The Probit model solved by directly integrating the MNV distributions gives the mean route flows. While, the Probit solved by Monte Carlo simulations determines for each link error trial, the related route flow distribution related to the deterministic utilities (the link error term is fixed) and then the route flow average. By other words $\overline{Q_k} \neq f(\overline{Q_k}), \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$.

2.5. Extensions of the User Equilibrium

	Probit by direct integration			Probit by Monte Carlo simulations		
Q ^{od}	Route 1	Route 2	Route 3	Route 1	Route 2	Route 3
50	17	15	18	18	17	15
100	39	38	23	41	41	18
200	87	86	28	89	89	22

Table 2.1 – Assignment results for both Probit formulations and for the three levels of demand $Q^{od} = 50, 100, 200$.

2.5 Extensions of the User Equilibrium

The DUE and SUE have been criticized since users do not always choose routes with the minimal travel times. It is evidenced by survey data (see e.g. Zhu & Levinson 2015) that users often deviate from optimal choices. This means that they do not always choose routes with the minimal travel times for their trips. On the other hand, they are different in terms of socio-demographic characteristics and each user has his/her own purposes (e.g. go to work or go to do some leisure activity) and preferences for their trip choices. Other frameworks that consider different types of users' behavior (Sect. 2.5.1) and heterogeneity (Sect. 2.5.2) are discussed in the literature. In Sect. 2.5.3, it is summarized the differences between the different assignment models in terms of the users' behavior and users' heterogeneity.

2.5.1 Users' behavior in traffic assignment models

The assumption of users' perfect rationality is relaxed to account for a bounded rationality behavior (Mahmassani & Chang 1987). The concept of bounded rationality was introduced by the seminal works of Simon (1957, 1966, 1990, 1991) and adapted to departure time choice by Mahmassani & Chang (1987). The authors also discuss the first ideas to implement the bounded rational framework for route choices. In the bounded rationality framework, users choose *satisficing* routes, i.e. routes with perceived travel times that are inferior to the users' *aspiration levels*. The term *satisficing* stands for the combination of the words suffice and satisfy. The *aspiration levels* represent a set of goal variable that should not be surpassed for the users satisfaction. The most common definition of the *aspiration levels*, used in traffic assignment problems, is the indifference band (Mahmassani & Chang 1987).

Regret Theory (Bell 1982; Loomes & Sugden 1982) has also been extensively applied to traffic assignment problems (Chorus et al. 2006, 2008; Chorus 2010, 2012c,a,b; Chorus et al. 2013; Chorus 2014; Li & Huang 2016). Users aim to minimize their regret with respect to the unselected routes. They feel joy if they choose the route with the minimum travel time,

or regret otherwise.

Avineri (2006) implemented the Prospect Theory (Kahneman & Tversky 1979; Tversky & Kahneman 1992) to traffic assignment. Users evaluate their choices in terms of route travel times prospects that are framed as gains and losses against a reference point. According to Prospect Theory, users are: risk-seeking when confronted with prospects of gains; risk-averse when confronted with prospect of losses; and more sensible to losses and gains (loss effect).

In the literature, there are also other reference dependent models applied to traffic assignment (De Borger & Fosgerau 2008; Delle Site & Filippi 2011, 2012). Delle Site & Filippi (2011) considered exogenous reference points. While Delle Site & Filippi (2012) discusses an endogenous reference point Stochastic User Equilibrium. Rank-dependent expected utility models (Quiggin 1982) have also been adapted to route choice (see e.g. Razo & Gao 2013).

2.5.2 Users' heterogeneity in traffic assignment models

Each network user is different from each other and has different criteria for their own choices. These criteria are, for example: the trip purpose; the total travel time; the weather conditions; the expected travel time; the car occupancy; the car ownership; the time of the day and day of the week; the trip distance; the comfort and convenience; the personal preferences; or the travel cost. These criteria lead users to value travel time and/or travel time reliability differently.

The value of time (VOT) is the marginal cost between the route travel time (TT_k^{od}) and the travel monetary cost (TC_k^{od}) . The first ideas of VOT applied to traffic assignment as well as the mathematical formulation of the network equilibrium were introduced by Dafermos (1972, 1980, 1982) and Smith (1979). The perceived utility U_{km}^{od} for route k of od pair and user m is:

$$U_{km}^{od} = TC_k^{od} + VOT_m \times TT_k^{od}, \forall m \land \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.34)

where VOT_m is the value of time for user *m*; and TT_k^{od} is the distribution of travel times for route *k*.

There are discussed two approaches to model the VOT parameter. The first approach consists in splitting the users demand of each *od* pair into homogeneous classes of users with similar average VOT (Dafermos 1972, 1980, 1982; Yang et al. 2002). The second approach assumes that the VOT is continuously distributed across the demand of each *od* pair (Dial 1996, 1997; Leurent 1993, 1996, 1998; Lu et al. 2008; Zhang et al. 2013). The statistical distribution of VOT depends on the users' socio-demographic features and income. It can be
2.5. Extensions of the User Equilibrium

derived from survey data (see e.g. Small et al. 2005). Following this second approach, Lu et al. (2008) introduced the Bi-criterion User Equilibrium applied to dynamic traffic assignment. Later, considering the Probit model solved through Monte Carlo simulations, Zhang et al. (2013) extended the framework to include the distributions of the route travel times. Zhang et al. (2013) considered that VOT_m is normally distributed across the population, i.e. $VOT_m \sim N(\overline{\mu}_{VOT} = 20, \sigma_{VOT}^2 = 10)$, within a feasible range of $VOT_m \in [\alpha_{min} = 0.1; \alpha_{max} = 300]$.

Another factor that significantly influences the users' choices is the reliability of travel times (Bates et al. 2000). A transportation network with large travel times variability increases travel costs and uncertainty for users. van Lint et al. (2008) identified several sources that cause variability in the travel times, like special events, weather conditions or traffic conditions to name a few examples. In the literature, there are several models that account for the the travel times variability, i.e. the variance of the route travel times distributions. The network equilibrium corresponds to the Reliability-based User Equilibrium, where users are considered to have risk preferences. These are incorporated in the cost function through measures of travel time reliability. The two main approaches to model travel times reliability are: the mean-variance model (Jackson & Jucker 1982); and the scheduling-delay (Small 1982). In the case of the mean-variance model (Jackson & Jucker 1982), the perceived utility U_{km}^{od} for route k of od pair and user m is:

$$U_{km}^{od} = TC_k^{od} + \overline{TT_k^{od}} + VOR_m \times \sigma_k^{od}, \forall m \land \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.35)

where VOR_m is the value of reliability for user m. The value of reliability (VOR) represents the willingness of users to pay for a reduction in the route travel times variability, i.e. a reduction in the standard deviation of the route travel times. Carrion & Levinson (2012) present a review paper about the value of travel time reliability.

The scheduling delay (Small 1982) model considers that arriving at the destination later than the preferred arrival time will cause disutility. In the same spirit, Watling (2006) proposes the late-arrival penalized User Equilibrium. Users seek to minimize the route utility, that includes the generalized cost plus a late arrival penalty.

In the literature, there are other models to solve a Reliability-based User Equilibrium. The travel time budget (Shao et al. 2006; Shao et al. 2006; Lo et al. 2006; Lam et al. 2008) considers that users seek to minimize their expected travel times plus an extra time margin with respect to a specified arrival time. In the percentile User Equilibrium (Nie 2011), the reliability is measure as a percentile of the route travel times. In the bi-criterion User Equilibrium proposed by Wang et al. (2004), users seek to minimize both the expected and

variance of route travel times. In the added-variability model (Ordóñez & Stier-Moses 2010), the users' risk-aversion is modeled as a safety margin. The mean-excess traffic equilibrium (Chen & Zhou 2010; Chen et al. 2011b) incorporates two variables, one that measures the reliability of arriving on time and another one that measures the unreliability of late trips.

Another interesting approach to solve the Reliability-based User Equilibrium is based on a non-cooperative game where users are pessimistic about their travel times variability and show a risk-aversion behavior (Bell 2000; Bell & Cassir 2002). In the first proposition of this game by Bell (2000), there are two players: a user that aims to minimize his/her own travel cost; and a demon that wants to maximize his trip cost. This game is non-cooperative, meaning that both players are not aware of the choices of each other. Bell & Cassir (2002) proposes an extension of this game to multiple players, where several users aim to minimize their own travel costs in a non-cooperative way.

Jiang et al. (2011) proposes the Multi-criterion Dynamic User Equilibrium that considers both VOT and VOR in its formulation. The perceived utility U_{km}^{od} for route k of od pair and user m is:

$$U_{km}^{od} = TC_k^{od} + VOT_m \times TT_k^{od} + VOR_m \times \sigma_k^{od}, \forall m \land \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(2.36)

2.5.3 Summary of traffic assignment models

In Table 2.2, it is summarized the different assignment models described in the previous sections, in terms of the users' behavior and target goal for the users' choices.

2.6 Dynamic traffic assignment and traffic simulation

After the seminal works of Merchant & Nemhauser (1978a) and Merchant & Nemhauser (1978b), the dynamic traffic assignment has substantially evolved as discussed in the review paper of Peeta & Ziliaskopoulos (2001) and later updated by Viti & Tampère (2010). However, its implementation remains quite challenging to represent realistic traffic dynamics and users behavior. Moreover, the system input parameters might also be time-dependent, adding additional complexity to the mathematical traceability of the network equilibrium. The dynamic traffic assignment can be classified into the analytical approach (Sect. 2.6.1) and the simulation based approach (Sect. 2.6.2). In Sect. 2.6.3, the next challenges of dynamic traffic assignment are highlighted, with particular emphasis to the work developed in the next chapters of this thesis.

	• users have a perfect information about route travel times and		
1 st Wardrop principle traffic states.			
	 users aim to minimize their own perceived travel times. 		
	• users have an imperfect information about route travel times and		
Random Utility	traffic states.		
	 users aim to minimize their perceived own travel times. 		
Prospect Theory	 users are time prospect maximizers. 		
	 users choose among probabilistic alternatives that involve risk. 		
	• users are risk-seeking and risk-averse depending on the time		
	prospect.		
	 users are more sensible to gains than losses (loss-effect). 		
Bounded Rationality	 users are bounded rational. 		
	 users choose satisficing routes that satisfy their AL. 		
Regret Theory	• users are regret-averse.		
	• users choose the route that minimizes their regret compared to		
	the other routes in Ω^{od} .		
VOT	 users are heterogeneous and value their travel time differently. 		
	 users choose the route that minimizes their marginal cost. 		
VOR	 users are willing to pay to reduce the travel time reliability. 		
	 users choose the route that minimizes their marginal cost. 		

Table 2.2 – Summary of assignment models discussed in the previous sections.

2.6.1 Analytical approach

The analytical approach is suitable to study the properties of dynamic traffic assignment frameworks, such as its existence and uniqueness. In this approach, the network equilibrium is calculated at each time instant. Analytical approaches have been proposed in the literature via several frameworks: the variational inequality (Friesz et al. 1993; Huang & Lam 2002; Lo & Szeto 2002; Szeto & Lo 2004, 2006; Han et al. 2013); nonlinear complementary problem (Wie et al. 2002; Ban et al. 2008; Han et al. 2011); fixed point problem (Szeto et al. 2011); differential variational inequality (Friesz et al. 2013; Friesz & Meimand 2014); and differential complementary problem (Ban et al. 2012). Other studies discuss graphical methods to determine the Dynamic System Optimum (Muñoz & Laval 2006) and the Dynamic User Equilibrium (Laval 2009).

In the literature, several studies analyzed the unicity and existence of the dynamic user equilibrium considering several of the previous frameworks (see e.g. Akamatsu 2000; Wie et al. 2002; Huang & Lam 2002; Szeto & Lo 2006; Nie & Zhang 2010; Iryo 2011; Corthout et al. 2012). Wie et al. (2002) investigates the existence and uniqueness of the link-based Dynamic

User Equilibrium, considering the nonlinear complementary problem formulation. The authors show that the existence of a solution for the Dynamic User Equilibrium is guaranteed by the Brouwer's fixed-point theorem. According to this theorem, the existence of a solution is true if the solution of fixed point problem is bounded. In this case, the route flows are non-negative and the sum of all routes flows connecting one od pair is equal to the total demand Q^{od} . Wie et al. (2002) also show that the uniqueness of the Dynamic User Equilibrium is guaranteed by imposing strict monotonicity conditions on the link travel cost and demand functions. Corthout et al. (2012) analyzed the non unique solutions of the dynamic traffic assignment problem. They show that the multiple, ambiguous priority ratios in the distribution of different flows in the outgoing links of a node is a source of the non-unicity of the network equilibrium.

2.6.2 Simulation approach

The simulation approach considers traffic simulations to calculate time-dependent path costs that account for congestion, shock-waves and spillback effects. The assignment is done through a quasi-static approximation as function of the route travel times. This approach is able to capture the traffic dynamics and driver's behavior. However, the existence and uniqueness of the network equilibrium might not be guaranteed. Several studies consider this dynamic traffic assignment framework for large scale applications, using different traffic simulators: DYNASMART applied to the city of Chicago (USA) (Ji & Geroliminis 1994; Mahmassani et al. 2013); DYNAMIT applied to the city of Beijing (China) (Ben-Akiva et al. 2012); AIMSUN applied to the city of Melbournne (Australia) (Shafiei et al. 2018); Symuvia (Leclercq 2007; Laval & Leclercq 2008) applied to Villeurbarnne and the 3rd and 6th districts of Lyon (France) (Ameli et al. 2018).

2.6.3 Statement of contribution beyond the literature

The main focus of this thesis is put on the application of different kinds of the users' behavior considering a dynamic implementation with a traffic simulator at different network scales. Most of the studies in the literature focus in the dynamic implementation of the DUE and SUE models. Nevertheless, there are a few studies that pay attention to the users' bounded rational behavior (e.g. Ji & Geroliminis 1994; Mahmassani & Liu 1999). Up to now, the Prospect and Regret theories deal with static traffic assignment problems on small city networks. In the follow-up of this Part I, the influence of the users' behavior on a city network performance using a mesoscopic Lighthill-Whitham-Richards (LWR) traffic model is investigated. To this end, the three models previously mentioned (i.e. Prospect Theory, Bounded Rationality and

2.6. Dynamic traffic assignment and traffic simulation

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Regret Theory) are considered and the tests performed on a synthetic Manhattan network. For the first time, the dynamic implementation of Prospect Theory, considering distributions of travel times, is investigated. The differences between several tunings of Prospect Theory and the benchmark DUE and SUE are analyzed. A methodological framework considering the ideas of bounded rationality, the users' indifferent and strict preferences and distributions of travel times is proposed. In this framework, users are assigned on different routes according to a specific rule that depends on their preferences. It generalizes the initial ideas of users strict preferences proposed by Zhao & Huang (2016). The influence of the users preferences and level of bounded rationality on the network performance is also investigated. These studies are the first to infer the role of the users behavior on a city network internal and outflow capacities as well as its mean speed.

In a second Part II, the work developed in this thesis contributes to the development of a dynamic traffic assignment framework for multi-regional networks, where the traffic states are simulated by an MFD model. This includes the definition and characterization of regional paths as well as the formulation of the regional network equilibrium. For the definition and characterization of the regional paths, a set of trips and the city network partitioning are considered. In a first time, three methods are proposed and tested to gather the regional paths and define the regional choice sets. Two of these methods are based on an extensive city of trips in the city network and its partitioning. The other method is based on shortest path calculations directly on the regional network, where a supply-oriented cost function is proposed. The latter is related with the flow capacity of the incoming links to the nodes in the city network that allow to travel between adjacent regions. In a second time, four methods are proposed to calculate distributions of trip lengths to characterize the regional paths. The important role of the proper trip lengths definition for the MFD-based models is also highlighted. In a third step, the regional network equilibrium are formulated based on the distributions of trip lengths and the time evolution of the mean speed inside the regions. This dynamic traffic assignment framework is further extended to consider bounded rational and regret-averse users.

Influence of the users risk-aversion and risk-seeking behavior on a traffic network performance: a simulation study

Abstract

In this chapter, we investigate the traffic network response to user's trip choices for probabilistic route solution process under risk. For this, we consider the application of Prospect Theory for representing the user's decisions and a mesoscopic Lighthill-Whitham-Richards (LWR) traffic model for characterizing traffic flow dynamics. We analyze the network performance in terms of its internal and outflow capacities as well as its internal mean speed compared to more classical route choice models like the Deterministic and Stochastic User Equilibrium (DUE and SUE). In a network setting with few alternatives, we show that the network internal and outflow capacities and internal mean speed increase compared to the SUE. The user's risk-aversion and risk-seeking behavior in terms of route travel time prospects is balancing the uncertainties and they are more likely to act with like being perfectly rational, i.e. optimizing their own route travel times. Moreover, the route flows at equilibrium for the PT implementations lie in between the SUE and DUE ones.

Keywords: Prospect Theory; User's risk-aversion and risk-seeking behavior; Network performance; LWR model; Traffic simulation.

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3.1 Introduction

The simulation of traffic networks requires the definition of mathematical models to track vehicle's trips. Route choice is a critical component of such models as it describes the distribution of travel demand over the available routes. The latter directly influences the network performance and it is then important to study the network response to the loading process. The concept of route choice modeling is related to the user's routes selection between origin and destinations (od) pairs in the city network. It was first introduced by Wardrop (1952). According to the first Wardrop's principle, users aim at minimizing their own travel times. This approach considers that they are selfish, fully informed and have a perfect perception of the route travel times. This case corresponds to the Deterministic User Equilibrium (DUE). As an extension to the DUE, Daganzo & Sheffi (1977) introduced the Stochastic User Equilibrium (SUE) to account for the users' inaccurate perception of route travel times. Daganzo & Sheffi (1977) and Daganzo (1982) assumed that route travel times are normally distributed, introducing the Probit model to route choice modeling. It is able to capture the correlation between overlapping routes, i.e. routes that share links in common. But, the implementation of this model in the dynamic context is scarce because it requires to integrate a density function of a multivariate normal distribution over all possible routes for one origin-destination (od) pair. One solution is to solve these integrals using a simulation approach. Of particular interest for this study, we focus on the Monte Carlo simulations discussed by Sheffi (1985). We also consider that route travel times are gamma distributed (Nielsen 1997).

The DUE and SUE assume that users are cost minimizers. In this chapter, we aim to test more advanced descriptions of the user's behavior and evaluate how it influences the network performance compared to the DUE and SUE. In the literature, alternative models applied to route choice have been considered. Regret Theory considers that users aim to minimize their perceived regret with respect to the other unselected routes (e.g. Chorus 2014; Li & Huang 2016). The ideas of bounded rationality and satisficing behavior introduced by Simon (1957, 1966, 1990, 1991) were adapted to departure time modeling (Mahmassani & Chang 1987) and later to route choice (Huang & Lam 2002; Szeto & Lo 2006). Users are driven by aspiration levels that represent a set of threshold that should be verified for their satisfaction. This represents the satisficing behavior. It comes from the concatenation between the words satisfy and suffice. In the route choice context, users are satisfied with any route that has an inferior travel time to their aspiration level. Prospect Theory (PT) introduced by Kahneman & Tversky & Kahneman (1992) to the economic field, models user's

choices between probabilistic alternatives that involve risk. It was adapted to route choice by Avineri & Prashker (2004). Avineri (2006) extended the concept of the User Equilibrium to account for the user's risk-taking behavior, using PT. He stated that at equilibrium no user can increase his/her own travel time prospect by unilaterally changing routes. Connors & Sumalee (2009) generalized the prospect user equilibrium for stochastic networks. After the seminal works of Avineri & Prashker (2004) and Avineri (2006), PT has also been applied in the literature to model: departure time choice (Fujii & Kitamura 2004; Jou et al. 2008); route choice (Avineri & Prashker 2004; Viti et al. 2005; Avineri 2006; Connors & Sumalee 2009; Sumalee et al. 2009; Gao et al. 2010; Xu et al. 2011); or bus lines choice (Avineri 2004).

In the application of PT to route choice, route travel times are evaluated as travel time prospects in terms of gains and losses against a reference point. These gains and losses are balanced through separable decision weights. In PT, users are: *risk-averse* when confronted with prospects of gains; *risk-seeking* when confronted with prospects of losses; and more sensible to losses than gains (i.e. the *loss effect*). There are two important factors that influence the route flows at equilibrium calculated through PT: (i) the setting of the reference point T_0 (Avineri 2006; Connors & Sumalee 2009); and the set of the user's risk-aversion parameter that measures the user's sensitivity to gains and losses (Avineri & Bovy 2008; de Palma et al. 2008).

The application of PT to route choice are based on static implementations and small networks. To the best of the authors knowledge, there are only two studies (Xu et al. 2011; Yang & Jiang 2014) that discuss an extension of PT to account for the route travel times uncertainties. But, these studies are again based on a static setting of PT. The application of PT has not yet been tested in detail in a dynamic context, i.e. considering a traffic simulator to calculate time-dependent route costs that account for congestion, shock-waves and spillback effects. In this study, we revisit the concept of Prospect-based User Equilibrium to investigate the influence of the user's choices for probabilistic alternatives under risk, on the network performance at an aggregated level. We focus our analysis on both internal and outflow network capacity as well as on the internal mean speed. As a benchmark, we evaluate the network performance against the DUE and SUE models. We also analyze the sensitivity of the PT to the setting of the reference point and the user's risk-aversion parameters. We consider a dynamic implementation of PT, on a Manhattan network. Time-dependent route travel times are calculated through a a Lighthill-Whitham-Richards (LWR) mesoscopic traffic simulator (Leclercq & Becarie 2012).

This chapter is organized as follows. In Sect. 3.2, we discuss the methodological frame-

work. In Sect. 3.3, we introduce the test scenario and discuss the results of the dynamic simulation at both the individual route flows and the aggregated network level. In Sect. 3.4, we outline the conclusions.

3.2 Methodological framework

3.2.1 Prospect Theory: basic formulation

The application of PT consists of two steps: the editing phase, where time prospects are framed as gains and losses against a reference point T_0 ; and an evaluation phase, where the maximum route time prospect is chosen. The time prospect $X_k(t_k)$ of route k is:

$$X_k(t_k) = v_k(t_k)\omega(p_k), \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(3.1)

where $v_k(t_k)$ is the value function and t_k is the deterministic travel time of route k; $\omega(p_k)$ is the weighting function for gains and losses; p_k is the probability that the perceived travel time of route k is a gain or a loss; Ω^{od} is the route choice set; and Ξ is the set of all od pairs of the city network.

For the definition of $v_k(t_k)$ and $\omega(p_k)$, we adopt the definitions of Kahneman & Tversky (1979) and Tversky & Kahneman (1992).

The value function $v_k(t_k)$ is defined as:

$$v_{k}(t_{k}) = \begin{cases} (T_{0} - t_{k})^{\alpha^{PT}}, & \text{if } t_{k} \leq T_{0} \\ -\lambda^{PT} (t_{k} - T_{0})^{\beta^{PT}}, & \text{if } t_{k} > T_{0} \end{cases}$$
(3.2)

where T_0 is the reference point; $\alpha^{PT} \leq 1$ and $\beta^{PT} \leq 1$ represent the degrees of diminishing sensitivity for gains and losses, respectively; and $\lambda^{PT} \geq 1$ is the loss-aversion degree. This definition of $v_k(t_k)$ is concave for gains and convex for losses. The parameters α^{PT} and β^{PT} control its concavity and convexity. Note that if $\alpha^{PT} = \beta^{PT} = 1$ users are pure loss averse. In Fig. 3.1, we show the shape of $v_k(t_k)$.

The weighting function $\omega(p)$ is defined as:

$$\omega(p_k) = \begin{cases} \frac{p_k^{\gamma^{PT}}}{(p_k^{\gamma^{PT}} + (1-p_k)^{\gamma^{PT}})^{\frac{1}{\gamma^{PT}}}}, & \text{if } t_k \le T_0\\ \frac{p_k^{\delta^{PT}}}{(p_k^{\delta^{PT}} + (1-p_k)^{\delta^{PT}})^{\frac{1}{\delta^{PT}}}}, & \text{if } t_k > T_0 \end{cases}$$
(3.3)

where $\gamma^{PT} > 0$ and $\delta^{PT} > 0$ capture the distortion in the perception of the probability p_k for gains or losses, respectively. These parameters also control the curvature of $\omega(p_k)$ as

defined in Eq. 3.3. This definition of $\omega(p_k)$ has some important properties: (i) w(0) = 0; (ii) w(1) = 1; (iii) is asymmetrical with an inflection point at 0.3 (Prelec 1998); and (iv) it overweights small probabilities and underweights higher ones. In Fig. 3.1, we show the shape of $\omega(p_k)$.



Fig. 3.1 – *Left:* Value function $v_k(t_k)$. *Right:* Probability weighting function $\omega(p_k)$. These functions are defined by Kahneman & Tversky (1979) and Tversky & Kahneman (1992).

The application of PT to route choice depends on the definition of the reference point T_0 to evaluate the time prospects as gains or losses and on the calibration of the set of $(\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT})$, that represent the set of the user's risk-aversion parameters.

The setting of the reference point T_0 has not been consensual in the literature (de Palma et al. 2008). Avineri (2006) and Connors & Sumalee (2009) considered an exogenous definition of T_0 . Avineri & Bovy (2008) proposed to consider the mean or median of the route travel times to define T_0 . Gao et al. (2010) proposes to consider T_0 as a latent variable. The authors propose to define T_0 as: the free-flow travel time; the worst travel time; or the mean travel time. Ben-Elia & Shiftan (2010) also considers the mean travel times. To determine T_0 , Zhou et al. (2014) considered the average travel times calculated from the route travel time distributions of the different alternatives. Also note that, T_0 is context dependent and may vary across users. For this study, we consider a common reference point T_0 for all users sharing the same od pair (that is T_0^{od}) and three endogenous definitions:

$$\mathcal{T}_0^{od} = \operatorname{mean}(\overrightarrow{V}^{od}) \tag{3.4}$$

3.2. Methodological framework

$$T_0^{od} = \operatorname{median}(\overrightarrow{V}^{od}) \tag{3.5}$$

$$\mathcal{T}_0^{od} = \text{mode}(\overrightarrow{V}^{od}) \tag{3.6}$$

where \overrightarrow{V}^{od} is a vector that contains the average route travel times for the od pair.

For the calibration of the user's risk-aversion parameters, we consider two sets of values discussed in the literature: $(\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT}) = (0.88, 0.88, 2.25, 0.61, 0.69)$ (Tversky & Kahneman 1992); and $(\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT}) = (0.37, 0.57, 1.51, 0.74, 0.74)$ (Xu et al. 2011). Note that these parameters are also context dependent. So, one should be careful in drawing conclusions when considering the set of parameters proposed by Tversky & Kahneman (1992), since they were not calibrated for route choice context. But, the set of parameters presented in Xu et al. (2011) were calibrated in a route choice experiment.

3.2.2 Prospect Theory Stochastic User Equilibrium: solution framework

Considering the basis of Prospect Theory, users aim to maximize their travel time prospect $X_k(t_k), \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. Then, at the Prospect-based User Equilibrium, the time prospects of all used routes are equal to the maximum time prospect value for each od pair. Moreover, under equilibrium conditions, no user can increase his or her own time prospect $X_k(t_k)$ by unilaterally changing routes. This definition of equilibrium was introduced by Avineri (2006). Our mathematical formulation follows the work of Xu et al. (2011). Mathematically, the Prospect-based User Equilibrium can be described as (Xu et al. 2011):

$$Q_k^{od}(\max(X_k^{od}(t_k^{od})) - X_k^{od}(t_k^{od})) = 0, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$

$$(3.7)$$

$$\begin{cases} Q_k^{od} > 0, & \text{if } X_k^{od}(t_k^{od}) = \max(X_k^{od}(t_k^{od})) \\ Q_k^{od} = 0, & \text{if } X_k^{od}(t_k^{od}) \le \max(X_k^{od}(t_k^{od})) \end{cases}$$
(3.8)

$$\sum_{k} Q_{k}^{od} = Q^{od}, \forall (o, d) \in \Xi$$
(3.9)

$$q_a \ge 0, \forall a \in \Gamma_a \tag{3.10}$$

$$Q_k^{od} \ge 0, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(3.11)

where Q_k^{od} is the flow of route k of the od pair; q_a is the flow of link a; Γ_a is the set of links of the graph that represents the traffic network; and Q^{od} is the total demand for the od pair.

To determine the Prospect-based User Equilibrium defined by the system of equations Eq. 3.7 to Eq. 3.11, we consider the Method of Successive Averages (or MSA). Our implementation of the PT considers gamma distributed route travel times (Nielsen 1997), with scale parameter η_a and shape parameter ζ_a . To account for the route travel time distributions, we make use of Monte Carlo simulations (Sheffi 1985). We consider that the distribution of travel times are defined at the link level and discretize them into M samples. Let t_a^i be a sample i of the travel time of link $a, \forall a \in \Gamma_a$. We assume that the link utilities are additive, to calculate the sample i of the travel time of route k, t_k^i , as:

$$t_{k}^{i} = \sum_{a \in \Gamma_{a}} t_{a}^{i} \delta_{ak}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi \land \forall i = 1, \dots, M$$
(3.12)

where δ_{ak} is a dummy variable that equals 1 if route k travels on link a, or 0 otherwise.

For each sample i = 1, ..., M, we locally solve the corresponding User Equilibrium problem considering PT. In more detail, each sample t_k^i is evaluated in terms of travel time prospects $X_k(t_k^i)$ (Eq. 3.1) and framed as a gain or a loss depending on the reference point T_0^{od} . We also have to calculate the probability p_k . For this, we discretize the route travel time distributions into small bins and we calculate the surface area of each bin. This defines a set of probabilities for each route k of the od pair. These probabilities are then considered as a probability of a gain or a loss depending on the value of t_k^i compared against T_0^{od} . Then, for each od pair, users choose the route with the highest travel time prospect, based on an all-or-nothing process. The new temporary route flows, $Q_k^{od,*}$, correspond to averaging all of the choices made for each sample set. $Q_k^{od,*}$ is then used to update the new route flows $Q_k^{od,i+1}$ at iteration j + 1, as:

$$Q_k^{od,j+1} = Q_k^{od,j} + \alpha_j \{Q_k^{od,*} - Q_k^{od,j}\}, \forall k \in \Omega^{od} \land \forall (o,d) \in \Xi$$
(3.13)

where $Q_k^{od,j}$ represents the route flows at iteration *j* of the MSA; and α_j is the descent step of the MSA.

This process is repeated at each iteration j of the MSA. To ensure the good convergence properties of the MSA, one should properly choose the descent step α_j . For the theoretical convergence of the algorithm, the following two conditions should be satisfied (Sheffi 1985):

$$\sum_{j=1}^{\infty} \alpha_j = \infty \tag{3.14}$$

3.3. Dynamic implementation of PT on a Manhattan network

$$\lim_{j \to \infty} \alpha_j \to 0 \tag{3.15}$$

In this study, we consider the following definition of α_j , that satisfies both Eq. 3.14 and Eq. 3.15: $\alpha_j = \frac{1}{i}$. We consider two stopping criteria for the MSA:

- the number of violations N(λ) (Sbayti et al. 2007), that represent the number of cases where |Q_k^{od,j+1} Q_k^{od,j}| is superior to a pre-defined path convergence threshold Φ, for each od pair. The convergence is achieved when N(λ) ≤ Φ, for each od pair.
- a maximum number of j iterations N_{max} . That is $j \leq N_{max}$.

We present the solution algorithm based on the MSA implementation and the previous description, in Algorithm 2. A mesoscopic LWR traffic simulator is used to update the route travel times. The network loading is repeated until the equilibrium conditions are reached.

3.3 Dynamic implementation of PT on a Manhattan network

3.3.1 Test scenario definition

For the dynamic implementation, we consider the Manhattan network composed by 134 links shown in Fig. 3.2. All links have a similar length of 100 meters. Traffic lights control all intersections. A cycle of 45 seconds is considered and the green light duration for the horizontal links is 30 seconds.

A triangular fundamental diagram is considered for each lane of the network, with the following parameters: u = 15 (m/s), for the free-flow speed; w = 5 (m/s) for the wave speed; and $k_{jam} = 0.2$ (veh/m/lane) for the jam density. The case study network, has six entries (identified by o1 to o6 in Fig. 3.2) and exits (identified by d1 to d6 in Fig. 3.2). For entry, we consider a constant inflow (demand) of 1.0 (veh/s) that is equally assigned to the six exits during the simulation period. The entry links (i.e., from o1 to 6) have two lanes. The total link flow is equally assigned on each lane. There is no capacity restriction at the exits. In total there are 36 possible od pairs. To define the choice set Ω^{od} , we consider the 3 K-shortest paths per od pair. This gives a total of 108 routes. The total simulation period is T = 3000 seconds. For the MSA convergence, we set $\Phi = 0$ and $N_{max} = 250$. For the Monte Carlo simulations, a total of M = 5000 samples are considered.

Initialize j = 1, η_a , ζ_a , $\alpha_{j=1} = 1$. Initialize the route flows $Q_k^{od,j=1} = 0$, $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. Perform an initial network loading. **while** $N(\lambda) \ge \Phi$ **or** $j \le N_{max}$ **do** Set $Q_k^{od,j} = Q_k^{od,j+1}$, $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. Discretize the link travel time distributions into M samples. Update the endogenous reference point T_0^{od} . Calculate the set of probabilities p_k for each route k of each od pair. **for** i=1 to M **do** Update the set of samples $t_k^i, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. Calculate the value function $v_k(t_k)$ (Eq. 3.2) and the weighting function $\omega(p)$ (Eq. 3.3), $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$.

Input the traffic network, demand scenario and simulation duration T.

Calculate the route choice set Ω^{od} , $\forall (o, d) \in \Xi$.

Determine the time prospect $X_k(t_k)$, $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$ (Eq. 3.1).

For each od pair, users are assigned to the route with the maximum travel prospect based on an all-or-nothing assignment.

end

Update the new route flows $Q_k^{od,*}$, $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$, based on an averaging of the users choices over all M samples.

Update the route flows based on Eq. 3.13.

Run the LWR mesoscopic simulator (Leclercq & Becarie 2012).

Based on the link travel times, fit a gamma distribution to update the set of η_a and ζ_a .

Calculate $N(\lambda)$. Update $\alpha_j = \frac{1}{j}$. Set j = j + 1.

end

Save the route flows: $Q_k^{od,j+1}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$.

Algorithm 2: Dynamic implementation algorithm of the PT model previously described.

3.3. Dynamic implementation of PT on a Manhattan network





3.3.2 Analysis of the individual route flows and their sensitivity to T_0^{od} and the risk-aversion parameters

In this section, we first analyze the sensitivity of the PT implementation to the setting of T_0^{od} and to the set of users' risk-aversion parameters. Second, we analyze the individual route flows for the different settings of PT compared to the DUE and SUE. In this study, we consider three definitions of T_0^{od} and two sets for the users risk-aversion parameters. Considering the DUE and SUE cases, we have a total of 8 simulation scenarios. Each simulation scenario is identified by a model label as listed in Table 3.1. We also list the number of descent iterations required for each simulation scenario to converge.

To analyze the sensitivity of the PT implementation to the setting of T_0^{od} and to the set of users' risk-aversion parameters, we:

- i. fix the set of users' risk aversion parameters $(\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT})$ and change T_0^{od} as defined by Eq. 3.4 to Eq. 3.6. This allows to investigate the sensitivity of the route flows to T_0^{od} , for both sets of users' risk aversion parameters.
- ii. fix T_0^{od} and change the set of users' risk aversion parameters (α^{PT} , β^{PT} , λ^{PT} , γ^{PT} , δ^{PT})

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Model	T^{od}_0	Parameters	ID Model	MSA
				<i>j-th</i> iteration
DUE	\sim	\sim	1	89
SUE	\sim	\sim	2	22
ΡT	Mean	ΚT	3	31
ΡT	Median	ΚT	4	33
ΡT	Mode	ΚT	5	28
ΡT	Mean	Xu	6	42
ΡT	Median	Xu	7	42
PT	Mode	Xu	8	36

Table 3.1 – Descent step iterations of the MSA are listed. These values are listed for the eight simulation scenarios. For the PT, each scenario is identified by a T_0^{od} and a set of the user's risk-aversion parameters $(\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT})$. Each of the simulation scenarios is identified by an ID Model as listed in the table.

KT parameters				
	Median	Mode		
Mean	0.027	0.017		
Median	\sim	0.022		

Xu parameters				
	Median	Mode		
Mean	0.017	0.023		
Median	\sim	0.023		

Table 3.2 – sensitivity to T_0^{od} , for the KT (*top*) and Xu (*bottom*) parameters.

Mean	Median	Mode
0.041	0.035	0.033

Table 3.3 – sensitivity to the user's risk-aversion parameters $(\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT})$.

by considering the parameters defined by KT (Tversky & Kahneman 1992) and Xu (Xu et al. 2011). This allows to investigate the sensitivity of the route flows to the users' risk aversion parameters, for the three settings of T_0^{od} .

For the analysis of both cases i. and ii., we calculate the sum square of the residuals between the route flows at equilibrium for all possible combinations of the PT simulation scenarios. The sum square of the residuals for case i. are listed in Table 3.2. While, the sum square of the residuals for case ii. are listed in Table 3.3. As one can observe, the implementation of PT is approximately equally sensible to a change in T_0^{od} rather than on the

users' risk-aversion parameters ($\alpha^{PT}, \beta^{PT}, \lambda^{PT}, \gamma^{PT}, \delta^{PT}$).

We now analyze the route flows calculated through the 6 PT settings compared to the DUE and SUE. In Fig. 3.3 and Fig. 3.4, we show the different route flows for all the 8 simulation scenarios and all 36 od pairs. We observe that the route flows for the PT settings do not show significant differences compared to the SUE, for several od pairs. But, for other od pairs they tend to approach the DUE route flows. This is due to the low number of prospects (i.e., the low number of routes listed in Ω^{od}) that are evaluated as well as the definition of T_0^{od} . According to these three definitions of T_0^{od} (Eq. 3.4 to Eq. 3.6), routes with the lowest travel times per od pair will be mainly evaluated as prospect of gains. While, routes with longer travel times will be evaluated as prospect of losses and thus not probable for the user's choices since they are prospect maximizers. Considering these three definitions of T_0^{od} , we always have at least one route that is mostly framed as a loss. This is due to the route travel times will be framed as a loss, yielding low flows for these routes at equilibrium.

3.3.3 Analysis of the aggregated traffic states

In this section, we analyze the influence of the user's choices for probabilistic alternatives that involve risk on the network performance. We investigate changes in the network internal and outflow capacity as well as on its internal mean speed compared to the DUE and SUE models. The network performance is evaluated through the Macroscopic Fundamental Diagram (MFD). We are interested in investigating the critical accumulation of vehicles n_c and the critical production P_c of the MFD obtained for the different settings of the PT, compared against the values for the reference models. In Fig. 3.5 and Fig. 3.6, we show the evolution of the total travel distance (TTD) as well as the outgoing flow Q_{out} as function of the total travel time (TTT), for the DUE, SUE and the 6 settings of the PT. As one can observe, there is a large points overlap of the MFD functions as well as of the outflow Q_{out} versus TTT. To better highlight the differences between the models, we define three criteria that represent:

 the relative difference between the average TTD of the different PT settings (TTD*) and of the reference models (TTD^{ref}):

$$\alpha_{TTD} = \frac{\overline{TTD^*} - \overline{TTD^{ref}}}{\overline{TTD^{ref}}} \times 100$$
(3.16)

• the relative difference between the average TTT of the different PT settings $(\overline{TTT^*})$

3.3. Dynamic implementation of PT on a Manhattan network



Fig. 3.3 – Route flow distributions for the 8 simulation scenarios and for the od pairs: o = 1, ..., 6; and d = 1, 2, 3. Each simulation scenario is identified by the Model ID as listed in Table 3.1.

3.3. Dynamic implementation of PT on a Manhattan network



Fig. 3.4 – Same as in Fig. 3.3, but for the od pairs: o = 1, ..., 6; and d = 4, 5, 6.

3.3. Dynamic implementation of PT on a Manhattan network



Fig. 3.5 – (*i*) Total travel distance (TTD) [in m] as function of the total travel time (TTT) [in s]. (*ii*) α_{TTD} versus α_{TTT} for the three PT settings. (*iii*) Vehicles outflow (Q_{out}) as function of the Total Travel Time (TTT). (*iv*) $\alpha_{Q_{out}}$ versus α_{TTT} for the three PT settings. In subplots (*i*) and (*iii*), the results are shown for the DUE, SUE and the three settings of PT considering the KT parameters. In subplots (*ii*) and (*iv*), the circle dots represent the relative differences between the three PT settings and the DUE, while the cross dots represent the relative differences between the three PT settings and the SUE.

3.3. Dynamic implementation of PT on a Manhattan network



Fig. 3.6 – Same as in Fig. 3.5, but for the Xu parameters.

3.3. Dynamic implementation of PT on a Manhattan network

and of the reference models $(\overline{TTT^{ref}})$:

$$\alpha_{TTT} = \frac{\overline{TTT^*} - \overline{TTT^{ref}}}{\overline{TTT^{ref}}} \times 100$$
(3.17)

 the relative difference between the average Q_{out} of the different PT settings (Q_{out}^{*}) and of the reference models (Q_{out}^{ref}):

$$\alpha_{Q_{out}} = \frac{\overline{Q_{out}^*} - \overline{Q_{out}^{ref}}}{\overline{Q_{out}^{ref}}} \times 100$$
(3.18)

The average values for TTD, TTT and Q_{out} are calculated for the simulation interval between 500 and 2500 seconds, for the 8 model settings. Based on this, we calculate α_{TTD} , α_{TTT} and $\alpha_{Q_{out}}$ and we estimate confidence intervals for these three criteria. The results are shown in Fig. 3.5 for the KT parameters and in Fig. 3.6 for the Xu parameters. The relative differences between the PT settings and the DUE are represented by the circle dots, while for the SUE are represented by the cross dots. These three criteria allow us to analyze the network capacity and performance. If $\alpha_{TTD} < 0$, the network internal capacity decreases compared with the reference model. In this case, the accumulation of vehicles inside the network is higher and congestion might spread backwards, increasing the average waiting times for vehicles to enter the network. The network inflow capacity is consequently reduced. If $\alpha_{TTT} < 0$, the mean speed of vehicles inside the network is higher than the reference model. If $\alpha_{Q_{out}} > 0$, the outflow capacity of the network is higher compared against the reference model.

One can observe in Fig. 3.5 and Fig. 3.6 that, in general, there are no significant differences between the six PT implementations and the DUE. The only exception is model 8, where the network capacity is reduced by $\sim 5\%$ compared to the DUE. In this case, the accumulation increases and the outflow capacity decreases. On the other hand, the network capacity and mean speed increases for the PT implementations compared to the SUE. The only exception is model 8, where there are not many significant differences. The increase of the network capacity means that the network is less congested compared to the SUE case and the outflow capacity increases.

In summary, in a scenario setting with few alternatives, we show that the user's riskaversion and risk-seeking is balancing the uncertainties of the route travel times and people are more likely to act as personal optimizers, i.e. they tend to minimize their own travel times. This means that a route travel time prospect maximization behavior tends to be similar to a

cost minimization behavior, in terms of individual travel times.

3.4 Conclusions

In this chapter, we analyze the implementation of Prospect Theory considering that users perceive route travel times with uncertainty in a dynamic context. The latter is modeled through Monte Carlo simulations. We consider time-dependent cost paths that account for congestion and spillback effects. For this, we considered a dynamic LWR mesoscopic dynamic simulator (Leclercq & Becarie 2012). We compare the individual route flows and investigate the network capacity and performance. The tests are performed on a Manhattan network. We show that the implementation of PT approximately equally sensible to a change in T_o^{od} than in the set of the user's risk-aversion parameters. The route flows at the network equilibrium for the six PT implementations are in between the SUE and the DUE ones. In a network setting with few alternatives, we show that in terms of the network performance, there are not significant differences between the six PT implementations and the DUE. However, in most of the PT implementations, the network internal and outflow capacities and the mean speed increase compared to the SUE. The time prospect maximization behavior is balancing the route travel times uncertainties and users tend to act more likely as perfectly rational beings for their route choices.

As future research, we note that these results should be further investigated considering a more complex network topology and demand scenarios. This work can also be extended to account for heterogeneous population of users, for example, with preferences for their transportation mode. The idea is to split the heterogeneous population of users into homogeneous classes with similar preferences in terms of prospects. Then, for each class, one defines a T_0^{od} and a set of the risk-aversion parameters.

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Effects of users' bounded rationality on a traffic network performance: a simulation study

Abstract

In this chapter, we revisit the principle of bounded rationality applied to dynamic traffic assignment to evaluate its influences on network performance. We investigate the influence of different types of bounded rational user behavior on: (i) route flows at equilibrium; and (ii) network performance in terms of its internal, inflow and outflow capacities. We consider the implementation of a bounded rational framework based on Monte Carlo simulation. A Lighthill-Whitham-Richards (LWR) mesoscopic traffic simulator is considered to calculate time-dependent route costs that account for congestion, spillback and shockwave effects. Network equilibrium is calculated using the Method of Successive Averages. As a benchmark, the results are compared against both Deterministic and Stochastic User Equilibrium. To model different types of bounded rational user behavior we consider two definitions of user search order (stochastic and strict preferences) and two settings of the indifference band. We also test the framework on a toy Braess network to gain insight into changes in the route flows at equilibrium for both search orders and increasing values of aspiration levels.

Keywords: Satisficing behavior; Users preferences; Network performance; LWR model; Traffic Simulation.

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4.1 Introduction

The first notions of traffic assignment were introduced by Wardrop (1952). According to the first Wardrop principle, users aim to minimize their personal route travel times. This leads to a network equilibrium called the Deterministic User Equilibrium (DUE) and it is that most commonly used in dynamic traffic assignment (DTA) problems. Under DUE conditions, no user can decrease his/her own travel time by unilaterally switching routes. However, the first Wardrop principle assumes that users are perfectly rational and perceive all routes and network traffic states perfectly although information on route travel times (i.e., traffic states) is not necessarily perfect. To overcome this problem, Daganzo & Sheffi (1977) and Daganzo (1982) introduced the Stochastic User Equilibrium (SUE), to take into account the uncertainty of route travel times. The Multinomial Logit and C-Logit are the Random Utility models (RUM) most commonly used in DTA problems. Nonetheless, both these models present several limitations when dealing with correlations between routes. In this study we focus in particular on the Probit model solved using Monte Carlo simulations (Sheffi 1985).

Revealed (Zhu 2011) and stated (Avineri & Prashker 2004) preference surveys show that users tend to choose sub-optimal routes instead of optimal ones (Zhu & Levinson 2015). We emphasize that a sub-optimal route is understood as a route with a longer travel time than the minimum one for the origin-destination (od) pair. In the literature on static traffic assignment, there are other alternative model frameworks that take into account different types of user behavior. One example is the Prospect Theory (Kahneman & Tversky 1979; Tversky & Kahneman 1992) which consider the user's risk-seeking and risk-aversion behavior. It was adapted to the context of route choice by Avineri (2006). In the Prospect Theory, users evaluate the different routes in terms of time prospect and choose the route with the maximum prospect. Users are risk-averse when confronted with prospects of gains and riskseekers when confronted with prospects of losses and are more sensitive to losses than gains (loss effect). Another example is the Regret Theory (Bell 1982; Loomes & Sugden 1982). The users aim to minimize their regret with respect to the non-selected routes (Chorus 2012b; Li & Huang 2016). If the users choose the route with the minimum travel time, they will feel joy or feel regret otherwise. Another example is the notion of bounded rationality introduced by the seminal works of Simon (1957, 1966, 1990, 1991). He stated that users' choices are driven by aspiration levels (AL), which represent a set of goal or target variables that should be achieved or exceeded for the users' satisfaction. In his original idea, the user searches until a satisfactory alternative is found. This term used to describe this process was coined by Simon as *satisficing*, which stands for the combination of satisfy and suffice. In this study, we focus on the application of the notion of bounded rationality in a dynamic context, by considering distributions of route travel times and a traffic simulator. The goal of this study is to investigate the influence of bounded rational user behavior on individual route flows and network performance. This type of study is very important for decision-making in transportation planning. As an example, let's consider that a municipality foresees to increase a transportation network performance. To this end, the engineers plan to construct a new road to redistribute the traffic and alleviate the congestion in the network. Through this study, considering that users are boundedly rational, it is possible to evaluate if the performance of the network increases and whether or not the construction of the new road is a good planning decision.

Mahmassani & Chang (1987) discussed the first notion of bounded rationality applied to traffic assignment, but no mathematical formulation was given. To define users AL, Mahmassani & Chang (1987) introduced the concept of *indifference band* (IB), where a route is *satisficing* if the difference between its travel cost and that of the best available route is lower than a given threshold (or IB). The implementation of bounded rationality in traffic assignment is challenging as: (i) the calibration of the AL is context dependent (Vreeswijk et al. 2013); and (ii) the BR-UE solutions are not unique (Lou et al. 2010; Di et al. 2013, 2014). Thus, to analyze the BR-UE solutions, some authors have focused on the analysis of the best and worst BR-UE flows of the network (Lou et al. 2010; Di et al. 2013; Eikenbroek et al. 2018). Moreover, the AL can change from user to user. A thorough review of bounded rationality in traffic assignment was provided in Di & Liu (2016). There are two main ingredients that dictate bounded rational network equilibrium: (i) the definition of the AL that dictates whether a route is *satisficing* or not; and (ii) the user's search order that defines how users are guided in their choice of a *satisficing* route.

For a route to be considered as *satisficing*, its route utility must satisfy:

$$U_k \le AL^{od}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(4.1)

where U_k is the perceived route utility; AL^{od} is the aspiration level we consider in this chapter, to be defined at the od level; Ω^{od} is the route choice set for the od pair; and Ξ is the set of all od pairs of the network.

The *AL*^{od} can be calibrated exogenously by route choice surveys or calibrated endogenously by explicit formulations. The most commonly used definition is based on the concept of indifference band (Mahmassani & Chang 1987; Huang & Lam 2002; Szeto & Lo 2006):

$$AL^{od} = \min(\vec{V}) + \Delta^{od}, \forall (o, d) \in \Xi$$
(4.2)

where \vec{V} is a vector containing all deterministic route utilities V_k , $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$ and Ω^{od} contains N routes. Δ^{od} is the tolerance or IB at the od level.

Ge & Zhou (2012) proposes a variable definition of the IB (Δ^{od}):

$$AL^{od} = \min(\vec{V}) + \max(|U_p - U_q|\delta_p\delta_q), \forall p, q \in \Omega^{od} \land p \neq q \land \forall (o, d) \in \Xi$$

$$(4.3)$$

where δ_p and δ_q are dummy variables that equal 1 if routes p and q belong to Ω^{od} , respectively.

Ge et al. (2015) analyzed the BR-DUE equilibrium, considering exogenously fixed AL and fixed and endogenously variable AL. In their model framework, the authors showed that the DUE is a special case of the BR-DUE and discussed the existence conditions of the BR-DUE. However, the uncertainty on the travel times was not considered.

Di & Liu (2016) highlighted that a bounded rational behavior can be due to the user's habits and inertia, or their cognitive costs or individual preferences. In this chapter, we focus our attention on the user's preferences as a bounded rational behavior to define the search order for the satisficing alternatives. Zhao & Huang (2016) defined a search order based on a strict preference order for all users sharing the same od pair. This strong assumption allowed obtaining unique BR-UE solutions. To the authors knowledge, the framework of Zhao & Huang (2016) has never been tested in a dynamic context, i.e. considering a traffic simulator and time-dependent path costs. In addition, its dynamic implementation using a traffic simulator is highly challenging because it requires solving sub-optimization problems to calibrate the AL of the sub-most preferred routes. Thus, a framework capable of solving the global optimization problem is required and discussed further on in this chapter. On the other hand, users may also have an indifferent preference for any of the satisficing routes (i.e., that satisfy Eq. 4.1). This is adopted from the notions discussed in (Aquiar et al. 2016). In this case, we consider that all users sharing the same od pair have a similar indifference preference. The choice is modeled by uniform random sampling of any of the *satisficing* routes. Users are then assigned to the *satisficing* route sampled.

Szeto & Lo $(2006)^1$ discussed an analytical BR-UE dynamic traffic assignment model. The authors proposed a route swapping algorithm, but no clear definition of the users search

¹The BR-UE (Mahmassani & Chang 1987) and Tolerance-based Dynamic User Optimum principle (Szeto & Lo 2006) have been used interchangeably in the traffic assignment literature. For the sake of simplicity, we refer to both as BR-UE.

order was discussed. Instead, the authors targeted certain users on the most congested routes and switched them to less congested ones for each od pair. Moreover, the BR-UE solutions were not unique. Han et al. (2015) discussed a dynamic simultaneous departure time and route choice bounded rational framework. However, neither of these frameworks included travel time distributions. In this chapter, we revisit the notions of bounded rationality by considering the distribution of travel times rather than deterministic values.

The literature includes a large number of applications of a bounded rational framework to static (Di et al. 2013) and dynamic traffic assignment (Szeto & Lo 2006; Han et al. 2015), transportation planning (Gifford & Checherita 2007), traffic policy making (Marsden et al. 2012), congestion pricing (Lou et al. 2010) and traffic safety (Sivak 2002). However, to the author's knowledge, there is no study in the literature that investigates the influence of users' preferences (indifferent and strict) for a bounded rational behavior on individual route flows and network performance in terms of the internal level of congestion and inflow and outflow capacities. The goal of this chapter is to fill this gap. We consider time-dependent path costs that account for congestion, shock-waves and spillback effects calculated using a mesoscopic Lighthill-Whitham-Richards (LWR) model (Leclercq & Becarie 2012). A spillback effect is the reduction of a link capacity that spreads over other connected links in the network. To model bounded rationality behavior, we relax the definition of the search order of the DUE and SUE frameworks (Sheffi 1985). In both the DUE and SUE cases, users are assigned to the routes with the minimum travel times based on an all-or-nothing procedure. The search order is relaxed to account for the users' indifferent and strict preferences. In the case of the indifferent preference search order, users present indifference behavior when choosing any of the satisficing routes, whereas in the case of the strict preference search order (Zhao & Huang 2016), users are assigned to the most preferred route if this route is perceived as satisficing (Eq. 4.1), or to the first sub-most preferred route that satisfies Eq. 4.1. We make use of Monte Carlo simulations (Sheffi 1985) to account for travel times distribution and consider the classical Method of Successive Averages to calculate the network equilibrium. First, we test the bounded rationality methodology in a toy Braess network and consider a simple linear static and flow dependent utility function. We then consider the two settings of the search order previously mentioned and the AL^{od} defined exogenously. These initial tests allow acquiring insight into how the route flows at equilibrium change according to the two definitions of the search order and increasing values of AL^{od}. Second, for the dynamic implementation, we also consider the two settings of the users' search order (i.e. indifferent and strict preferences) and the concept of the IB (Eq. 4.2 and Eq. 4.3) to define the AL^{od} . The dynamic tests are performed on a Manhattan network. We investigate the influence

of the definition of the search order on the individual route flows and analyze the network performance in terms of the internal, inflow and outflow capacities, given the two search orders and different values of the AL^{od} . The results are compared against both DUE and SUE as benchmarks.

This chapter is organized as follows. In Sect. 4.2, we discuss the bounded rational model framework considered in this chapter. In Sect. 4.3, we discuss a simple static test scenario on the Braess network, considering both the indifferent and strict preferences search order. In Sect. 4.4, we discuss the influence of the bounded rationality behavior on the network performance also considering the two search orders. In Sect. 4.5, we outline the conclusions of this chapter.

4.2 Bounded rational framework

The analysis of the effect of users' behavior on network performance in terms of its internal inflow and outflow capacities is very important for policy makers, in particular when determining policies aimed at increasing network performance. In this chapter, we focus on two types of bounded rational user behavior.

We start by introducing the general formulation of the route utilities. The perceived route utility, U_k , is:

$$U_{k} = V_{k} + \epsilon_{k}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$

$$(4.4)$$

where V_k is the deterministic route utility; and ϵ_k is the uncertainty or error term as often referred to in the literature.

The DUE assumes that users are utility minimizers and the error terms ϵ_k are set to 0. Users are assigned based on an all-or-nothing procedure to the route with the minimum travel time. In the case of the SUE, users are also utility minimizers, but they perceive travel times with uncertainties, meaning that the error terms ϵ_k are not 0. Theoretically, the Probit model (Daganzo & Sheffi 1977) is the most attractive model for solving the SUE. However, it requires the computation of a covariance matrix and integrating the multivariate normal distribution. The complexity of the computation increases with the number of routes per od pair. An alternative to this is to use Monte Carlo to consider the distributions of route travel times (Sheffi 1985). We consider that the error terms are defined at the link level (i.e., ϵ_a , $\forall a \in \Gamma$) instead at the route level. This allows capturing existing correlations between different routes sharing the same links. Sheffi (1985) proposed to consider link travel times that are normal distributed and to truncate the negative travel times. This skews the

4.2. Bounded rational framework

distributions and a positive defined travel times distribution is to be preferred. In this chapter, we consider that the terms ϵ_a are gamma distributed following Nielsen (1997). The principle of the Monte Carlo simulations is to discretize the error terms ϵ_a into M samples or draws and locally solve DUE problems. For each error draw, the deterministic utility for route k is defined as U_k^m , m = 1, ..., M. In short, DUE is solved one for all considering the utility U_k for each route. The SUE corresponds to the average of M Monte Carlo trials, where the utilities U_k^m are adjusted for each trial considering the link error terms values. It is sufficient to explain how we extend DUE to account for bounded rational (BR-DUE), as the extension of SUE is exactly similar, i.e. we have to solve a BR-DUE problem for each Monte Carlo trial of link error terms and then average the results to get the BR-SUE solutions. Mahmassani & Chang (1987) introduced the first notions of bounded rationality applied to route choice. Lou et al. (2010) and Di et al. (2013) formulated the BR-DUE mathematically, but without defining preference rules among satisficing routes. Under BR-DUE, all users are satisfied with their choices and no longer consider switching routes. It should be noted that the DUE is an extreme case of the BR-DUE (i.e. when $\Delta^{od} = 0$). The idea is that users are assigned to satisficing routes instead of optimal routes (i.e., routes with the minimum perceived travel times). A satisficing route should satisfy Eq. 4.1, i.e. $U_k \leq AL^{od}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. Let us define ω^{od} as the set of *satisficing* routes. The users are then assigned to one route depending on the preference rule. In this chapter, we consider that the search order is defined according to the user's preferences (indifferent and strict preferences, see below). The previous description of BR-SUE was given based on Monte Carlo trials as it helps to make the connection with BR-DUE. We can also provide a formal definition of the BR-SUE independently of the solution method. Let P_k be the probability that route k is chosen for one od pair:

$$P_{k} = P("U_{k} \leq AL^{od''} \cap \text{choosing route k according to the preference rule})$$
$$= P(U_{k} \leq AL^{od}) \times P(\text{choosing route k according to the preference rule})"U_{k} \leq AL^{od''})$$
(4.5)

The second part of the equation is the conditional probability of route k being chosen when k is perceived as *satisficing*. Its value depends on the preference rule. We consider two behavioral rules to represent the user's search order. We consider indifferent preferences, where users are uniformly assigned to *satisficing* routes. In this case, $P(\text{choosing route k according to the preference rule}, "U_k \leq AL^{od''}) = \frac{1}{|\omega^{od}|}$, where |.| is the number of *satisficing* routes listed in ω^{od} . This number is at least equal to 1, as route k is *satisficing*. A close form for this probability cannot be provided as the number of other satisficing routes than k, is a random variable whose distribution is intractable in the general case. Interestingly, Monte Carlo trials for link error terms make the calculation of $|\omega^{od}|$ straightforward, for each Monte Carlo iteration step since all satisficing paths are then known. We also consider a strict preference order (Zhao & Huang 2016), where users are selecting a satisficing route according to a pre-defined list of preferences Υ^{od} . The users are always choosing the satisficing route of highest rank in this list Υ^{od} . Again, the probability $P(\text{choosing route k according to the preference rule}, "<math>U_k \leq AL^{od"}$) does not have a closed form, but Monte Carlo trials permit to determine the unique assignment at each iteration.

The idea of the strict preference order was introduced by Zhao & Huang (2016), to deal with the non-uniqueness of the equilibrium solution. However, we highlight two main differences between our methodology and that discussed in Zhao & Huang (2016). First, we consider that routes are *satisficing* if and only if their perceived utility satisfies: $U_k = V_k \leq AL^{od}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$ for the BR-DUE; or $U_k^m \leq AL^{od}, \forall m = 1, ..., M \land \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$ for the BR-SUE. Zhao & Huang (2016) consider that routes are *satisficing* according to the strict preference order, i.e. the users are first assigned to the most preferred route and then consecutively to the sub-preferred routes, until all the users are assigned. Second, we consider that AL is defined at the od level (i.e., AL^{od}), while Zhao & Huang (2016) considers its definition at the route level. We also assume that all users sharing the same od pair have the same AL^{od} . We consider that is more realistic from the user's perspective to set a global AL^{od} instead of establishing AL for the sub-preferred routes based on the most preferred ones.

In this chapter, we consider the two definitions of AL^{od} as defined in Eq. 4.2 and Eq. 4.3.

To reach a solution for the BR-SUE and simulate the probability term P(route k is satisficing) (see Eq. 4.5), we consider Monte Carlo simulations as discussed in Sheffi (1985) and the classical Method of Successive Averages (MSA). The MSA solves a fixed point problem and is commonly used in traffic assignment to solve both the DUE and SUE (Sheffi 1985). The Monte Carlo simulations consist in discretizing the distributions of the link travel times into M samples or draws and solving BR-DUE problems locally. For each discretization, we identify the *satisficing* routes and assign the users based on an all-or-nothing assignment following the search order established. If the search order is considered to be the indifferent preferences, all the users are assigned randomly to any of the *satisficing* routes. On the other hand, if the search order follows a strict user preference order, all users are assigned to the first *satisficing* route found on this strict sequence of preferences. The new temporary route flows, Q_k^* , correspond to averaging all the local BR-DUE solutions. This corresponds to the temporary route flows Q_k^* , that will be used to

4.2. Bounded rational framework

update the new route flows Q_k^{j+1} at iteration j + 1, as:

$$Q_k^{j+1} = Q_k^j + \alpha_j \{Q_k^* - Q_k^j\}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$

$$(4.6)$$

where Q_k^j represent the route flows at iteration j of the MSA; and α_j is the descent step. This process is repeated at every descent step of the MSA algorithm.

The sequence of descent steps α_j guarantees the convergence of the MSA. For the theoretical convergence of the algorithm, the following two conditions must be satisfied (Sheffi 1985):

$$\sum_{j=1}^{\infty} \alpha_j = \infty \tag{4.7}$$

$$\lim_{j \to \infty} \alpha_j \to 0 \tag{4.8}$$

One definition of α_j that satisfies both of the previous conditions is: $\alpha_j = \frac{1}{j}$. We consider this definition of α_j in this chapter. Other definitions of the descent step size are discussed in the literature (Polyak 1990; Liu et al. 2007; Taale 2008; Chen et al. 2011a).

A commonly used convergence or stopping criterion is based on the comparison between the current and the previous descent step of the MSA that must be lower to a pre-defined threshold. Instead we consider the number of violations $N(\lambda)$ and the relative gap (Sbayti et al. 2007). $N(\lambda)$ represents the number of cases where $|Q_k^{j+1} - Q_k^j|$ is higher than a pre-defined path convergence threshold Φ . Note that Φ represents an upper bound. The convergence of the algorithm is achieved if $N(\lambda) \leq \Phi$. The relative gap for the DUE is (Sbayti et al. 2007):

$$Gap = \frac{\sum_{o} \sum_{d} \sum_{k \in \Omega^{od}} Q_k^{od} (V_k^{od} - \min(V^{od}))}{\sum_{o} \sum_{d} Q^{od} \min(V^{od})}$$
(4.9)

where Q^{od} is the total demand for the od pair; and V_k^{od} is the average travel time of route k; and min (V^{od}) is the minimum route travel time for the od pair.

The Gap function (Eq. 4.9) represents the difference between the travel costs and the equilibrium travel costs. Thus, under perfect DUE conditions, Gap = 0. This means that all users choose the routes with the minimum travel times. Under SUE conditions, the Gap is higher than 0, however small. In this case not all users choose the routes with the minimum travel times. In the case of bounded rationality, the Gap value increases as AL^{od} increases. The Gap function is also a measure of how close users are to the equilibrium route travel times (or T^{UE}). The definition of the GAP as defined in Eq. 4.9 is valid for DUE and SUE and informs on how far we are from the DUE. For both the BR-DUE and BR-SUE convergence,

we modify the Gap function as follows:

$$Gap^{BRUE} = \frac{\sum_{o} \sum_{d} \sum_{k \in \omega^{od}} Q_k^{od} \max(V_k^{od} - AL^{od}, 0)}{\sum_{o} \sum_{d} Q^{od} AL^{od}}$$
(4.10)

Thus, under BR-DUE or BR-SUE conditions, the Gap is about 0 if $\min(V^{od}) \leq V_k^{od} \leq AL^{od}$, $\forall (o, d) \in \Xi$ and the equilibrium condition is fulfilled. Note that throughout the chapter, we use the definition of the Gap as in Eq. 4.9 as an indicator that measures how far the bounded rational equilibria from the DUE; and Eq. 4.10 as the equilibrium convergence criterion for the MSA.

We present the solution algorithm of this framework in Algorithm 3. Note that the difference between Algorithm 3 and that proposed by Sheffi (1985) is that we assign the users to satisficing routes instead of routes with the minimal travel times. They are assigned to these satisficing routes according to one of the search orders discussed previously (i.e. indifferent or strict preferences) at every descent step of the MSA. The first step before entering the MSA loop consists in calculating the route choice set Ω^{od} , for each od pair. It defines the set of routes for the users' choices. We then perform an initial loading on these routes and consider the number of violations, the GAP (Eq. 4.10) and the maximum number of iterations for the MSA convergence criteria. The corresponding tol, Φ and N_{max} are set. It is also necessary to define the input scale (η) and shape (ζ) parameters of the link travel time gamma distributions for the first Monte Carlo simulations. We then enter in the MSA loop and the AL^{od} is first updated based on the average route travel times (see Eq. 4.2 or Eq. 4.3). The next step consists in performing the link error sampling considering the η and ζ parameters. This is done through Monte Carlo simulations. The algorithm then loops over all the M error samples and locally solves the BR-DUE problems. For each sample, the route utilities are computed to identify the *satisficing* routes based on AL^{od} . This defines the *satisficing* set of routes ω^{od} . Users are assigned based on the pre-defined search order (indifferent or strict preferences) based on an all-or-nothing procedure to one route in ω^{od} . It should be noted that in the case of solving the BR-SUE and taking the indifferent preferences into account, it is necessary to repeat the all-or-nothing assignment on the *satisficing* routes A times. The users' choices for the local BR-DUE correspond to averaging the previous choices. By applying the law of large numbers, when A is large, we converge to the same average values. The new temporary route flows Q_k^* correspond to the average of all the local BR-DUE choices. The new route flows Q_k^{j+1} are updated according to Eq. 4.6 and the network loading is updated. To determine time-dependent link costs that consider congestion, shock-waves and spillback effects, we run an LWR mesoscopic traffic simulator (Leclercq & Becarie 2012). The link

travel time distributions are obtained based on the simulated vehicle travel times. To update η and ζ , we fit a gamma distribution to each link travel time distribution. The updated values of η and ζ will be used to perform the error samplings in the next MSA descent step. The Gap^{BRUE} (Eq. 4.10) and number of violations $N(\lambda)$ are updated based on the new average route travel times through the individual vehicles travel times. This process is repeated until convergence is achieved. Note that Algorithm 3 also allows solving the BR-DUE by setting $\eta = 0$ and $\zeta = 0$.

Input the AL^{od} (if they are set exogenously). Input the network, demand scenario and simulation duration T. Calculate the route choice set Ω^{od} for each od pair. Perform an initial network loading. Set $N(\lambda) > \Phi$ and $Gap^{BRUE} > tol$. Initialize $j = 1, \eta, \zeta, \alpha_j = 1$ and $Q_k^{j=1} = 0$. Set the MSA stopping criterion tol. while $Gap \ge tol \text{ or } N(\lambda) \ge \Phi \text{ or } j \le N_{max}$ do Set $Q_k^j = Q_k^{j+1}$. If set endogenously, update the AL^{od} based on Eq. 4.2 or Eq. 4.3. Perform *M* error samplings at the link level, based on η and ζ . for m=1 to M do Compute the route utilities. Determine the *satisficing* routes and update ω^{od} , $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. Based on the defined search order, perform an all-or-nothing assignment ². If $\omega^{od} = \emptyset$, all users are assigned to the minimum utility route. end Update the new route flows $Q_k^*, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$, based on an averaging of the users choices over all error samples. Update the route flows according to Eq. 4.6. Run the LWR mesoscopic simulator (Leclercq & Becarie 2012). Based on the link travel times, fit a gamma distribution to update η and ζ . Calculate the Gap (Eq. 4.10) and the number of violations $N(\lambda)$. Update $\alpha_j = \frac{1}{i}$. Set i = i + 1. end

Save the route flows: Q_k^{j+1} , $\forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$. **Algorithm 3:** Dynamic implementation algorithm of the *satisficing* model.

4.3 First tests on a toy network

We first test the bounded rational model framework discussed in the previous section, on a toy Braess network and consider a static flow dependent utility function. The goal of these simple

4.3. First tests on a toy network



Fig. 4.1 – Braess network.

initial tests are to assess and acquire insight into how the route flows at equilibrium change according to the two definitions of the search order (i.e. indifferent and strict preference search order) and increasing values of AL^{od} . The AL^{od} are defined exogenously.

4.3.1 Definition of the test network

For the first test, we consider that the perceived travel times (i.e., route utility) depend only on route flows and route free-flow travel times. We resort to the following definition of the perceived route utility, $U_k(Q_k)$:

$$U_k(Q_k) = \sum_{a \in \Gamma_a} (V_a(q_a) + \epsilon_a) \delta_{ak}, \forall k \in \Omega^{od}$$
(4.11)

where $V_a(q_a) = \theta_1 t_a + \theta_2 q_a$ and $q_a = \sum_{l \in a} \delta_{al} Q_l$; t_a is the link free-flow travel time of link a; q_a is the flow of link a; δ_{al} is a dummy variable that equals 1 if route l uses link a, or 0 otherwise; Q_l is the total flow of route l; and ϵ_a is the error term associated with link a. θ_1 and θ_2 are parameters set to 1.

For the static tests, we consider the Braess network (Fig. 4.1). The choice set is: $\Omega_k = \{1,4;2,5;1,3,5\}, \forall k = 1,2,3$. The following sets of link free-flow travel times are considered: $t_1 = 5, t_2 = 45, t_3 = 10, t_4 = 30, t_5 = 5$.

For the MSA convergence, we set $tol = 10^{-2}$, $\Phi = 0$ and $N_{max} = 10000$. A total demand of $Q^{od} = 10$ is considered. As a reference of user perfect rationality, we consider the DUE. Note that the ϵ_a terms are set to 0 for both the DUE and the BR-DUE calculations. For the BR-SUE calculations, we consider a gamma distribution with a shape parameter set to $\eta_a = 1$ and a scale parameter set to $\zeta_a = 4$; and a total of M = 2000 error samples. The BR-DUE and BR-SUE are calculated based on Algorithm 3, except that the link travel times are not updated considering the LWR mesoscopic traffic simulator (Leclercq & Becarie 2012). Instead, we consider the route utility as defined in Eq. 4.11. The link travel times are only sampled at the initiation of the MSA descent procedure.

4.3.2 Indifferent preference search order and exogenous *AL*^{od}

In this section, we analyze both the BR-DUE and BR-SUE results considering the users' indifferent preference search order and the AL^{od} defined as in Eq. 4.2. We also analyze the algorithm's convergence towards the equilibrium solution through the Gap function. To define the search order, we consider a uniform distribution to simulate the user's choices among the set of *satisficing* routes ω^{od} . This procedure must be repeated many times to reach convergence by the Law of large numbers (on average) with the same solution of route flows. Then, for each value of AL^{od} , we repeat the assignment procedure 1000 times and calculate the average route flows and corresponding standard deviation. We do so for both the BR-DUE and BR-SUE calculations. First, under DUE conditions, only routes 1 and 3 are used. This means that $T^{UE} = U_1 = U_3 < U_2$ and corresponds to the route flows: $Q_1 = 1.7$, $Q_2 = 0$ and $Q_3 = 8.3$. Note that T^{UE} is the route travel times at the User Equilibrium. Under SUE conditions, only routes 1 and 3 are *satisficing*. But, due to the users' perception of travel times, there is a residual flow on route 2. The route flows are $Q_1 = 3.5$, $Q_2 = 0.3$ and $Q_3 = 6.2$.

We first analyze the BR-DUE results, calculated for increasing values of Δ^{od} . These results are listed in Table 4.1. The first test consists in reproducing the perfect rationality behavior, by setting $\Delta^{od} = 0 \implies AL^{od} = T^{UE} = 46.7$. The route flows under BR-DUE are similar to the DUE. Then, to analyze the equilibrium results for increasing values of $\Delta^{od} \in [0, +\infty[$, we must first identify the critical points for the BR-DUE, that is to say the utility values of each route when the total demand Q^{od} is assigned to each of the routes. We first consider $Q_1 = 10$, $Q_2 = 0$ and $Q_3 = 0$, which yields $U_1 = 55$. Similarly for route 2, $U_2(Q_1 = 0, Q_2 = 10, Q_3 = 0) = 60$, and route 3, $U_3(Q_1 = 0, Q_2 = 0, Q_3 = 10) = 50$. These critical points play an important role in analyzing the equilibrium solutions. The minimum of the critical points indicate the value of ALod from which the objective function is no longer convex. We analyze the BR-DUE route flows for increasing values of AL^{od} in more detail. For $AL^{od} \in [T^{UE}, 50]$, the users switch from route 3 to 1. Note that the users switch from the *satisficing* routes with higher route flows to the ones with lower route flows. For $AL^{od} \in [50, 55]$, the algorithm does not converge to the same solution as evidenced by the standard deviation values listed in Table 4.1. For example, for $AL^{od} = 50$, two feasible solutions are found: $(Q_1 = 5, Q_2 = 0, Q_3 = 5)$ which yields $(U_1 = 50, U_2 = 55, U_3 = 40)$; and $(Q_1 = 0, Q_2 = 0, Q_3 = 10)$ that yields $(U_1 = 45, U_2 = 60, U_3 = 50)$. The convergence of the algorithm to any of these feasible solutions depends on the initial loading of the network for the MSA algorithm. This explains why we do not converge to the same set of route flows for
4.3. First tests on a toy network

Δ^{od}	AL ^{od}	Q_1/Q^{od}	Q_2/Q^{od}	Q_3/Q^{od}	U_1	U_2	U_3	Gap
0	46.6	0.17 ± 0.00	0.00 ± 0.00	0.83 ± 0.00	46.7	58.3	46.7	0.00
1	47.0	0.20 ± 0.00	0.00 ± 0.00	0.80 ± 0.00	47.0	58.0	46.0	0.00
2	47.3	0.23 ± 0.00	0.00 ± 0.00	0.77 ± 0.00	47.3	57.7	45.4	0.01
3	47.7	0.27 ± 0.00	0.00 ± 0.00	0.73 ± 0.00	47.7	57.3	44.7	0.02
4	48.0	0.30 ± 0.00	0.00 ± 0.00	0.70 ± 0.00	48.0	57.0	44.0	0.03
5	50.0	0.22 ± 0.16	0.00 ± 0.00	0.78 ± 0.16	47.2	57.8	45.6	0.06
15	60.0	0.41 ± 0.19	0.01 ± 0.01	0.58 ± 0.19	49.0	56.0	41.6	0.12
20	65.0	0.34 ± 0.14	0.17 ± 0.07	0.49 ± 0.21	46.7	58.3	39.8	0.19
30	66.3	0.37 ± 0.26	0.25 ± 0.15	0.37 ± 0.26	46.2	58.8	37.5	0.34
40	76.3	0.33 ± 0.27	0.35 ± 0.28	0.32 ± 0.26	44.8	60.2	36.5	0.46
50	86.3	0.34 ± 0.27	0.33 ± 0.26	0.33 ± 0.26	45.1	59.9	36.5	0.44
75	105.0	0.33 ± 0.27	0.33 ± 0.27	0.33 ± 0.27	45.0	60.0	36.6	0.45
100	136.5	0.33 ± 0.26	0.33 ± 0.26	0.34 ± 0.27	45.1	59.9	36.8	0.43

Table 4.1 – BR-DUE route flows for different values of the AL^{od} . The Gap values represent average values based on 1000 repetitions of the BR-DUE calculations.

 $AL^{od} \ge 50$. For $AL^{od} \in [55, 60[$, route 2 becomes *satisficing* and users switch from routes 3 and 1 to route 2. For $AL^{od} \ge 60$, the route flows will converge to 1/3 as the value of AL^{od} increases. This represents the users indifference for choosing any of the *satisficing* routes. Under SUE conditions

We investigate the algorithm's convergence for different values of Δ^{od} , that corresponds to different values of AL^{od} , as shown in Fig. 4.2. To do this, we consider a total of 50 descent steps j of the MSA algorithm, despite the convergence criterion of $Gap \leq 10^{-2}$ being verified for a lower number of j. This allows observing that the solution no longer changes after the convergence criterion is satisfied. In Fig. 4.2, we show the evolution of the Gap and route flows for increasing values of j, for the DUE and $AL^{od} = T^{UE}$, 48, 53, 100. For all four cases, the Gap value converges to a constant value for increasing values of j as well as the route flows.

We analyze the BR-SUE results for increasing values of Δ^{od} . These results are listed in Table 4.2. We first confirm that the route flows under BR-SUE and SUE are similar, by setting $\Delta^{od} = 0$. For $AL^{od} \in [42.6, 55]$, the users change from route 3 to 1. For $AL^{od} \ge 57$, route 2 becomes *satisficing* and the users also start choosing this route. The comparison of the BR-DUE and BR-SUE results for $AL^{od} \ge 65$ are of particular interest. In both cases, the route flows converge to 1/3 when the value of AL^{od} is sufficiently large. This represents the users' indifference for choosing any of the *satisficing* behaviors, since all the routes comply with the condition defined by Eq. 4.1. The effect of the perception of the route travel times

4.3. First tests on a toy network



Fig. 4.2 – Gap (left) and route flows (right) as a function of the increasing number of MSA descent steps j for the DUE and several values of $AL^{od} = TT^{UE}$, 48, 53, 100.

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Δ^{od}	AL ^{od}	Q_1/Q^{od}	Q_2/Q^{od}	Q_3/Q^{od}	U_1	U_2	U_3	Gap
0	42.6	0.34 ± 0.00	0.03 ± 0.00	0.63 ± 0.00	48.1	56.9	42.5	0.06
1	43.5	0.34 ± 0.00	0.03 ± 0.00	0.63 ± 0.00	48.1	56.9	42.5	0.06
2	44.6	0.34 ± 0.00	0.03 ± 0.00	0.63 ± 0.00	48.1	56.9	42.5	0.06
3	45.5	0.34 ± 0.00	0.03 ± 0.00	0.63 ± 0.00	48.1	56.9	42.5	0.06
4	46.5	0.34 ± 0.00	0.03 ± 0.00	0.63 ± 0.00	48.1	56.9	42.5	0.06
5	47.6	0.34 ± 0.00	0.03 ± 0.00	0.63 ± 0.00	48.1	56.9	42.5	0.06
15	56.4	0.40 ± 0.00	0.03 ± 0.00	0.57 ± 0.00	48.7	56.3	41.3	0.08
20	59.7	0.42 ± 0.00	0.09 ± 0.00	0.49 ± 0.00	48.3	56.7	39.8	0.13
30	67.7	0.39 ± 0.01	0.23 ± 0.00	0.39 ± 0.00	46.6	58.4	37.7	0.22
40	76.9	0.35 ± 0.00	0.32 ± 0.01	0.35 ± 0.00	45.4	59.6	36.9	0.27
50	86.8	0.33 ± 0.00	0.33 ± 0.00	0.34 ± 0.00	45.1	59.9	36.7	0.29
75	111.9	0.33 ± 0.00	0.33 ± 0.00	0.33 ± 0.00	45.0	60.0	36.7	0.29
100	136.7	0.33 ± 0.00	0.33 ± 0.00	0.33 ± 0.00	45.0	60.0	36.7	0.29

Table 4.2 – BR-SUE route flows for different values of the AL^{od}.

explains the small differences verified in the route flows between the BR-DUE and BR-SUE for the same value of AL^{od} . For example, it is interesting to consider the case where $\Delta^{od} = 40$. The BR-DUE route flows are $(Q_1 = 3.3; Q_2 = 3.5; Q_3 = 3.2)$ and the BR-SUE route flows are $(Q_1 = 3.5; Q_2 = 3.2; Q_3 = 3.5)$. It can also be seen from the BR-SUE results shown in Table 4.2, that the MSA algorithm converges to the same solution, as evidenced by the standard deviation of the route flows. To solve the BR-SUE, we solve M BR-DUE problems locally, and since the search order is the indifference preferences, the users are assigned Atimes for each BR-DUE problem. By applying the Law of large numbers, we converge on average to the same solution when A is sufficiently large.

We also observe that for both the BR-DUE and BR-SUE results, the average \overline{Gap} values increase as we increase AL^{od} , as expected. This represents the effect of the *satisficing* behavior, where users choose *satisficing* routes instead of the routes with the shortest travel times.

4.3.3 Strict preference search order and exogenous AL^{od}

In this section, we analyze the BR-DUE results calculated considering an exogenous definition of AL^{od} and a strict preference search order (Zhao & Huang 2016). We calculate the BR-DUE results for the Braess network (Fig. 4.1), considering the six possible strict preference search orders (Υ^{od} , $\forall k = 1, 2, 3$). For the calculations, we consider our bounded rational model framework and the model discussed by Zhao & Huang (2016). The mathematical

4.3. First tests on a toy network

			Our model					Zhao	& Huang (2	2016)		
AL ^{od}	Q_1/Q^{od}	Q_2/Q^{od}	Q_3/Q^{od}	U_1	U_2	U_3	Q_1/Q^{od}	Q_2/Q^{od}	Q_3/Q^{od}	U_1	U_2	U_3
					Prefere	ence ord	er $\Upsilon^{od} = 1$	23				
46.6	0.17	0.00	0.83	46.7	58.3	46.7	0.17	0.00	0.83	46.7	58.3	46.6
47.5	0.25	0.00	0.75	47.5	57.5	45.0	0.25	0.00	0.75	47.5	57.5	45.0
50.0	0.50	0.00	0.50	50.0	55.0	40.0	0.50	0.00	0.50	50.0	55.0	40.0
52.5	0.87	0.13	0.00	52.5	52.5	30.0	0.75	0.00	0.25	52.5	52.5	35.0
55.0	1.00	0.00	0.00	55.0	50.0	30.0	1.00	0.00	0.00	55.0	50.0	30.0
					Prefere	ence ord	er $\Upsilon^{od} = 1$	3 2				
46.6	0.17	0.00	0.83	46.7	58.3	46.7	0.17	0.00	0.83	46.7	58.3	46.6
47.5	0.25	0.00	0.75	47.5	57.5	45.0	0.25	0.00	0.75	47.5	57.5	45.0
50.0	0.50	0.00	0.50	50.0	55.0	40.0	0.50	0.00	0.50	50.0	55.0	40.0
52.5	0.75	0.00	0.25	52.5	52.5	35.0	0.75	0.00	0.25	52.5	52.5	35.0
55.0	1.00	0.00	0.00	55.0	50.0	30.0	1.00	0.00	0.00	55.0	50.0	30.0
					Prefere	ence ord	er $\Upsilon^{od} = 2$	13				
46.6	0.17	0.00	0.83	46.7	58.3	46.7	~	\sim	\sim	\sim	\sim	\sim
47.5	0.25	0.00	0.75	47.5	57.5	45.0	\sim	\sim	\sim	\sim	\sim	\sim
50.0	0.50	0.00	0.50	50.0	55.0	40.0	\sim	\sim	\sim	\sim	\sim	\sim
55.0	0.75	0.25	0.00	50.0	55.0	30.0	0.50	0.00	0.50	50.0	55.0	40.0
60.0	0.50	0.50	0.00	45.0	60.0	30.0	0.125	0.125	0.75	45.0	60.0	45.0
65.0	0.25	0.75	0.00	40.0	65.0	30.0	0.00	0.50	0.50	40.0	65.0	40.0
70.0	0.00	1.00	0.00	35.0	70.0	30.0	0.00	1.00	0.00	35.0	70.0	30.0
					Prefere	ence ord	er $\Upsilon^{od} = 2$	31				
46.6	0.17	0.00	0.83	46.7	58.3	46.7	\sim	\sim	\sim	\sim	\sim	\sim
47.5	0.13	0.00	0.87	46.3	58.7	47.5	\sim	\sim	\sim	\sim	\sim	\sim
50.0	0.00	0.00	1.00	45.0	60.0	50.0	\sim	\sim	\sim	\sim	\sim	\sim
55.0	0.00	0.00	1.00	45.0	60.0	50.0	0.50	0.00	0.50	50.0	55.0	40.0
60.0	0.00	0.00	1.00	45.0	60.0	49.9	0.125	0.125	0.75	45.0	60.0	45.0
65.0	0.00	0.50	0.50	40.0	65.0	40.0	0.00	0.50	0.50	40.0	65.0	40.0
70.0	0.00	1.00	0.00	35.0	70.0	30.0	0.00	1.00	0.00	35.0	70.0	30.0
					Prefere	ence ord	er $\Upsilon^{od} = 3$	12				
46.6	0.17	0.00	0.83	46.7	58.3	46.7	0.17	0.00	0.83	46.7	58.3	46.6
47.0	0.15	0.00	0.85	46.5	58.5	47.0	0.15	0.00	0.85	46.5	58.5	47.0
48.0	0.10	0.00	0.90	46.0	59.0	48.0	0.10	0.00	0.90	46.0	59.0	48.0
49.0	0.05	0.00	0.95	45.5	59.5	49.0	0.05	0.00	0.95	45.5	59.5	49.0
50.0	0.00	0.00	1.00	45.0	60.0	50.0	0.00	0.00	1.00	45.0	60.0	50.0
					Prefere	ence ord	er $\Upsilon^{od} = 3$	21				
46.6	0.17	0.00	0.83	46.7	58.3	46.7	0.17	0.00	0.83	46.7	58.3	46.6
47.0	0.15	0.00	0.85	46.5	58.5	47.0	0.15	0.00	0.85	46.5	58.5	47.0
48.0	0.10	0.00	0.90	46.0	59.0	48.0	0.10	0.00	0.90	46.0	59.0	48.0
49.0	0.05	0.00	0.95	45.5	59.5	49.0	0.05	0.00	0.95	45.5	59.5	49.0
50.0	0.00	0.00	1.00	45.0	60.0	50.0	0.00	0.00	1.00	45.0	60.0	50.0

Table 4.3 – Route flow distribution for the Braess network for different values of the *AL* and under BR-DUE conditions. A set of strict preferences is considered for the search order.

methodology discussed by Zhao & Huang (2016) is not suitable for a dynamic implementation considering a traffic simulator. This is because it requires solving sub-optimization problems to calibrate the AL of the sub-preferred routes. In this section, we compare the route flows calculated considering the two frameworks and the six preference search orders. The AL^{od} are set exogenously according to each strict preference order. We apply the model discussed by Zhao & Huang (2016), considering that the utility of the most preferred route is equal to the value of the aspiration level AL^{od} ; and the route flows of the remaining routes correspond to the result obtained by solving the sub-UE problem, as done by Zhao & Huang (2016). The results are listed in Table 4.3.

It can be seen that when $AL^{od} = TT^{UE} = 46.6$, the route flows obtained for both models are equivalent to the DUE result. Thus, both models are able to reproduce the users' perfect rationality whatever the preference order.

Consider the first strict preference order $\Upsilon^{od} = 1, 2, 3$. For $47.5 \leq AL^{od} < 50$, in both models the users switch directly from route 3 to the most preferred route 1. The flows on these two routes are equal for both models. But in our model, route 2 is not selected because it is not considered as *satisficing* whereas in the model of Zhao & Huang (2016), the assignment problem solved is: $U_1 = A_1$ and $U_2 = U_3$. Under sub-User Equilibrium (sub-UE) conditions, $U_2 > U_3$. This means that the remaining users that have not chosen the most preferred route 1 will choose route 3. In our model, the users are assigned to the most preferred route until the *satisficing* condition (Eq. 4.1) is satisfied. Users are then assigned to the sub-preferred routes if and only if they are *satisficing*. Since route 2 is not *satisficing*, the remaining users choose route 3. Thus, both models yield similar route flows for these two values of AL^{od} . For $AL^{od} = 52.5$, route 2 becomes *satisficing* for our model. Thus the users will switch according to the strict preference order Υ^{od} . Thus, the users will first switch from route 3 to 2 and then from 2 to 1. In the case of the model of Zhao & Huang (2016), the sub-UE solution corresponds to $U_2 > U_3$. Thus, no user chooses route 2. For $AL^{od} \ge 55$, all the users choose the most preferred route 1 for both models.

Consider the second strict preference order $\Upsilon^{od} = 1, 3, 2$. In this case, the users switch directly from route 3 to the most preferred route 1 as AL^{od} increases. In the case of our model, the users are assigned to the most preferred route until it is considered as *satisficing*. Then, the remaining users are assigned to the sub-preferred route 3. In the case of the model of Zhao & Huang (2016), the sub-UE solution also corresponds to $U_2 > U_3$ and thus no users choose route 2. So, for this strict preference order, both models give similar route flows as AL^{od} increases.

Consider the third strict preference order $\Upsilon^{od} = 2, 1, 3$. Given this preference order and for $AL^{od} \leq 50$, route 2 is not *satisficing* for our model. Therefore, the users will switch from route 3 (the less preferred) to the second most preferred route 1. The model of Zhao & Huang (2016) cannot be applied for $AL^{od} < 55$, since $AL^{od} \neq U_2$. This would lead to a violation of the strict preference order assumption. We make this assumption more flexible. Although route 2 is the most preferred route, it is not considered as *satisficing* and the users choose other most preferred routes that are *satisficing*. This is the case of route 1. In the case of our model, for $AL^{od} \geq 55$, all the users switch from route 1 to 2 (the most preferred one). In the case of the model of Zhao & Huang (2016), the users will switch from route 1 to routes 2 and 3 (for $AL^{od} = 55$ and $AL^{od} = 60$) and then from 3 to 2 (for $AL^{od} = 65$ and

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 $AL^{od} = 70$). Although route 3 is that least preferred, the users switch from route 1 to 3. Note that we solve the following assignment problem for the model of Zhao & Huang (2016): $AL^{od} = U_2$ and $U_1 = U_3$.

Consider the fourth strict preference order $\Upsilon^{od} = 2, 3, 1$. In the case of our model, for $AL^{od} \leq 60$, route 2 is not *satisficing*. Therefore, all the users switch from route 1 to 3 in accordance with the strict preference order. For $AL^{od} \geq 60$, route 2 becomes *satisficing* and the users switch from route 3 to 2. In the case of the model of Zhao & Huang (2016), the condition $AL^{od} = U_2$ is satisfied only for $AL^{od} \geq 55$. For $AL^{od} \geq 55$, we observe a route flow pattern similar to that in the previous strict preference order ($\Upsilon^{od} = 2, 1, 3$) for the same reasons discussed previously.

Consider the fifth and sixth strict preference orders $\Upsilon^{od} = 3, 1, 2$ and $\Upsilon^{od} = 3, 2, 1$. In the case of our model, route 2 is not *satisficing* for these two strict preference orders. Thus, users switch directly from route 1 to 3, as AL^{od} increases. For $AL^{od} \ge 50$, all users choose the most preferred route 3. In the case of the model of Zhao & Huang (2016), we solve the following assignment problem: $AL^{od} = U_3$ and $U_1 < U_2$ (sub-UE problem). Since $U_1 < U_2$ for all the listed values of AL^{od} , the remaining users that have not chosen route 3 choose route 1 for both strict preference orders. This is why we observe similar route flows for both models and both strict preference orders.

In summary, we validate our bounded rational framework considering a strict user's preference search order, by comparing the route flows at equilibrium with the results obtained by the model of Zhao & Huang (2016). Moreover, our bounded rational framework is suitable for dynamic implementation with a traffic simulator and will be tested in the next section.

4.4 Dynamic implementation on a Manhattan network

In this section, we investigate the influence of different types of bounded rational user behavior on: (i) individual route flows; (ii) network performance in terms of its internal, inflow and outflow capacities. To do this, we consider the implementation of the bounded rational framework described in Algorithm 3. To determine the time-dependent cost paths that account for congestion, shock-waves and spillback effects, we consider a mesoscopic LWR traffic simulator (Leclercq & Becarie 2012). The tests are performed on a Manhattan network. We consider the indifferent and strict preference search orders and both definitions of the AL^{od} , as in Eq. 4.2 and Eq. 4.3.

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Fig. 4.3 – Manhattan network.

4.4.1 Test scenario definition

For the dynamic implementation, we consider the Manhattan network composed of 134 links, as shown in Fig. 4.3. All the links have the same length of 100 meters. Traffic lights regulate all the intersections. A green light duration of 45 seconds is considered for the traffic lights of the horizontal links whereas a duration of 15 seconds is considered for the traffic lights of the vertical links. Green times are set in the West-East and in the North-South directions. The offsets considered are of 10 and 20 seconds.

A triangular fundamental diagram is considered for each lane of the network, with the following parameters: u = 15 (m/s), for the free-flow speed; w = 5 (m/s) for the wave speed; and $k_{jam} = 0.2$ (veh/m/lane) for the jam density. The entry links (i.e., from O1 to 6) have two lanes. The total link flow is assigned equally on each lane.

The Manhattan network shown in Fig. 4.3, has six entries (identified by O1 to O6 in Fig. 4.3) and exits (identified by D1 to D6 in Fig. 4.3). For each of the six entries, we consider a constant inflow (demand) of 0.5 (veh/s). There is no capacity restriction at the exits. There is a total of 36 possible od pairs. To define the choice set Ω^{od} , we consider 3 paths per od pair. These paths are calculated using a K-shortest path algorithm. This gives a total of 108 routes, considering the 36 possible od pairs.

For the dynamic tests and the bounded rational route choice model, we consider the endogenous definitions of the indifference band for AL^{od} as defined by Eq. 4.2 and Eq. 4.3 and two settings of the search order:

- an *indifferent* preference search order, where users randomly choose any of the *satisficing* alternatives; or, the least worst if there are no *satisficing* alternatives.
- a *strict preference* search order, where users have a strict preference for the routes with the most reliable travel times. We consider the variances of the route travel times as the time reliability indicator. Then, the set of strict preference is built by ordering the routes from the lowest to the highest variance value for each od pair. This set of preferences is updated at every descent step of the MSA, based on the route travel time distributions of the previous simulation.

Considering this search order, users seek *satisficing* alternatives based on this set of strict preferences and on AL^{od} . Similarly, for the strict preference search order discussed in Sect. 3.3, the users choose only the most preferred route if it is perceived as *satisficing*, i.e. that conforms to Eq. 4.1. Then, if the most preferred route is not perceived as *satisficing*, the users consider the other most preferred routes until they find one that is *satisficing*. If none of the routes are *satisficing*, the users choose the route with the minimal travel time.

As a reference, we consider the DUE and SUE. To solve the SUE, we consider the Probit model with gamma distributed error terms and use Monte Carlo simulations (Sheffi 1985). For the indifference band defined by Eq. 4.2, we consider three exogenous values for Δ^{od} : 0; 100; and 500. We have a total of 10 simulation scenarios, considering both search orders defined above. The total simulation period is T = 3000 seconds. For the convergence, we set $tol = 10^{-2}$, $\Phi = 0$ and $N_{max} = 250$.

4.4.2 Analysis of the individual route flows

In this section, we analyze the individual route flows for the 10 simulation scenarios. Each scenario is identified by one ID number, as listed in Table 4.4. We also list the Gap values in Table 4.4, that are calculated using Eq. 4.9. In Fig. 4.6, we show the distributions of the average route travel times for the 10 simulation scenarios. Note that, the average travel time per route for each scenario (i.e., the average of these distributions) is also listed in Table 4.4. In Fig. 4.4 and Fig. 4.5, we show the route flow distributions for each od pair of the network and all ten scenarios.

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Fig. 4.4 – Route flow distributions for the 10 simulation scenarios and for the od pairs: o = 1, ..., 6; and d = 1, 2, 3. Each simulation scenario is identified by the Model ID equivalent to the ID values listed in Table 4.4.

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Fig. 4.5 – Same as in Fig. 4.4, but for the od pairs: o = 1, ..., 6; and d = 4, 5, 6.

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Fig. 4.6 – Average route travel time distributions for the DUE, SUE and different settings of the indifference band.

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Model	ID Model	Preference	Gap	$\frac{TT_k}{[s]}$
DUE	1	\sim	0.3	315
SUE	2	\sim	0.3	295
IB $(\Delta^{od} = 0)$	3	Indifferent	0.3	294
IB ($\Delta^{od} = 100$)	4	Indifferent	7.3	337
IB ($\Delta^{od} = 500$)	5	Indifferent	14.7	332
IB (Ge & Zhou 2012)	6	Indifferent	16.2	350
IB $(\Delta^{od} = 0)$	7	Strict	68.0	312
IB ($\Delta^{od} = 100$)	8	Strict	68.8	297
IB ($\Delta^{od} = 500$)	9	Strict	68.8	297
IB (Ge & Zhou 2012)	10	Strict	69.1	297

Table 4.4 – The Gap value and the average travel times per route $\overline{TT_k}$ [in s] calculated from the distributions shown in Fig. 4.6 are also listed. These values are listed for the DUE, SUE and different settings of the indifference band.

We analyze the individual route flows shown in Fig. 4.4 and Fig. 4.5. By setting $\Delta^{od} = 0$ (Model 3), we observe that for the indifferent preference search order, we obtain similar route flows compared to the SUE (Model 2). However, this is not observed for the strict preference search order, when comparing $\Delta^{od} = 0$ (Model 7) and the SUE (Model 2). This is due to the specific definition of the search order, where the routes with the most reliable travel times (i.e. with the lowest variances) may not correspond to the routes with the lowest travel times. This is also evidenced by the Gap values listed in Table 4.4, for the settings of the strict preference search order. Also note that in the case of the indifferent preference search order, setting $\Delta^{od} = 0$, only the lowest travel time route per od pair is considered as satisficing at each descent step of the MSA. For the indifferent preference search order, the users' indifference increases as we increase Δ^{od} from 0 to 500,. The route flows will then converge to 1/3 for all the od pairs (Model 5, in Fig. 4.4 and Fig. 4.5). For $\Delta^{od} = 500$, the indifference band is sufficiently high with the result that all the routes in Ω^{od} for all od pairs are *satisficing*. Thus, the users can choose any of the routes. Since the users' indifference increases, they are will choose routes with higher travel times and consequently the Gap value also increases. Note that here, the Gap indicates how far the simulation results are from the DUE; also it is calculated as in Eq. 4.9. On the other hand, the distributions of the average route travel times (Fig. 4.6) also shift towards longer travel times due to an increase in user indifference. The average travel times per route also increase from 295 seconds for $\Delta^{od} = 0$ to 332 seconds for $\Delta^{od} = 500$. The strict preference search order reduces the variances of the distributions of the average route travel times compared to the indifferent preference search order.

4.4.3 Analysis of the aggregated traffic states of the network

In this section, we analyze the network performance in terms of its inflow and outflow capacities and internal accumulation of vehicles, through the Macroscopic Fundamental Diagram (MFD). We investigate the critical accumulation of vehicles n_c and the critical production P_c of the MFD obtained for the different settings of bounded rationality, compared against the values for the DUE and SUE, i.e. the reference models. To better highlight these differences, we define three criteria that represent:

 the relative difference between the average TTD of the different PT settings (TTD*) and of the reference models (TTD^{ref}):

$$\alpha_{TTD} = \frac{\overline{TTD^*} - \overline{TTD^{ref}}}{\overline{TTD^{ref}}} \times 100$$
(4.12)

 the relative difference between the average TTT of the different PT settings (TTT*) and of the reference models (TTT^{ref}):

$$\alpha_{TTT} = \frac{\overline{TTT^*} - \overline{TTT^{ref}}}{\overline{TTT^{ref}}} \times 100$$
(4.13)

• the relative difference between the average TTD of the different PT settings $(\overline{Q_{out}^*})$ and of the reference models $(\overline{Q_{out}^{ref}})$:

$$\alpha_{Q_{out}} = \frac{\overline{Q_{out}^*} - \overline{Q_{out}^{ref}}}{\overline{Q_{out}^{ref}}} \times 100$$
(4.14)

The analysis of the three criteria is simple. If $\alpha_{TTD} < 0$, the network capacity decreases compared with the reference model. The vehicles accumulation inside the network is higher and congestion might spread backwards, increasing the average waiting times for vehicles to enter the network. The network inflow capacity decreases. Moreover, if the accumulation inside the network increases, the outflow performance of the network might also decrease. If $\alpha_{TTT} < 0$, the mean speed of vehicles inside the network is higher than the reference model. If $\alpha_{Q_{out}} > 0$, the outflow performance of the network is higher the reference model.

We show the evolution of the total traveled distance (TTD) as well as the outgoing flow Q_{out} as a function of the total travel time (TTT) for the indifferent (Fig. 4.7) and strict (Fig. 4.8) preference orders. The average values for TTD, TTT and Q_{out} are calculated for

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Fig. 4.7 – (*i*) Total travel distance (TTD) [in m] as function of the total travel time (TTT) [in s]. (*ii*) α_{TTD} versus α_{TTT} for the four settings of the indifference band. (*iii*) Vehicles outflow (Q_{out}) as function of the Total Travel Time (TTT). (*iv*) $\alpha_{Q_{out}}$ versus α_{TTT} for the four settings of the indifference band. In subplots (*i*) and (*iii*), the results are shown for the DUE, SUE and the four settings of the indifference band. In subplots (*ii*) and (*iv*), the circle dots represent the relative differences between the four settings of the indifference band and the DUE. The cross dots represent the relative differences between the four settings of the indifference band and the SUE. These results are for the indifferent preferences search order.

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Fig. 4.8 – Same as in Fig. 4.7, but for the strict preferences search order.

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the simulation interval between 500 and 2500 seconds, for the 10 model settings. We then calculate α_{TTD} , α_{TTT} and $\alpha_{Q_{out}}$ and estimate confidence intervals for these three criteria. The results are shown in Fig. 4.7 for the indifferent preference order and in Fig. 4.8 for the indifferent preference order. Our results show that the network capacity is higher for the strict preference search order case. This is observed by comparing the Δ^{od} = 500 for both search orders, where the TTD is much lower for the indifferent preference search order compared to the strict preference search order. It can also be seen that the network capacity is approximately similar for the strict preference search order and the different settings of the indifference band. While, for the indifferent preference search order, the network capacity decreases with an increase of the Δ^{od} . This is also evidenced in Fig. 4.7 (ii) by the decrease of α_{TTD} as Δ^{od} increases. The average waiting time for the vehicles to enter the network also increase. The average waiting times per vehicle are: 51 s for the DUE; 52 s for the SUE; 52 s for $\Delta^{od} = 0$; 54 s for $\Delta^{od} = 100$; 61 s for $\Delta^{od} = 500$; and 57 s for the setting of the indifference band defined by Ge & Zhou (2012). Note that these are the averaging waiting times for the indifferent preference search order. On the other hand, since the network capacity is approximately similar for the strict preference search order and the different settings of Δ^{od} , the average waiting times per vehicle to enter the network are similar. The average waiting times for the strict preference search order are: 74 s for $\Delta^{od} = 0$; 73 s for $\Delta^{od} = 100$; 75 s for Δ^{od} = 500; and 74 s for the setting of the indifference band defined by Ge & Zhou (2012). From Fig. 4.7 and Fig. 4.8, we can also observe a clear impact of the users' search order on the total travel time spent on the network. For example, for $\Delta^{od} = 500$, the α_{TTT} is larger for the strict preference compared to the indifferent preference search order. This induces a lower vehicles mean speed and a lower internal network performance. Also, in the case of the indifferent preference search order, users will tend to choose routes with higher travel times as Δ^{od} increases. This leads to an increase of the accumulation of vehicles inside the network and consequently users spend more time to complete their trips. Also, the outflow Q_{out} of vehicles decreases as Δ^{od} increases (see Fig. 4.7 and Fig. 4.8). Note that a lower

outflow Q_{out} means lower system efficiency.

In summary, we show that different types of bounded user rationality have different impacts on the network performance. Considering the indifferent preference search order where users present an indifference behavior for all of the *satisficing* routes, as Δ^{od} increases, the internal and outflow capacities of the network decrease. However, when considering the strict user preference order, both the internal and outflow capacities of the network are approximately similar as Δ^{od} increases.

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4.5 **Conclusions**

Users' route choices determine the level of congestion on a road network. Thus understanding the effects of users' behavior is important for transportation network planning policies. In this chapter, we investigated the influence of two types of bounded rational behavior, considering users' preferences for the search order (i.e. indifferent and strict preferences), on individual route flows and network performance. To do this, we considered a dynamic implementation of a bounded rational framework, using a mesoscopic LWR traffic simulator (Leclercq & Becarie 2012). The route costs were time-dependent and accounted for congestion, shock-waves and spillback effects. To model the bounded rationality behavior, we relaxed the definition of the search order of the DUE and SUE frameworks (Sheffi 1985). Thus, instead of using an all-or-nothing procedure to assign the users to the route(s) with the minimum travel time(s), they were assigned according to a more flexible definition of the search order according to user preferences. We also considered both definitions of the indifference band (Eq. 4.2 and Eq. 4.3) for AL^{od}. To account for the distributions of travel times, we used Monte Carlo simulations (Sheffi 1985) and algorithm based on the Method of Successive Averages was presented to solve the network equilibria.

This work extended the framework of bounded rationality applied to dynamic traffic assignment modeling in some directions. First, it incorporates the stochasticity of route travel times that are treated through Monte Carlo Simulations. Second, this framework accounts for indifferent and strict users' preferences for their route choices. Our framework is reduced to the DUE or SUE, if the search order is defined for users that are utility minimizers. Third, this framework extends the work of Zhao & Huang (2016) to a dynamic context and considering the setting of the indifference band. In our framework, we do not need to solve sub-optimization problems to calibrate the aspiration levels of the sub-preferred routes.

To first assess and gain insight into the changes of route flows at equilibrium, AL^{od} , and for both user search orders, we considered a static implementation on the toy Braess network. The results obtained with the indifferent preference search order revealed that: (i) the bounded rational model framework is able to reproduce both DUE and SUE; (ii) when AL^{od} is sufficiently large, the route flows converge to 1/3, showing the user indifference for the route choice; (iii) the algorithm discussed converges. Also, based on this simple numerical test, we showed that we converge towards the same solution of the BR-SUE calculated, based on averaging over all local BR-DUE problems. In the second test, considering the strict user preference order, we showed that the route flows calculated between our model and the model of Zhao & Huang (2016) reach good agreement. This validated our methodology applied to

determine the search order in a dynamic context.

We also investigated the influence of the two settings of the user's search order on the individual route flows and network performance, considering both definitions of AL^{od} as defined in Eq. 4.2 and Eq. 4.3. These tests were performed in a dynamic context, using the mesoscopic LWR traffic simulator (Leclercq & Becarie 2012). We first showed that we were able to reproduce the SUE, by setting $\Delta^{od} = 0$ for the indifferent preference search order. For the strict preference search order, we did not obtain route flows similar to the SUE when setting $\Delta^{od} = 0$. This is due to the fact that routes with the most reliable travel times did not necessarily have the minimal travel time per each od pair. We also showed that for the indifferent preference search order, the route flows also tended to 1/3 as we increased Δ^{od} .

We then showed that bounded user rationality had a significant impact on network performance. For the indifferent preference search orders, the network inflow capacity decreased as Δ^{od} increased; and the network performance decreased as Δ^{od} increased. The outflow Q_{out} also decreased as Δ^{od} increased. For the strict preference search order, the network capacity was approximately similar for the different settings of the indifference band. However, since users were allowed to choose routes with longer travel times as Δ^{od} increased, the TTT increased and the internal performance of the network decreased. In brief, we showed that different types of bounded rationality have clearly different influences on network performance. This is very important when guiding policy makers to decide the best measures to implement in order to increase network performance.

As future work, we can extend this work in many directions. We first plan to extend this work to the macroscopic fundamental diagram (MFD) simulation. We also plan to extend this framework to heterogeneous classes of users. The heterogeneity can either be included in the search order or on the setting of the AL^{od} . And, we also plan to extend this model to a day-to-day assignment, by considering a learning process (e.g., based on reinforcement learning models) either on the AL^{od} or the users search order definition. We also emphasize that further research in the setting of the AL^{od} is required. The setting of the preference orders in the search process allows to consider heterogeneous classes of users, with a preference for transportation mode, for example. However, we note that this users heterogeneity can also be included in the setting of the AL instead of the search order. In this case, the total demand Q of the od pair should be split into homogeneous groups of users with the same preference. The AL should then be defined per od and class of users. For each class of users, they are assigned based on an all-or-nothing assignment to one of the routes listed in ω^{od} .

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Overview of Part I: Dynamic network loading and users behavior

In the following, the outline of this first part of the thesis is provided, summarizing the influence of different kinds of users behavior on the network performance. In the previous Chapter 3 and Chapter 4, the network performance was evaluated considering the dynamic implementation of Prospect Theory and of a Bounded Rational framework, compared against the DUE and SUE, i.e. the benchmark models. To finalize the discussion of this first part of the thesis, the application of Regret Theory is also considered and the results are discussed in Sect. I.1. As such, the three major behavioral theories identified in the literature review are covered. In Sect. I.2, the effect of different behavioral rules on a Manhattan network performance is summarized.

I.1 Influence of the regret-aversion behavior on the network performance

Regret Theory was introduced by Bell (1982) and Loomes & Sugden (1982) and applied to the route choice modeling by the seminal works of Chorus et al. (2006). The goal of the users is to minimize their perceived regret with respect to the other unselected routes. If there is a route that has a lower travel time than the one selected by the users, they will feel regret. Otherwise, if the chosen route is the one with the minimal travel time, users feel joy. The Regret Theory framework applied to route choice has been developed by the several works of Chorus et al. (2008), Chorus (2010), Chorus (2012c), Chorus (2012a), Chorus (2012b),

I.1. Influence of the regret-aversion behavior on the network performance

Chorus et al. (2013), Chorus (2014) and Li & Huang (2016). The perceived regret H_k^{od} is (Chorus 2014; Li & Huang 2016):

$$H_k^{od} = h_k^{od} - R(y) + \epsilon_k, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(I.1)

where h_k^{od} is the average regret of route k; ϵ_k is the error term of route k. The regret function R(y) is calculated as (Chorus 2014; Li & Huang 2016):

$$R(y) = 1 - e^{-\delta^{od}y}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(4.15)

where $y = \min(h_k^{od}) - h_k^{od}$ and $\delta^{od} \in [0, +\infty[$ is the regret aversion parameter. Note that for $\delta^{od} = 0$, the Regret Theory model reduces to the classical SUE. For $\delta^{od} = \infty$, users are pure regret-averse and all choose the route with the minimal travel time for the od pair.

Li & Huang (2016) discuss a static implementation framework of Regret Theory considering that the error terms ϵ_k are i.i.d. Gumbel variables. In this thesis, the travel times are considered to be gamma distributed (Nielsen 1997) and defined at the link level (ϵ_a). Monte Carlo simulations are used to calculate the network equilibrium. The framework of the Monte Carlo simulations and the Method of Successive Averages is similar to the one described in Sect. 2.3.1.4. The difference lies in the definition of the perceived regret function (Eq. I.1). Considering that $t_k^i, \forall k \in \Omega^{od}$ is a sample *i* of the travel time of route *k*, Eq. I.1 and Eq. 4.15 have to be modified as:

$$H_k^{od} = t_k^i - R(y), \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(4.16)

$$R(y) = 1 - e^{-\delta^{od}y}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(4.17)

where $y = \min(t_k^i) - t_k^i$.

For each set of t_k^i , $\forall k \in \Omega^{od}$, users choose the route with the minimum perceived regret H_k^{od} , based on an all-or-nothing procedure. For each set of t_k^i , $\forall k \in \Omega^{od}$ and the new temporary route flows for the MSA algorithm are obtained by averaging all the users' choices for all samples. This process is repeated at each descent step of the MSA algorithm, until the network equilibrium is reached. The network equilibrium corresponds to the Regret Theory Stochastic User Equilibrium (RT-SUE). Under RT-SUE conditions, no user can reduce his/her own perceived regret H_k^{od} by unilaterally changing routes. Note that, the η_a and ζ_a parameters of the gamma distribution, for each link a, are updated according to the simulated link travel times by the traffic LWR simulator at each descent step. Furthermore, to calculate t_k^i , link

additive utility functions are assumed.

The dynamic implementation of Regret Theory is performed on the same Manhattan network as shown in Fig. 3.2 and Fig. 4.3. The same network settings as described in Eq. 3.3.1 and Eq. 4.4.1 are considered. The route choice set Ω^{od} is calculated using a K-shortest path algorithm in distance. A maximum of three routes per od pair are considered. To calculate time-dependent cost paths, a dynamic LWR mesoscopic simulator (Leclercq & Becarie 2012) is used. A total simulation period T = 3000 seconds is set. For the MSA convergence, the parameters are set to $tol = 10^{-2}$, $\Phi = 0$ and $N_{max} = 250$. Three values of $\delta^{od} = 0, 1, 10$ are set.

The network performance considering the Regret Theory, is assessed through the Macroscopic Fundamental Diagram (MFD) (see Fig. I.1 (i)) as well as through its outflow function Q_{out} (see Fig. I.1 (iii)), compared against the DUE and SUE equilibria. To better highlight the differences between the different models and the benchmark ones, three criteria were established in the two previous chapters: α_{TTD} (see Eq. 3.16 and Eq. 4.12); α_{TTT} (see Eq. 3.16 and Eq. 4.13); $\alpha_{Q_{out}}$ (see Eq. 3.16 and Eq. 4.14). The average values for TTD, TTT and Q_{out} are calculated for the simulation interval between 500 and 2500 seconds, for all five model settings. The α_{TTD} , α_{TTT} and $\alpha_{Q_{out}}$ as well as confidence intervals are then calculated. The results are shown in Fig. I.1 (ii) for the α_{TTD} versus α_{TTT} and in Fig. I.1 (iv) for the $\alpha_{Q_{out}}$ versus α_{TTT} . The circle and cross dots represent the relative differences between the Regret Theory settings and the DUE and SUE, respectively.

First one can observe that as expected, by setting $\delta^{od} = 0$, the RT-SUE reduces to the classical SUE as shown by the MFD in Fig. I.1 (i). Moreover, for $\delta^{od} = 0$: $\alpha_{TTD} \sim 0$; $\alpha_{TTT} \sim 0$; and $\alpha_{Q_{out}} \sim 0$. Second, the mean speed of vehicles inside the network is $\sim 4\%$ lower for the three δ^{od} settings than the DUE. Compared to the SUE, the mean speed is approximately similar. This is evidenced by the α_{TTT} values shown in Fig. I.1 (ii). The network capacity increases with δ^{od} , as evidenced by the α_{TTD} values in Fig. I.1 (ii). For $\delta^{od} = 0$, the network capacity is $\sim 2\%$ inferior than the DUE. But, for $\delta^{od} = 1, 10$, the network capacity is similar as the DUE. For $\delta^{od} = 0$, the network capacity is similar to the SUE. But, it shows an increase of $\sim 3\%$ for $\delta^{od} = 1, 10$. The outflow performance is similar for $\delta^{od} = 0$ and both reference models. But, the case for $\delta^{od} = 1$ is $\sim 3\%$ larger compared to the SUE and $\sim 3\%$ inferior for $\delta^{od} = 10$ compared to the DUE.

In summary, the users' regret aversion behavior influences the network mean speed as well as internal and outflow capacities. But, for this specific network setting, the differences are inferior to $\sim 5\%$ compared to the reference models. In the next section, these results are compared against the ones of the Prospect Theory and Bounded Rationality.

I.1. Influence of the regret-aversion behavior on the network performance



Fig. I.1 – (*i*) Total travel distance (TTD) [in m] as function of the total travel time (TTT) [in s]. (*ii*) α_{TTD} versus α_{TTT} for the three δ^{od} values. (*iii*) Vehicles outflow (Q_{out}) as function of the Total Travel Time (TTT). (*iv*) $\alpha_{Q_{out}}$ versus α_{TTT} for the three δ^{od} values.

I.2. Global comparison of behavioral models

Prospect Theory			Speed	Internal capacity		Outflow capacity	
Aversion parameters	T_0^{od}	DUE	SUE	DUE	SUE	DUE	SUE
KT	mean	1	1	\downarrow	1	\sim	~
KT	median	\sim	1	\downarrow	1	\sim	\sim
KT	mode	1	1	\downarrow	1	\downarrow	1
Xu	mean	1	1	\downarrow	1	\downarrow	1
Xu	median	1	1	\downarrow	1	\downarrow	\uparrow
Xu	mode	\downarrow	↑	\downarrow	1	\downarrow	\uparrow

Bounded Rationality			Speed	Interna	al capacity	Outflo	w capacity
Preference order	Δ^{od}	DUE	SUE	DUE	SUE	DUE	SUE
Indifferent	0	1	\sim	\sim	\sim	\sim	\sim
Indifferent	100	\sim	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow
Indifferent	500	1	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow
Indifferent	Ge & Zhou (2012)	\sim	\downarrow	\downarrow	\downarrow	\downarrow	\downarrow
Strict	0	\downarrow	\downarrow	\sim	1	\sim	\sim
Strict	100	\downarrow	\downarrow	1	1	↑	\uparrow
Strict	500	\downarrow	\downarrow	1	1	↑	\uparrow
Strict	Ge & Zhou (2012)	\downarrow	↓	1	1	1	1

Regret Theory	Mean Speed		Internal capacity		Outflow capacity	
δ^{od}	DUE	SUE	DUE	SUE	DUE	SUE
0	\downarrow	~	\rightarrow	~	\sim	\sim
1	\downarrow	\sim	\sim	1	\sim	\uparrow
10	\downarrow	\downarrow	\sim	\uparrow	\downarrow	\sim

Legend:

↓: superior to 5% ~: no effect (margin of 2%)
↓: margin ∈ [2,5]%

 \uparrow : superior to 5% \uparrow : margin ∈ [2,5]%

Table I.1 – Summary of the Manhattan network performance, including mean speed, internal and outflow capacities, considering the: (i) users' risk-aversion and risk-seeking behavior (Prospect Theory) discussed in Chapter 3; (ii) users' bounded rationality discussed in Chapter 4; and (iii) users' regret-aversion (Regret Theory) discussed in Sect. I.1.

I.2 Global comparison of behavioral models

In this Part I of this thesis, the influence of different kinds of users behavior on the network performance is investigated. The latter is evaluated through the analysis of the Macroscopic Fundamental Diagram and outflow function Q_{out} compared to the DUE and SUE models, considered as the benchmarks.

The tests are conducted on a Manhattan network and focused on an homogeneous population of users. They have similar decision rules that are set according to the risk-aversion and risk-seeking (Prospect Theory) and regret-aversion (Regret Theory) users' behavior, as well as bounded rational users are considered. The influence of these type of users' behavior

I.2. Global comparison of behavioral models

on the network mean speed, internal and outflow capacities are summarized in Table I.1. This table gives an overview about how the network performance is affected by different kinds of users' behavior. One can observe that in general, the mean speed increases in comparison to both benchmark equilibria, when users show a risk-aversion and risk-seeking behavior. The internal and outflow capacities of the network increase compared to the SUE, but decrease with respect to the DUE. The users' indifferent preference behavior decrease both the internal and outflow capacities, while the users' strict preferences show an opposite trend. The users indifference for the route choice decreases the network mean speed decreases with respect to both benchmark equilibria. The users' regret-aversion behavior decreases, in general, the network mean speed as well as both internal and outflow capacities compared to the DUE. For some settings of the regret-aversion model, the internal and outflow capacities increase compared to the SUE.

The results of the Part I of this thesis were presented at the 7th International Symposium on Dynamic Traffic Assignment DTA2018.

Part II

Dynamic Traffic Assignment framework for multi-regional MFD-based models



Introduction of multi-regional MFD-based models with route choices: the definition of regional paths

Abstract

Up to now, few attention has been given to build a dynamic traffic assignment framework for Macroscopic Fundamental Diagram (MFD) based models. The first step consists in identifying the regional paths to define the regional choice set. The purpose of this chapter is to propose three methods to gather the regional paths. Two of these methods are based on a set of trips in the city network and on the city network partitioning. They rely on an exhaustive search in the city network and are set as the reference methods. The other method is based on K-shortest paths calculated in the regional network. The three methods are tested on the 6th district Lyon network (France). We show that the reference methods require a large size of the trips set. This is highly time consuming for large city network and we propose an alternative method. We show that this method gives a set of regional paths with a high level of similarity compared to the reference methods. It is also able to find in ~80% of the cases, the most significant regional path for each regional OD pair, compared to the reference methods. But, it only lists the regional paths in ~50% of the cases when considering the strict similarity criterion compared to the reference methods.

Keywords: Regional paths; Regional Choice set; Trips; MFD models.

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5.1. Introduction

5.1 Introduction

An aggregated traffic modeling has caught more attention from the scientific community after the seminal works of Daganzo (2007) and Geroliminis & Daganzo (2008). The city network (Fig. 5.1 (a)) is partitioned into regions (Fig. 5.1 (b)), where the traffic conditions are approximately homogeneous. The traffic states inside each region are governed by the Macroscopic Fundamental Diagram (MFD). It represents the relationship between the average circulating flow and the accumulation of vehicles inside the region. The partition of the city network into regions defines the regional network (Fig. 5.1 (c)), where the connections between regions depend on the directions of the ingoing and outgoing links of their border nodes in the city network. In Fig. 5.1 (c), these connections are represented by the gray arrows. Let X be the set of regions that define the regional network. In multi-regional systems, the MFD dynamics characterizes the exchange flows between regions. For this, the design of an aggregated dynamic traffic assignment framework is required (see e.g. Yildirimoglu & Geroliminis 2014; Yildirimoglu et al. 2015). The basis of a dynamic traffic assignment framework is the definition of paths. In Fig. 5.1 (a), we show three examples of paths (or trips) in the city network. A trip corresponds to a sequence of traveled links from the origin (o) to the destination (d) nodes in the city network. As shown in Fig. 5.1 (a), each trip crosses a specific sequence of regions, defining a regional path. In this chapter, two types of paths on the regional network are considered:

- regional paths, that represent the ordered sequence of crossed regions from the regional Origin (O) to the regional Destination (D). In Fig. 5.1 (b), we show the corresponding regional paths to the blue and green trips.
- internal paths, that represent internal trajectories of vehicles inside one given region. In this case, the regional O and D correspond to the region that defines the internal path. In Fig. 5.1 (b), we show an example of an internal path highlighted in purple.

The regional and internal paths, where users will be assigned for their travels on the regional network, define the regional choice set Ω^{OD} . One solution would be to enumerate all the possible regional paths for the OD pair. But, not all regional and internal paths have the same significance level considering the trips on the city network as well as its topology. A regional path might be associated to one or more trips in the city network, as shown in Fig. 5.1 (a) by the green trips. This induces the significance level of a regional path. For example, consider two regional paths that have associated 1 and 100 trips, respectively. The regional path defined by 100 trips is much more significant than the one defined by only one



Fig. 5.1 – (a) City network and three trips. The green trips define a different regional path than the blue trip. (b) Partition of the city network shown in (a) where the corresponding regional paths to the blue and green trips are shown. (c) Regional network corresponding to the partition of the city network shown in (b), where the connection between the adjacent regions are represented by the gray arrows.

trip, because it is more probable to be used by users on the city network. The goal of this work is to propose three methods to identify the most significant paths to define Ω^{OD} , considering the topology of the city network and the definition of the regions. In this chapter, we assume that the partition of the city network is given and the regions are well-defined. The three methods are implemented on the 6th Lyon (France) district network, that is divided into eight regions. Based on a static analysis, we analyze the regional choice sets recovered for some regional OD pairs and discuss the advantages and inconveniences of each one of the three methods.

The reminder of this chapter is organized as follows. In Sect. 5.2, we introduce the methodological framework for the three methods to define the regional choice set. In Sect. 5.3, we analyze the regional choice sets calculated by the three methods for the 6^{th} Lyon (France) district network and some regional OD pairs. In Sect. 5.4, we outline the conclusions of this chapter.

5.2 Methodological framework

In this chapter, we propose three methods to define the set of regional paths. The first two methods (Method 1 and 2) are based on the calculation of a set of trips in the city network. For this, we need to sample N_{od} od pairs in the city network and calculate the trip connecting each one. Let Γ be the set of calculated trips. The differences between these two methods are related to the sampling:

- *Method 1:* the sampling of the *N_{od}* od pairs is independent of the partition of the city network. In Fig. 5.2 (a), we show an example of three trips that represent three different regional paths. Each of these trips are sampled independently of the city network partitioning.
- *Method 2:* for each regional OD pair, the sampling of the N_{od} od pairs is done inside these specific O and D regions. In Fig. 5.2 (b), we show an example of three trips where: their origin nodes are sampled inside the same Origin region; and their destination nodes are sampled inside the same Destination region.

For both methods, the regional paths are gathered based on the trips listed in Γ and on the partition of the city network. They are then ordered by their significance level, considering the number of trips that define each one of them. Let Ψ be the set of regional paths defined by the trips listed in Γ . The regional choice set Ω^{OD} gathers the K most significant regional paths for each OD pair. The application of these two methods depends on the number of

5.2. Methodological framework



Fig. 5.2 – (a) Application example of *Method 1*, where the od pairs are sampled independent of the city network partitioning. Three trips that define three different regional paths are shown. (b) Application example of *Method 2*, where the od pairs are sampled inside the specific Origin and Destination regions. Three examples of trips, where their od pairs are specifically sampled inside the Origin and Destination regions, as shown. These three trips define three different regional paths for the same regional OD pair. (c) Application example of *Method 3*. The gray circles represent the regions of the regional network. The gray arrows represent the connections between adjacent regions. The gray circles are numbered from 1 to 7 and represent the seven regions of the city network partition shown in Fig. 5.1 (b).

 N_{od} od pairs that are sampled as well as on the algorithm used to calculate the trips between each od pair. A proper setting of N_{od} is then necessary for these two methods. This will be investigated in more detail in the next section.

Methods 1 and 2 are based on an exhaustive search of the city network topology through the calculation of a set of trips. These are the reference methods. While they might be applicable for small city networks, they are time consuming for large scale applications (e.g. the whole urban area). This is because both of these methods require the computation of a large number of trips to define Γ . Moreover, the calculation of the trips is insensible to the definition of the regions borders. Depending on the city network topology, a trip might cross the same border several times. Consider for example the border between two regions A and B. If one has a trip that crosses several times this border, by the definition of regional path, one may end up with a meaningful regional path defined as the sequence ABABABA. This is another limitation of methods 1 and 2 that might happen when the regional borders are not well defined. Note that, for example, a border between two regions is not well defined if it is located in a two-ways main street, where the two street directions are not located in the same region. Thus, we introduce a third method (Method 3), where the regional paths are directly calculated on the regional network. It does not require any prior knowledge about the demand and is only based on network features. In Fig. 5.2 (c), we show an example of a regional network, where the numbered gray circles from 1 to 7 represent the different regions. The

gray arrows represent the possible connections between adjacent regions. Note that, these connections depend on the directions of the incoming and outgoing links of the border nodes in the city network, between two adjacent regions. For example, in Fig. 5.2 (c), it is possible to travel from region 1 to 2 and vice-versa. But, it is only possible to travel from region 2 to 4 and not from region 4 to 2.

The connection costs between regions $(C_{r_ir_j})$ are calculated based on the flow capacity (q_{al}^c) for each lane *l* of link *a* of the city network (Fig. 5.1 (a)) that allows to travel from region r_i to r_j . The link costs of the regional network (Fig. 5.2 (c)) $C_{r_ir_i}$ are estimated as:

$$C_{r_i r_j} = \sum_{a} \sum_{l=1}^{N_{lanes}} \frac{1}{q_{al}^c \delta_{aij}}, \forall a \in \Gamma_a \land \forall i \in X \land \forall j \in \Lambda$$
(5.1)

where N_{lanes} is the total number of lanes of link a; Γ_a is the set of all links of the city network; Λ is the set of adjacent regions to region i; q_{al}^c is the flow capacity of lane I of link a; and δ_{aij} is a dummy variable that equals 1 if link a allows to travel from region r_i to region r_j . We consider a standard value of $q_{al}^c = 1800$ [veh/h].

For each regional OD pair, where the Origin and Destination regions are different, we run a K-shortest paths calculation in this graph (Fig. 5.2 (c)), considering the connection costs calculated through Eq. 5.1. The K regional paths that are found directly define the regional choice set Ω^{OD} . For the case, where the Origin and Destination regions are the same, we consider that the regional choice set Ω^{OD} is defined only by internal paths. Method 3 has a light computational cost and avoids meaningful regional paths, when an acyclic search algorithm to calculate the paths is used.

5.3 Regional paths and choice sets analysis

In this section, we implement the three methods introduced in the previous section. We consider the 6^{th} Lyon (France) district network, that is divided into eight regions, as shown in Fig. 5.3. This network has 757 links and 431 nodes.

To calculate the base of trips Γ , for Methods 1 and 2, we consider:

- different values of N_{od}: 40; 80; 200; 400; 600; 800; 1200; and 1600.
- the K-shortest path (SP) and the A* algorithms to calculate the trips for each od pair.



Fig. $5.3 - 6^{th}$ Lyon (France) district network divided into 8 regions.

5.3.1 Sensibility of methods 1 and 2 to the set of trips Γ

In this section, we analyze the dependence of Methods 1 and 2 on the number of od pairs (N_{od}) considered for the sampling and on the algorithm used to calculate the trips. A proper setting of N_{od} should be related with the city network coverage. A lower value of N_{od} does not guarantee that all links and nodes of the city network are visited. For low values of N_{od} , the variability of regional paths that are found is larger. If one applies Methods 1 and 2 considering a low value for N_{od} , different regional paths might be found in different trials. It is then important for these two methods to ensure a good coverage of the city network by the set of trips Γ that is initially generated. For this, we define two criteria that estimate the percentage of the graph nodes $(N_{cov}^{nodes}(N_{od}))$ and links $(N_{cov}^{links}(N_{od}))$ coverage by the set of trips that are calculated based on N_{od} :

$$N_{cov}^{nodes}(N_{od}) = \sum_{i=1}^{N_{nodes}} \frac{N_{used}^{nodes}(N_{od})}{N_{nodes}}$$
(5.2)

$$N_{cov}^{links}(N_{od}) = \sum_{i=1}^{N_{links}} \frac{N_{used}^{links}(N_{od})}{N_{links}}$$
(5.3)

where $N_{used}^{nodes}(N_{od})$ and $N_{used}^{links}(N_{od})$ represent the total number of nodes and links, respectively, visited by the trips; and N_{nodes} and N_{links} represent the total number of nodes and links, respectively, defining the city network.

For the estimation of $N_{used}^{nodes}(N_{od})$ (Eq. 5.2) and $N_{used}^{links}(N_{od})$ (Eq. 5.3), we consider the set of values of N_{od} previously stated. For each value of N_{od} , we sample 100 sets of trips and calculate the average and standard deviations for $N_{used}^{nodes}(N_{od})$ (Eq. 5.2) and $N_{used}^{links}(N_{od})$ (Eq. 5.3). In Fig. 5.4, we show the evolution of average values $N_{cov}^{nodes}(N_{od})$ (top panel) and $N_{cov}^{links}(N_{od})$ (bottom panel), for the different values of N_{od} considered. The standard deviation is also shown by the bars. We estimate $N_{used}^{nodes}(N_{od})$ and $N_{used}^{links}(N_{od})$ for both *Method 1* and *Method 2* as well as for the application of the SP and A* algorithms to calculate the trips. As one can observe, larger values of N_{od} ensure a better coverage of the city network as expected. This should also reduce the variability of the regional paths that are found for different regional OD pairs.

5.3.2 Regional paths: a comparative analysis between the three methods

In this section, we compare the set of regional paths Ψ obtained through the application of the three methods. We first analyze the total number of regional paths that is possible to obtain from the trips listed in Γ , for Methods 1 and 2. We consider different values of N_{od} and both SP and A* algorithms. The results are listed in Table 5.1. Method 2 provides a larger number of regional paths than Method 1. Moreover, similar conclusions can be drawn for both methods and for the A* compared to the SP algorithm. However, not all of these regional paths are significant to define the regional choice set Ω^{OD} .

Λ/ .	Meth	nod 1	Method 2		
IN od	SP	A*	SP	A*	
40	107	113	158	180	
80	131	143	210	232	
200	150	168	312	336	
400	165	187	383	459	
600	177	193	445	475	
800	191	198	457	509	
1200	187	206	489	539	
1600	190	207	506	549	

Table 5.1 – Number of regional paths found as function of N_{od} and for both algorithms SP and A^{*} to calculate the trips.

We analyze the regional choice sets calculated for some regional OD pairs. To do this



Fig. 5.4 – Evolution of average of $N_{cov}^{nodes}(N_{od})$ (top panel) and $N_{cov}^{links}(N_{od})$ (bottom panel) as function of N_{od} . To calculate the averages and standard deviations, we consider 100 trials of trips for each value of N_{od} . The standard deviations are represented by the vertical bars. The results are shown both *Method 1* and *Method 2* as well as for the application of the SP and A* algorithms to calculate the trips.

analysis, we have to separate the regional paths into two types: (i) regional paths where the Origin and Destination regions are the same; and (ii) regional paths where the Origin and Destination regions are different. For case (i), we consider three regional OD pairs: 1-1; 5-5; and 7-7. For case (ii), we consider the following regional OD pairs: 3-4; 4-3; 1-6; and 6-1. To define the regional choice set Ω^{OD} for each of these OD pairs, we set a maximum of three most significant regional paths. For methods 1 and 2, we take into account different values of N_{od} and both SP and A* algorithms.
5.3. Regional paths and choice sets analysis

In Table 5.2, we summarize the regional choice sets for case (i). Methods 1 and 3 give similar Ω^{OD} . For *Method 2*, we observe that the level of significance of the regional paths depends on N_{od} . For low values of N_{od} , in some cases only one or two regional paths are found at maximum. For larger values of N_{od} (i.e. 1200 and 1600), when the graph coverage is close to 1 (see Fig. 5.4), we obtain similar Ω^{OD} . We now analyze the regional choice sets for the regional OD pairs considered for case (ii). We list the Ω^{OD} for the four OD pairs in Table 5.3 for methods 1 and 3 and in Table 5.4 for methods 2 and 3. Similarly to previous case (i), we can observe that for methods 1 and 2, the significance level of the regional paths depend on N_{od} . But, for N_{od} =1200 and 1600, when we ensure a good graph coverage with a low standard deviation (Fig. 5.4), the Ω^{OD} are similar for these OD pairs. These results enhance the importance of ensuring a good graph coverage for the application of methods 1 and 2.

We also investigate the similarities between all OD pairs of the network. In this analysis, we only consider the Ω^{OD} obtained through methods 1 and 2 when N_{od} =1600. By the application of method 3, we find in general the most significant regional path for these OD pairs, compared to both methods 1 and 2 (see Table 5.3 to Table 5.5). But, in most of the cases, we do not find the same regional paths for the second and third most significant ones. We investigate the latter in more detail. For this, we consider the sets of regional paths Ψ obtained through the three methods, reduced to the three most significant regional paths per regional OD pair. We compare these sets in terms of their similarity and strict similarity of the most significant regional paths for each OD pair. Let Ψ_{M_i} and Ψ_{M_j} be the reduced sets of regional paths obtained through methods M_i and M_j , respectively. The similarity between Ψ_{M_i} and Ψ_{M_j} are evaluated by the criterion $\alpha_{similarity}^{M_i,M_j}$:

$$\alpha_{similarity}^{M_i M_j} = \frac{\sum_p \delta_p^{M_i M_j}}{N_{total}^{M_i}}, \forall p \in \Psi_{M_i} \land i \neq j$$
(5.4)

where $\delta_p^{M_i M_j}$ is a dummy variable that equals 1 if regional path p that is listed in Ψ_{M_i} is also listed in Ψ_{M_j} , or 0 otherwise; and $N_{total}^{M_i}$ is the total number of regional paths that define Ψ_{M_i} for method M_i .

The strict similarity criterion between regional paths are evaluated through the criterion $\alpha_{strictsimilarity}^{M_iM_j}$:

$$\alpha_{strict\ similarity}^{M_iM_j} = \frac{\sum_O \sum_D \sum_p \delta_p}{N_{total}^{M_i}}, \forall p \in \Psi_{M_i} \land i \neq j$$
(5.5)

where δ_p is a dummy variable that equals 1 if regional path p that is listed in Ψ_{M_i} is also listed

5.3. Regional paths and choice sets analysis

				Met	hod 1: SF	⊃ & A*				
0	D				N _{od}					Method 3
		40	80	200	400	600	800	1200	1600	
1	1	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	5	5	5	5	5
7	7	7	7	7	7	7	7	7	7	7

in Ψ_{M_i} with the same level of significance, or 0 otherwise.

				M	ethod 2	: SP				
0	D				N _{od}					Method 3
		40	80	200	400	600	800	1200	1600	
		1	1	1	1	1	1	1	1	1
1	1	1,2,1	1,2,1	1,2,1	1,2,1	1,2,1	1,2,1	1,2,1	1,2,1	\sim
		\sim	\sim	1,2,3,1	1,3,1	1,2,3,1	1,2,3,1	1,2,3,1	1,2,3,1	\sim
		5	5	5	5	5	5	5	5	5
5	5	\sim	5,4,5	5,2,5	5,4,5	5,2,5	5,2,5	5,2,5	5,2,5	~
		\sim	5,2,5	5,4,5	5,2,5	5,6,4,5	5,6,5	5,6,5	5,6,5	\sim
		7,3,7	7	7	7	7	7	7	7	7
7	5	7,6,8,7	7,8,7	7,3,7	7,8,7	7,3,7	7,8,7	7,8,7	7,8,7	\sim
		7,3,5,7	7,3,7	7,5,7,6,8,7	7,3,7	7,8,7	7,3,7	7,3,7	7,3,7	~

				Ν	Nethod 2:	A*				
0	D				N _{od}					Method 3
		40	80	200	400	600	800	1200	1600	
		1	1	1	1	1	1	1	1	1
1	1	1,3,1	1,3,1	1,2,1	1,2,1	1,2,1	1,2,1	1,2,1	1,2,1	\sim
		\sim	1,2,1	1,3,1	1,3,1	1,3,1	1,3,1	1,3,1	1,3,1	\sim
		5	5	5	5	5	5	5	5	5
5	5	5,4,5	5,2,5	5,4,5	5,6,5	5,2,5	5,6,5	5,2,5	5,2,5	\sim
		5,6,5	5,7,3,5	5,6,4,5	5,2,5	5,6,5	5,2,5	5,6,4,5	5,6,5	\sim
		7,3,7	7	7	7	7	7	7	7	7
7	5	7,5,7	7,3,5,7	7,3,7	7,3,7	7,8,7	7,3,7	7,3,7	7,8,7	\sim
		7,3,5,7	7,3,7,6,8,7	7,6,8,7	7,5,7	7,3,7	7,5,7	7,8,7	7,3,7	\sim

Table 5.2 – Regional choice set for three different regional OD pairs: 1-1; 5-5; and 7-7. The regional paths are listed for the three methods and both SP and A* algorithms used to calculate the trips, for *Method 1* and *Method 2*. The regional choice sets are listed from the first to the third most frequent regional paths for *Method 1* and *Method 2*. For *Method 3* the three K-shortest paths are listed.

he third most frequent ones for Method 1. While, for Method 3 the three K-shortest paths are listed.	^{$-$} or <i>Method 1</i> , the regional paths are listed for both the SP and A [*] algorithms used to calculate the trips.	Table 5.3 – Regional choice set for four different regional OD pairs: 3-4; 4-3; 1-6; and 6-1. The regional
	The regional paths are listed from the first tc	paths are listed for Method 1 and Method 3

6	щ	4	ω	0		6		<u> </u>			4		ω			0	
⊢	6	ω	4			⊣		0			ω		4				
6,5,2,1 6,5,7,3,1 ~	1,2,5,6 1,2,5,7,6 \sim	4,5,7,3 4,6,5,7,3 4,6,5,2,3	3,2,5,6,4 3,5,6,4 ~	40		2 2	6,4,2,1	5 5	1,2,5,6	ζ	4,5,7,3 4,5,2,3	3,5,7,6,4	3,1,2,4	3,2,5,7,6,4	40		
6,5,2,1 6,4,2,1 6,8,7,3,2,1	1,2,5,7,6 1,2,5,6 1,2,4,5,6	4,5,7,3 4,6,5,7,3 4,5,2,3	3,2,4 3,2,5,6,4 ~	80		6,5,2,1 6,4,2,1	6,8,7,3,1	$^{1,2,5,6}_{\sim}$	1,2,5,7,6	4,6,5,7,3	4,6,8,7,3 4,5,7,3	3,2,5,6,4	3,2,5,7,6,4	3,2,4	80		
6,5,2,1 6,4,2,1 6,8,7,3,2,1	1,2,5,6 1,2,5,7,6 1,2,4,5,6	4,6,8,7,3 4,5,7,3 4,5,2,3	3,2,5,6,4 3,2,4 ~	200		6,4,2,1 6.8.7.3.1	6,5,2,1	$^{1,2,5,7,6}_{\sim}$	1,2,5,6	4,5,7,3	4,6,8,7,3 4,5,2,3	3,2,5,7,6,4	3,2,5,6,4	3,2,4	200		
6,5,2,1 6,8,7,5,2,1 6,8,7,3,1	1,2,5,6 1,2,5,7,6 1,2,4,6	4,5,7,3 4,6,5,7,3 4,6,8,7,3	3,2,5,6,4 3,2,4 3,5,2,4	400		6,4,2,1 6.8.7.3.1	6,5,2,1	1,2,5,7,6 1,2,4,5,7,6	1,2,5,6	4,6,8,7,3	4,5,2,3 4,5,7,3	3,2,5,7,6,4	3,2,5,6,4	3,2,4	400	N	Method
6,5,2,1 6,4,2,1 6,8,7,5,2,1	1,2,5,6 1,2,5,7,6 1,2,4,5,6	4,5,7,3 4,6,5,7,3 4,5,2,3	3,2,5,6,4 3,2,4 3,5,2,4	600	2 - - - - - - - - - - - - - - - - - - -	6,4,2,1 6.8.7.3.1	6,5,2,1	1,2,5,7,6 1,2,4,5,6	1,2,5,6	4,6,8,7,3	4,5,2,3 4,5,7,3	3,2,5,7,6,4	3,2,5,6,4	3,2,4	600	od	1: SP
6,5,2,1 6,4,2,1 6,8,7,5,2,1	1,2,5,6 1,2,5,7,6 1,2,4,5,6	4,5,7,3 4,6,5,7,3 4,6,8,7,3	3,2,5,6,4 3,2,4 3,5,2,4	800	01011	6,4,2,1 6,8,7,3,1	6,5,2,1	1,2,5,7,6 1,2,4,5,6	1,2,5,6	4,6,8,7,3	4,5,2,3 4,5,7,3	3,2,5,7,6,4	3,2,5,6,4	3,2,4	800		
6,5,2,1 6,8,7,5,2,1 6,8,7,3,2,1	1,2,5,6 1,2,5,7,6 1,2,4,5,6	4,5,7,3 4,6,5,7,3 4,5,2,3	3,2,5,6,4 3,2,4 3,5,2,4	1200	0101-101+	6,5,2,1 6.8.7.3.1	6,4,2,1	1,2,5,7,6 1,2,4,5,6	1,2,5,6	4,6,8,7,3	4,5,2,3 4,5,7,3	3,5,2,4	3,2,5,6,4	3,2,4	1200		
6,5,2,1 6,8,7,5,2,1 6,8,7,3,1	1,2,5,6 1,2,5,7,6 1,2,4,5,6	4,5,7,3 4,6,5,7,3 4,5,2,3	3,2,5,6,4 3,2,4 3,5,2,4	1600		6,4,2,1 6.8.7.3.1	6,5,2,1	1,2,5,7,6 1,2,4,5,7,6	1,2,5,6	4,6,8,7,3	4,5,2,3 4,5,7,3	3,5,2,4	3,2,5,6,4	3,2,4	1600		
6,5,2,1 6,7,5,2,1 6,8,7,5,2,1	1,2,5,6 1,2,4,6 1,2,5,7,6	4,5,7,3 4,2,3 4,5,2,3	3,2,4 3,5,2,4 3,7,5,4	Method 3	(),(),(),(),(),(),(),(),(),(),(),(),(),(6,7,5,2,1 6.8.7.5.2.1	6,5,2,1	1,2,4,6 1,2,5,7,6	1,2,5,6	4,5,2,3	4,5,7,3 4,2,3	3,5,4	3,5,2,4	3,2,4		Method 3	

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					Method	1 2: SP				
0					Š	po				Method 3
	-	40	80	200	400	600	800	1200	1600	
		3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4
ю	4	3,2,5,7,6,4	3,5,2,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,5,2,4
-		3,2,5,6,4	3,2,5,7,6,4	3,2,5,7,6,4	3,5,2,4	3,5,2,4	3,5,2,4	3,2,5,7,6,4	3,2,5,7,6,4	3,5,4
		4,5,2,3	4,5,2,3	4,5,2,3	4,5,2,3	4,5,2,3	4,5,2,3	4,5,2,3	4,5,2,3	4,5,7,3
4	с	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,2,3
-	_	4,6,8,7,3	4,6,5,7,3	4,6,8,7,3	4,6,8,7,3	4,6,8,7,3	4,6,8,7,3	4,6,8,7,3	4,6,8,7,3	4,5,2,3
		1,2,5,6	1,2,5,7,6	1,2,5,6	1,2,5,6	1,2,5,6	1,2,5,6	1, 2, 5, 6	1,2,5,6	1,2,5,6
	9	1,2,5,7,6	1, 2, 5, 6	1,2,5,7,6	1,2,5,7,6	1,2,5,7,6	1,2,5,7,6	1,2,5,7,6	1, 2, 5, 7, 6	1,2,4,6
	-	ζ	ζ	1,2,5,6,4,6	1,2,4,5,7,6	1,3,2,5,7,6	1,2,5,6,4,6	1,2,4,5,6	1, 2, 4, 5, 6	1,2,5,7,6
		6,4,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,4,2,1	6,5,2,1	6,5,2,1
9	-	6,5,2,1	6,4,2,1	6,4,2,1	6,4,2,1	6,4,2,1	6,4,2,1	6,4,2,1	6,4,2,1	6,7,5,2,1
		ζ	6,4,2,1	6,8,7,3,1	6,8,7,3,1	6,8,7,3,1	6,8,7,3,1	6,8,7,3,1	6,8,7,3,1	6,8,7,5,2,1
					Method	d 2: A*				
0					Ň	po				Method 3
		40	80	200	400	600	800	1200	1600	
		3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,5,6,4	3,2,4
m	4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,2,4	3,5,2,4
		3,1,2,5,6,4	ζ	3,2,5,4	3,5,2,4,2,4	3,5,2,4,2,4	3,5,2,4,2,4	3,5,6,4	3,5,6,4	3,7,5,4
		4,5,7,3	4,5,7,3	4,6,8,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3	4,5,7,3
4	с	4,6,5,7,3	4,6,5,7,3	4,5,7,3	4,6,5,7,3	4,6,5,7,3	4,6,5,7,3	4,6,5,7,3	4,6,5,7,3	4,2,3
-	_	4,6,5,2,3	4,5,2,3	4,5,2,3	4,6,8,7,3	4,5,2,3	4,6,8,7,3	4,5,2,3	4,5,2,3	4,5,2,3
		1,2,5,7,6	1,2,5,6	1,2,5,6	1,2,5,6	1,2,5,6	1,2,5,6	1,2,5,6	1,2,5,6	1,2,5,6
	9	1,3,2,5,6	1,2,4,5,6	1,2,5,7,6	1,2,5,7,6	1,2,4,5,6	1,2,5,7,6	1,2,5,7,6	1,2,5,7,6	1,2,4,6
-	-	1,2,5,6	1,3,2,5,7,6	1,2,4,6	1,2,4,6	1,2,5,7,6	1,2,4,5,6	1,2,4,5,6	1, 2, 4, 5, 6	1, 2, 5, 7, 6
		6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1	6,5,2,1
9		6,5,7,3,1	6,5,2,3,1	6,4,2,1	6,4,2,1	6,8,7,5,2,1	6,8,7,5,2,1	6,4,2,1	6,8,7,5,2,1	6,7,5,2,1
		6,4,2,1	6,8,7,5,2,1	6,8,7,5,2,1	6,8,7,3,1	6,5,7,3,1	6,4,2,1	6,8,7,5,2,1	6,4,2,1	6,8,7,5,2,1

Table 5.4 – Same as in Table 5.3, but for Method 2.

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5.3. Regional paths and choice sets analysis

	Shorte	st Pat	h		1	7*	
	M_1	M_2	M ₃		M_1	M_2	M ₃
M_1	\sim	0.85	0.74	M_1	\sim	0.84	0.65
M_2	0.85	\sim	0.78	M_2	0.84	\sim	0.59
<i>M</i> ₃	0.68	0.71	\sim	M_3	0.71	0.64	\sim

Table 5.5 – Similarity $(\alpha_{similarity}^{M_iM_j})$ between the three methods and considering both the SP and A^{*} algorithms to calculate the set of trips.

	Shorte	st Patl	۱		ŀ	\mathcal{I}_*	
	M_1	M_2	M_3		M_1	M_2	M ₃
M_1	\sim	0.66	0.47	M_1	\sim	0.70	0.40
M_2	0.66	\sim	0.48	M_2	0.70	\sim	0.37
<i>M</i> ₃	0.43	0.44	\sim	<i>M</i> ₃	0.44	0.41	\sim

Table 5.6 – Same as in Table 5.5, but for the strict similarity criterion $(\alpha_{strict \ similarity}^{M_iM_j})$.

Sh	ortest l	Path		A*	
	M_2	M ₃		M_2	M ₃
M_1	0.84	0.80	M_1	0.94	0.81
M_2	\sim	0.81	M_2	\sim	0.83

Table 5.7 – Same as in Table 5.5, but for the strict similarity criterion $(\alpha_{strict \ similarity}^{M_iM_j})$ applied for the most significant regional path of each regional OD pair.

The results are listed in Table 5.5 for the similarity criterion and in Table 5.6 for the strict similarity criterion. We also apply the strict similarity criterion for the most significant regional path of each regional OD pair. The results are listed in Table 5.7. Methods 1 and 2 provide very similar sets of regional paths, with a level of similarity of $\alpha_{similarity}^{M_1M_2} \sim 85\%$. Moreover, the regional paths are listed with the same level of significance in ~70% of the cases. The most significant regional paths are found in ~84% of the cases for the SP and ~94% of the cases for the A* algorithm comparing methods 1 and 2. Method 3 also gives regional path sets with a good level of significance compared to method 1 ($\alpha_{similarity}^{M_1M_3} \sim 60 - 70\%$) and method 2 ($\alpha_{similarity}^{M_2M_3} \sim 60 - 80\%$). The performance of method 3 is lower to find the regional paths with the same level of significance as method 1 ($\alpha_{strict similarity}^{M_1M_3} \sim 40 - 50\%$) and method 2 ($\alpha_{strict similarity}^{M_2M_3} \sim 60 - 80\%$). Method 3 is able to find the most significant regional path for each regional OD pair in ~80% of the cases compared to methods 1 and 2. These results enhance that the application of method 3 gives similar sets of regional paths as methods 1

and 2. Method 3 shows a good performance to find the most significant regional path for each regional OD pair, compared to the reference methods. However, the performance to list the three most significant regional paths for each OD pair is lower.

5.4 Conclusions

In this chapter, we discuss three methods to calculate the regional choice set. This corresponds to the first step to define a regional dynamic traffic assignment framework, for multi-regional systems MFD-based models. The three methods are tested on the 6th Lyon (France) district network, that is divided into eight regions. We show that we need to set a sufficiently large value of N_{od} to ensure a good city network coverage when applying methods 1 and 2. For $N_{od} \ge 1200$, we ensure a good city network coverage (i.e. $N_{cov}^{nodes}(N_{od}) \sim 1$ with a very low standard deviation, yielding $\frac{N_{od}}{N_{nodes}} \sim 3$) and we obtain similar regional choice sets, where the regional paths are listed with the same level of significance. Both of these methods are based on an exhaustive search of trips in the city network. They can be highly time consuming for large city networks applications. Method 3 shows to be a good alternative. It gives regional path sets with a very good level of similarity as the ones of the reference methods. It also shows a very good performance in finding the most significant regional path for each regional OD pair compared to reference methods. However, the level of strict similarity is reduced to ~50% when the three most significant regional paths per OD pair are considered.

6

Trip length estimation for the aggregated network models: scaling microscopic trips into regions

Abstract

One of the key ingredients for the Macroscopic Fundamental Diagram based traffic models is the definition of regional trip lengths inside regions. In this chapter, we propose four methods to estimate the distributions of regional trip lengths based on a set of trips in the city network and on the topology of the regional network. These methods differ from each other depending on the level of detail that we are considering to filter the trips inside each region of the regional network, i.e.: (i) no information about the regional Origin and Destination of the trips; (ii) the next region to be traveled by the trips; (iii) the previous and next regions traveled by the trips; and (iv) the related regional path defined by each trip. We test the four methods on the 6th district Lyon network. We first show that considering an average regional trip length for all vehicles traveling on the same region is not representative of all plausible regional trip lengths calculated by more refined methods. We propose a procedure to update the regional trip lengths when new regional Origin-Destination matrices are considered. Regarding the trip-based Macroscopic Fundamental Diagram model, we show that the regional trip lengths influence the predictions of the accumulations inside the regions. We also show that the regional trip lengths are influenced by the traffic states and highlight that they should be updated accordingly.

Keywords: Trip Lengths; Trip-based model; Macroscopic Fundamental Diagram

This chapter is based on a paper under review for publication on Transportation Research Part B: Methodological.

6.1 Introduction

The first ideas of a network level aggregated model were introduced by Godfrey (1969) and later revisited by Herman & Prigogine (1979), Mahmassani et al. (1984) and Daganzo (2007). For this, one needs to divide the city network (Fig. 6.1 (a)) into regions, where the traffic conditions are approximately homogeneous (Ji & Geroliminis 2012). In Fig. 6.1 (b), we show the partition of the city network and the set of regions that define the regional network (Fig. 6.1 (d)). The system dynamics inside each region is governed by a conservation equation, where the outflow is given by a well-defined relation between mean flow and accumulation, called the Macroscopic Fundamental Diagram (MFD) (Daganzo 2007). Using traffic data from the city of Yokohama (Japan), Geroliminis & Daganzo (2008) provided ground truth evidence of the MFD existence. Its existence and properties were also confirmed by other authors (Geroliminis & Sun 2011a; Ambühl & Menendez 2016; Loder et al. 2017). Up to today, the applications of the MFD in traffic models have mostly been for testing different control algorithms, see Haddad & Geroliminis (2012); Ekbatani et al. (2015); Ramezani et al. (2017); Yang et al. (In press); Kouvelas et al. (2017); Haddad (2017) and Zhong et al. (2017) for some examples.

The mathematical formulation of the MFD was introduced by Daganzo (2007), for a single region. The traffic dynamics is governed by a state equation that relates the accumulation of vehicles $(n_r(t))$ with the balance between the inflow $(Q_{in,r}(t))$ and outflow $(Q_{out,r}(t))$:

$$\frac{dn_r(t)}{dt} = Q_{in,r}(t) - Q_{out,r}(t), t > 0$$
(6.1)

Depending on the assumption made on $Q_{out,r}(t)$, one can distinguish two models in the literature: the accumulation-based model (Daganzo 2007; Geroliminis & Daganzo 2008); and the trip-based model (Arnott 2013; Fosgerau 2015; Lamotte & Geroliminis 2016; Mariotte et al. 2017).

The first implementation of the accumulation-based model assumes a constant mean trip length (\overline{L}) for all vehicles traveling inside the same region (Daganzo 2007). This assumption appears in several studies in the literature (see e.g., Gayah & Daganzo 2011; Haddad 2017). While empirical results from the Yokohama traffic data showed that this might be a reasonable assumption, further studies conclude that this might not be a universal law for all networks since changes in origins and destinations can have a significant influence on the trip lengths (Leclercq et al. 2015). Yildirimoglu & Geroliminis (2014) introduce the concept of regional path, that represents an ordered sequence of crossed regions from the regional Origin to the Destination (Fig. 6.1 (c)). The authors propose to consider different trip lengths for Dynamic traffic assignment for multi-regional transportation systems considering different kinds of users' behavior 121

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Fig. 6.1 – (a) Example of a city network. (b) Partition of the city network where two trips are represented. (c) Regional path defined by the trips shown in (b). (d) The regional network that corresponds to the city network partitioning shown in (b).

vehicles traveling on the same regional path and inside the same region. Ramezani et al. (2015) proposes a more refined approach, where the trip lengths are dynamically calculated depending on the exchange flows between adjacent regions and the accumulation of vehicles.

Arnott (2013) proposes a definition of the MFD dynamics centered on vehicle trip length L_r inside region r:

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 $L_r = \int_{t_{entry}}^{t_{exit}} v_r(n_r(s)) ds$ (6.2)

where t_{entry} and t_{exit} are the entry and exit times of the vehicle from the region; $t_{exit} - t_{entry}$ is the travel time of the vehicle inside the region; and $v_r(n_r(s))$ is the speed-MFD of region r. This is referred to as the trip-based model and has been investigated in detail by several authors in the literature (Arnott 2013; Fosgerau 2015; Lamotte & Geroliminis 2016; Leclercq et al. 2017; Mariotte et al. 2017). It allows to keep track of the distance traveled by each vehicle inside a region, while assuming the vehicle speed to be homogeneous and given by the MFD. This gives full liberty to define trip lengths from an unique value for all vehicles to individual values depending for example on the regional paths.

Both accumulation- and trip-based models require a proper estimation of trip lengths within regions. Yildirimoglu & Geroliminis (2014) mention that considering average trip lengths within regions are not representative. Instead, trip length distributions should be considered. In fact, as shown in Fig. 6.1 (b), different trips in the city network have different lengths inside each region they are crossing in the regional network. Thus, the design of methods able to define trip length distributions for the MFD-based models is required. The goal of this chapter is to fill this gap. We discuss four methods to calculate the trip length distributions inside each region, given a set of trips in the city network and the topology of the regional network. These methods consist in aggregating the lengths of the part of the trips inside each region, considering different levels of information about the regional network topology. They allow to define distributions of trip lengths for each region taking into account:

- (i) no information about the regional Origin and Destination of the trips.
- (ii) the next region to be traveled by the trips.
- (iii) the previous and next regions traveled by the trips.
- (iv) the related regional path defined by each trip.

We first investigate the application of these four aggregation methods on the 6th district of Lyon network (France), divided into eight regions. We analyze the distributions of trip lengths for each region, calculated through each of the four methods and discuss their differences. We discuss the dependence of the distributions of trip lengths on the regional Origin-Destination (OD¹) matrix. We introduce a procedure to update the trip lengths based on a new regional

¹Capital letters refer to regional OD's, while lower case letters refer to city network od's.

OD matrix without requiring to re-sample the set of trips in the city network. Secondly, we investigate the influence of the regional trip length distributions calculated through the four methods when performing simulation studies with the trip-based MFD model. For this, we consider the event-based scheme as detailed in Mariotte et al. (2017) and the Deterministic User Equilibrium (DUE) on the regional paths. We analyze the simulated traffic states considering each of the four methods to calculate the trip lengths. We discuss the importance of scaling the regional trip lengths, when new regional OD matrices are considered for the macroscopic traffic models. Finally, we discuss the influence of the traffic states and re-routing on the regional trip lengths.

The remainder of the chapter is organized as follows. In Sect. 6.2, we introduce the mathematical formulation of the proposed four methods to calculate the regional distributions of trips lengths. In Sect. 6.3, we analyze the distributions of trip lengths calculated through the four methods and for the 6th district of Lyon network (France). We discuss the sensitivity of the macroscopic trip lengths to the OD matrix and introduce a procedure to calibrate the trip length distributions based on a new regional OD matrix. In Sect. 6.4, we investigate the mutual relation between the trip length distributions and the traffic states, using a tripbased MFD model. We show the importance of updating the regional trip lengths, when new OD matrices are considered for the MFD-based traffic models. In Sect. 6.5, we outline the conclusions of this chapter.

6.2 Regional trip length distributions for MFD-based models: methodological framework

The MFD-based models for multi-regional systems require a good estimation of the regional trip lengths. Yildirimoglu & Geroliminis (2014) states that considering average regional trip lengths is not representative. Instead distributions of regional trip lengths for each region should be taken into account. In this section, we introduce four methods to calculate these distributions of regional trip lengths as well as their mathematical formulation.

For the multi-regional MFD-based models, one has to decompose the city network (Fig. 6.1 (a)) into regions with homogeneous traffic conditions. Let X be the set of these regions that define the regional network (Fig. 6.1 (b)). The regional network is a result of the city network partitioning (Saeedmanesh & Geroliminis 2016, 2017; Lopez et al. 2017; Casadei et al. 2018). There are several characteristics of the aggregated network that are different from the city network. First, in the aggregated network, we have regional Origin and Destination (OD) that correspond to regions instead of nodes as in the city network. Let W be the set of

6.2. Regional trip length distributions for MFD-based models: methodological framework

regional OD regions of the regional paths. Second, a trip in the city network corresponds to a set of directed links that go from the origin to the destination node. A regional path on the aggregated network correspond to an ordered sequence of regions that are crossed from the Origin to the Destination region (Fig. 6.1 (c)). Each trip in the city network only defines one regional path. But, one regional path can be defined by several trips. As an example, in Fig. 6.1 (b) we show two trips in the city network that are related to the same regional path on the aggregated network. Third, a trip in the city network has a well-defined trip length that corresponds to the sum of the link lengths. But, a regional path is characterized by a distribution of trip lengths inside each region that it crosses. This is because there are several trips with different trip lengths in the city network, that can define the same regional path. These trips also have different lengths inside each region they cross. This is observed in the example of the two trips in Fig. 6.1 (b) and puts in evidence the need of considering distributions of regional trip lengths.

Generically, a regional path p is defined by an ordered sequence of regions as:

$$p = (p_1, \dots, p_m, \dots, p_R), \forall m = 1, \dots, R \land m \in X$$
(6.3)

where p_1 is the Origin region and p_R is the Destination region; and R is the number of regions that define p.

For the methodology introduced in this chapter to calculate the regional distributions of trip lengths, we assume that the regional network topology is given as an input and we have a set of trips in the city network. Let Γ be the set of trips. To define Γ , one can consider trips gathered from GPS traces. However, these trips are endogenous since they depend on the regional OD matrix and on the congestion patterns in the city network. Instead, we consider a uniform sampling approach of N_{od} od pairs in the city network and calculate the shortest-path in distance for each od pair, using the Dijkstra algorithm. Based on the regional network topology and the set of trips Γ , we introduce the four methods to calculate the distributions of regional trip lengths. These methods are:

Method 1: no information about the regional Origin and Destination of the trips. This method follows the original idea of Daganzo (2007) and consists on a single average regional trip length (*L_i*) for all vehicles traveling on region *i*. The idea is to consider all trips that cross region *i*, independent of the previous and the next regions that these trips travel, to calculate an average regional trip length *L_i* as:

$$\overline{L_{i}} = \frac{\sum_{k} l_{ik}}{\sum_{k} \delta_{ik}}, \forall k \in \Gamma$$
(6.4)

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Fig. 6.2 – (a) Application example of method 1, where the trips 1 to 4 are aggregated for the green region. The length of the part of the trip k that occurs in region i is defined by the solid black lines. The black dots represent the origin nodes and the black arrow indicate the destination nodes of the trips. (b) Application example of method 2, where the trips 1 to 5 are aggregated to calculate the regional trip length. An example of a destination region is also shown by the pink region. The length of the part of the trips 1 to 5 that occur inside the pink region together with the internal trip 6, represented by the dot dashed black line, are aggregated for the calculation of the regional trip length. (c) Application example of method 3, to calculate the regional trip length for the green region and following the specific sequence of yellow-green-pink regions. (d) Application example of method 4, to calculate the regional trip length for the green region. Trips 1 and 2 define a common regional path as the sequence of regions blue, yellow, green and pink.

where I_{ik} is the length of the part of the trip k that occurs in region i; and δ_{ik} is a dummy variable that equals 1 if trip k travels on region i.

The distribution of regional trip lengths of region *i* is:

$$L_i = \{I_{ik}\delta_{rk}\}, \forall k \in \Gamma$$
(6.5)

6.2. Regional trip length distributions for MFD-based models: methodological framework

In Fig. 6.2 (a) we show the application of this aggregation method, for the green region. This region is highlighted and four trips are shown, where their origin nodes are represented by the black circles and the destination nodes by the arrow. Each trip is identified by an identification number. Three of these trips (i.e., trips 1, 2 and 4) are just crossing the green region, while one has its origin node inside the green region (i.e., trip 3). To calculate the distribution of regional trip lengths for the green region, we aggregate the length of the part of these trips that occur inside it. These lengths are represented by the solid black lines in Fig. 6.2 (a). Note that, despite internal trips (i.e., that have origin and destination nodes inside the green region) are not shown, they are also considered.

Method 2: next region to be traveled by the trips. The idea is to consider all trips that are crossing region *i* and that go to the same adjacent region, independent of their previous adjacent region. We filter the trips on Γ that cross region *i* and that go to the same adjacent region *j*. The average regional trip length L_{ij} to go from region *i* to *j* is calculated as:

$$\overline{L_{ij}} = \frac{\sum_{k} \delta_{ijk} l_{ik}}{\sum_{k} \delta_{ijk}}, \forall k \in \Gamma \land (\forall j \in \Lambda \lor j = i)$$
(6.6)

where δ_{ijk} is a dummy variable that equals 1 if trip k travels on region i and goes to region j; and Λ is the set of adjacent regions to i. Note that j = i represents the case of a destination region of the trips.

The distribution of regional trip lengths of region i that goes to j is:

$$L_{ij} = \{\delta_{ijk} I_{ik}\}, \forall k \in \Gamma$$
(6.7)

In Fig. 6.2 (b) we show the application of this aggregation method. Five examples of trips are shown for the green region. All of these trips have the same adjacent destination region (i.e. the pink one). Trip 2 has a destination node that is on the border between the green and the pink regions. The length of these trips that occur inside the green region are aggregated. This is represented by the solid black lines. Consider now the pink region shown in Fig. 6.2 (b), that is a common destination region of the trips represented on it. Trip 6 represents an example of an internal trip. In this case, the length of trips 1 to 6 that occur inside the pink region.

- *Method 3: the previous and the next regions traveled by the trips.* The idea is to consider all trips that are crossing region *i* and that are coming from the same previous adjacent region *h* and going to the same next adjacent region *j*. This is a more refined filtering of the trips compared to Method 2. In this case, we have to consider two distinct type of trips:
 - The first type corresponds to internal trips of region *i*. In this case, the average regional trip length $\overline{L_i}$ is:

$$\overline{L_{i}} = \frac{\sum_{k} \alpha_{ik} l_{ik}}{\sum_{k} \alpha_{ik}}, \forall k \in \Gamma$$
(6.8)

where l_{ik} is trip length of trip k inside region i; and α_{ik} is a dummy variable that equals 1 if trip k is an internal trip of region *i*.

The distribution of regional trip lengths of region i is:

$$L_i = \{\alpha_{ik} I_{ik}\}, \forall k \in \Gamma$$
(6.9)

- The second type corresponds to trips that are crossing region *i*. In this case, all trips traveling on region *i*, coming from the same previous adjacent region *h* and going to the next adjacent region *j* are aggregated to define the average regional trip length $\overline{L_{hij}}$, to go from region *h* to *j* and crossing region *i*:

$$\overline{L_{hij}} = \frac{\sum_{k} \delta_{hijk} I_{ik}}{\sum_{k} \delta_{hijk}}, \forall k \in \Gamma \land \forall (h, j) \in \Lambda \land h \neq j$$
(6.10)

where δ_{hijk} is a dummy variable that equals 1 if trip k comes from the previous region h and goes to the next region j, by crossing region i.

The distribution of regional trip lengths of region i, for trips coming from region h and going to region j is:

$$L_{hij} = \{\delta_{hijk} | l_{ik} \}, \forall k \in \Gamma$$
(6.11)

In Fig. 6.2 (c), we show an example of application of this method 3, for intermediate regions. For this, we consider the two trips that are coming from the yellow region (the equivalent to region h) crossing the green region (the equivalent to the region i) and going to the pink region (the equivalent to region j). The length of the part of these two trips inside the green region are aggregated together to calculate

the distribution of regional trip lengths L_{hij} . This is represented by the solid black lines.

Method 4: the related regional path p defined by each trip. The idea of this method follows the spirit of method 3, where we consider the local sequence of previous (h), current (i) and next (j) adjacent regions. However, for this method, we filter the trips by their specific related regional path. That is, we only consider the trips that cross region i following the same specific sequence hij of regions and that define the same regional path p. All trips that cross region i and define the same regional path p, are considered to calculate the average regional trip length of p on region i (L^p):

$$\overline{L_{i}^{p}} = \frac{\sum_{k} \delta_{ik}^{p} I_{ik}}{\sum_{k} \delta_{ik}^{p}}, \forall k \in \Gamma$$
(6.12)

where δ_{ik}^{p} is a dummy variable that equals 1 if trip k travels on region i and has associated the regional path p.

The distribution of regional trip lengths of the regional path p inside region i is:

$$L_i^p = \{\delta_{ik}^p l_{ik}\}, \forall k \in \Gamma$$
(6.13)

In Fig. 6.2 (d), we show the application of this method. Two trips that define the same regional path, defined by the sequence of the blue-yellow-green-pink regions, are shown. To determine L_i^p for the green region, we aggregate the length of the part of these trips inside this region. This is represented by the solid black lines.

These four methods allow us to define regional trip length distributions for each region of R, based on a set of trips Γ . These methods differ from each other based on the level of information of the regional network used to filter the trips listed in Γ . Method 1 is the most generic one, where all trips that cross the same region are considered for the aggregation. While, Method 4 is the more refined one in terms of the filtering. This method allows to define a specific distribution of regional trip lengths for a specific regional path that crosses a given region, based on the specific sub-set of trips that define this regional path. Thus throughout this chapter, we consider Method 4 as the reference. The distribution of trip lengths calculated through method 4 are independent of the regional OD matrix, since all trips from the Origin to the Destination are gathered by their related regional path.

The average trip length of regional path p can be directly calculated considering any of the previously discussed methods as follows:

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1. *Method* 1 (*M*₁):

$$\overline{L_p^{M_1}} = \sum_{m=1}^R \overline{L_{p_m}}$$
(6.14)

2. Method 2 (M_2) :

$$\overline{L_{p}^{M_{2}}} = \gamma \sum_{m=1}^{R-1} \sum_{l=m+1}^{R} \overline{L_{p_{m}p_{l}}} + \overline{L_{p_{R}p_{R}}}$$
(6.15)

where $\gamma = 1$ if $R \ge 2$.

3. *Method 3 (M*₃):

$$\overline{L_{p}^{M_{3}}} = \begin{cases} \overline{L_{p_{R}}} & \text{if } R = 1\\ \overline{L_{p_{1}p_{2}}} + \gamma \sum_{m=2}^{R-1} \overline{L_{p_{m-1}p_{m}p_{m+1}}} + \overline{L_{p_{R-1}p_{R}}} & \text{if } R \ge 2 \end{cases}$$
(6.16)

where $\gamma = 1$ if $R \ge 3$. Note that: $\overline{L_{p_R}}$ is calculated according to Eq. 6.8; $\overline{L_{p_1p_2}}$ and $\overline{L_{p_{R-1}p_R}}$ are calculated according to Eq. 6.6; and $\overline{L_{p_{m-1}p_mp_{m+1}}}$ is calculated according to Eq. 6.10.

4. *Method* 4 (*M*₄):

$$\overline{L_p^{M_4}} = \sum_{m=p_1}^{p_R} \overline{L_m^p}$$
(6.17)

While the four methods might give similar estimations of L_p (Eq. 6.14 to Eq. 6.17) for the mean value when there is symmetry in the shape of the regions and homogeneity in the distribution of demand and congestion, this might not be the case with the variance. For accumulation-based MFD model only the average regional trip lengths matter. However, for the trip-based MFD model, the variance of the regional trip length distributions play an important role. This is because the trip-based MFD model allow to consider individual vehicle trip lengths inside the regions and can significantly influence the dynamics of congestion (Lamotte et al. 2018).

It is important to stress out that these four methods to calculate the distributions of regional trip lengths strongly depend on the regional network definition (i.e., on the definition of the borders of regions) and on the set of trip Γ . A change in any of these two inputs will give different distributions of regional trip lengths. However, this methodology is applicable to any topology of the regional network and set of trips Γ . The only requirement is that the number of trips (N_{od}) should be statistically significant such that all the city network is sufficiently covered. This analysis is similar to the one discussed in Sect. 5.3.1. To define the set of

trips Γ , we consider in this chapter shortest-paths in distance. But, one can also consider more refined approaches to calculate these trips, like Frejinger et al. (2009) and Flötteröd & Bierlaire (2013). We also note that the calculation of the set of trips Γ is insensible to the topology of the regional network. These trips represent shortest-paths in distance and are calculated independently of the regional network topology. Then, scaling these trips to the aggregated level, they can cross more than one time the same region. One can filter these trips from the set Γ . However, in this chapter, we arbitrarily assign these trips to a single region with the largest travel distance. Further research is required to better account for such specific patterns.

The regional trip lengths are affected by some factors, such as, the traffic conditions (i.e., congestion patterns) and the regional OD matrix (Leclercq et al. 2015). In the next sections, we investigate the influences of these two factors on the regional trip lengths. We analyze the results calculated for methods 1, 2 and 3 against the reference, i.e. method 4.

6.3 A static analysis of the trip length distributions

In this section, we introduce the 6th district of Lyon network (France) and the MFD functions. We analyze the regional trip length distributions calculated using the four methods. We then discuss a procedure that allows to update the regional trip lengths when the OD matrix changes, without the need to re-sample the set of trips Γ .

6.3.1 Network definition

To test the proposed methods and calculate the trip length distributions, we consider the 6th district of Lyon network (France) shown in Fig. 6.3 (a). This network has 757 links, 431 nodes and divided into 8 regions. The MFD functions (Fig. 6.3 (b)) have been fitted using microscopic simulation results (Leclercq 2007) on the same network, with a typical morning peak of demand pattern. We assume a bi-parabolic shape for the MFD.

We sample $N_{od} = 10000$ od pairs and calculate the shortest-path in distance for each od pair. These trips define the set Γ and yield a total of 205 regional paths. We refer to the set of these 205 regional paths as Ψ . The set Γ defines a regional OD matrix between regions, see Table 6.1. We refer to this OD matrix as M. In Sect. 6.3.3, we also discuss a procedure to update the regional trip lengths for the trip-based MFD model, considering a new regional OD matrix M^* . For this purpose, we consider another sampling of $N_{od} = 10000$ od pairs, where there are more samples of od pairs on the origin region 1 and destination regions 4, 6 and 8. Then, we are considering more trips that go from the north to the south of the



Fig. 6.3 – (a) Lyon 6^{th} district network divided into 8 regions. (b) MFD function of each region.

city network (i.e., from region 1 to 4, 6 and 8). For each of the previous regional ODs, we sample 600 od pairs, out of the 10000. The remaining od pairs are uniformly sampled in the city network. We refer to this second regional OD matrix as M^* , see Table 6.1. Note that the regional OD matrix M has more uniform values across OD pairs than matrix M^* .

				De	stinati	on reg	lion		
		1	2	3	4	5	6	7	8
	1	165	258	135	153	96	133	125	171
_	2	215	298	164	176	147	202	184	282
ior	3	160	188	114	135	97	103	128	185
reg	4	156	247	105	104	96	106	155	175
jin	5	108	139	69	93	43	99	86	138
Orig	6	140	159	102	67	85	65	89	162
0	7	147	227	115	81	75	79	135	152
	8	199	272	141	132	103	149	151	175

D · ·		
Destin	ation	region

D	
Destination	region

		1	2	3	4	5	6	7	8
Origin region	1	127	214	102	632	132	557	139	567
	2	182	249	169	190	110	273	179	338
	3	143	165	79	114	81	98	99	165
	4	125	183	91	92	86	88	96	140
	5	83	112	52	73	50	84	67	85
	6	100	148	88	54	49	55	102	131
	7	125	164	100	92	47	52	99	122
	8	178	208	126	127	70	133	146	154

Table 6.1 – Number of trips between each macroscopic origin and destination regions, for the 6th Lyon district network. Top: Matrix M. Bottom: Matrix M*.

6.3.2 Analysis of the trip length distributions

In this section, we analyze the average regional trip lengths calculated by the methods 1, 2 and 3 compared against the reference method 4. We show the average regional trip lengths in Fig. 6.4. The blue crosses represent the average regional trip lengths that are calculated for each region, considering method 1 (see Eq. 6.4). For this method, we consider all trips that travel inside each region independently of their previous and next regions crossed. This gives just one average regional trip length for each region. The green triangles represent the average regional trip lengths calculated through method 2 (see Eq. 6.6) and for the full set of Λ as well as the internal trips of each specific region of the regional network. The black dots represent the regional trip lengths calculated through method 3, considering the specific sequence of crossed regions (see Eq. 6.10) as well as the internal trips to each specific region (see Eq. 6.8). The red dots represent the average regional trip length calculated through method 4 (see Eq. 6.12), considering each regional path that crosses each specific region.

One can observe from Fig. 6.4 that method 1 gives an average regional trip length for the regions that is not representative of all average values for all regional paths that are crossing each region, as evidenced by the red dots (i.e., the reference method 4). As observed in Fig. 6.4, the diversity of average trip lengths for each region increases from methods 1 to 4.

These four methods provide the regional trip lengths of each regional path that crosses each region of the regional network. So, it is relevant to estimate the relative differences between the regional trip lengths calculated through more aggregate methods (1 to 3) and the reference one, when assigning regional trip lengths to regional paths (p) inside the regions *i*. The relative differences β_{ip} are calculated as:

$$\beta_{ip} = \frac{\overline{L_i^{M_j}} - \overline{L_i^{M_4}}}{\overline{L_i^{M_4}}} \delta_i^p, \forall j = 1, 2, 3 \land \forall p \in \Psi$$
(6.18)

where δ_i^p is a dummy variable that equals 1 if regional path p crosses region i, or 0 otherwise. $\overline{L_i^{M_4}}$ is the average regional trip length calculated through Eq. 6.12 (Method 4). For method 1, $\overline{L_i^{M_j}}$ is calculated through Eq. 6.4. For method 2, $\overline{L_i^{M_j}}$ is calculated through Eq. 6.6, where $i = p_m$ is the current region and $j = p_{m+1}$ is the next region adjacent to i on the sequence of regional path p. For method 3, $\overline{L_i^{M_j}}$ is calculated through Eq. 6.10, where $i = p_m$ is the current region, $h = p_{m-1}$ is the previous region and $j = p_{m+1}$ is the next region adjacent to ion the sequence of regional path p.

The calculated relative differences β_{ip} are shown in Fig. 6.5. As one can observe, the relative differences β_{ip} decrease from methods 1 to 4. This clearly shows how far an average regional trip length calculated through method 1 is from all possible regional trip lengths calculated through method 1. The other three methods allow to obtain different average regional trip lengths for vehicles traveling inside the same region, but on a different sequence of regions (or regional path). Clearly, considering an average regional trip length for all vehicles traveling inside the same region is not representative of all possible regional trip lengths given by method 4 (i.e., the reference method). As shown by Leclercq et al. (2015), the hypothesis of method 1 is a strong limitation when applying MFD-based traffic models. This will be further investigated in Sect. 6.4.2.

We have also randomly selected the regional path 4-5-2 and show the trip length distributions per region for the four aggregation methods (Fig. 6.6). Fig. 6.6 shows the clear influence of the different filtering levels of the trips (i.e., the different methods 1 to 4) on the distributions of the regional trip lengths, at the region level. From method 1 to 4, the number of trips taken into account for the aggregation decreases, the standard deviation of the regional trip length distributions also decreases. That is, from methods 1 to 4, the diver-



Fig. 6.4 – Average regional trip lengths [in meters] calculated through the four methods and for the eight regions. The blue dots represent the average regional trip lengths for method 1 (see Eq. 6.4). The green dots represent the average regional trip lengths for method 2 (see Eq. 6.6). The black dots represent the average regional trip lengths for method 3 (see Eq. 6.8 and Eq. 6.10). The red dots represent the average regional trip lengths for method 4 (see Eq. 6.12).



Fig. 6.5 – Distribution of the relative differences β , between method l = 1, 2, 3, 4 (from the left to the right) and the reference method 4.

sity of trips that are considered for the calculation of the regional trip length distributions is reduced. A second interesting point is to compare methods 3 and 4 that take into account a more detailed calculation of the regional trip lengths following specific sequences of regions. We start by analyzing the calculation of the regional trip lengths for the origin (region 4) and destination (region 2) regions. To obtain the regional trip length distribution for method 3 and region 4, we consider all trips that have an origin node inside region 4 and that go next to region 5. This also includes trips that define other regional paths. But, in the case of method 4, we only consider the specific trips that define the regional path 4-5-2. The analysis for the destination region 2 is analogous. In the case of the intermediate region, the differences between both methods are smaller. But, in the case of method 3, we also consider trips that may define other different regional paths but that locally follow the same sequence of the intermediate regions, i.e. trips that are coming from region 4 and going to region 2 by crossing region 5. While, for method 4, we just consider the trips that specifically define regional path 4-5-2.

In summary, the diversity of average regional trip lengths that is possible to obtain for methods 2, 3 and 4 compared to method 1, for vehicles traveling inside the same region. We also show that the heterogeneity of trips considered by the four methods, at the region level, play an important role on the shape of the trip length distributions. Clearly methods 3 and 4 (the reference method) represent better the heterogeneity of regional trip lengths inside each region, than methods 1 and 2. Then, methods 3 and 4 have to be preferred.



Fig. 6.6 – Regional trip length distribution calculated through the four methods and for each region of the regional path 4-5-2. The total number of trips that are considered for each distribution is identified on the top of each subplot. Each row of the subplots represent the results for each method, while each column of subplots represent the region for each method. The horizontal red dashed lines represent the average of the trip length distributions.

6.3.3 Impact of the OD matrix on the trip lengths

In this section, we discuss a procedure to update the regional trip lengths based on the regional OD matrix (M) defined by the set of trips Γ as well as the trip lengths that are calculated and the new regional OD matrix M^* . Of course, one solution is to re-sample the trips based on the new regional OD matrix M^* , but this is time consuming, especially for large networks. This procedure is very useful as it updates the regional trip lengths considering the current set of trips Γ when the regional OD matrices changes over time, or when another trip-based MFD simulation has to be performed considering a different regional OD matrix different from the original one. The procedure is described below.

The trip lengths for the i-th region and for method 1, are estimated as:

$$\hat{L}_{i} = \frac{\sum_{O} \sum_{D} \sum_{r} \sum_{k} l_{ik}^{OD} \alpha_{r}^{OD}}{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ik} \alpha_{r}^{OD}}, \forall k \in \Gamma$$
(6.19)

where \hat{L}_i is the estimated average regional trip length for region *i*; I_{ik}^{OD} is the length of trip k on region i that has the regional OD pair; δ_{ik} is a dummy variable that equals 1 if trip kcrosses region i, or 0 otherwise. α_r^{OD} is a scaling factor based on the demand of regional OD pair of M weighted by the demand of the same regional OD pair of M^* , that crosses region i:

$$\alpha_{r}^{OD} = \begin{cases} \frac{n^{OD}}{n_{*}^{OD}}, \text{ if } n_{*}^{OD} \ge 1\\ 1, \text{ if } n_{*}^{OD} = 0 \end{cases}$$
(6.20)

where n^{OD} is the demand going from regional origin O to regional destination D of matrix M; and n_*^{OD} is similar but for the new regional OD matrix M^* . Such calculations are simple and allow to update trip lengths to dynamic variations of the regional OD matrix.

For method 2, the regional trip lengths to go from region i to the next adjacent region jare estimated as:

$$\hat{L}_{ij} = \frac{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ijk} I^{OD}_{ik} \alpha^{OD}_{r}}{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ijk} \alpha^{OD}_{r}}, \forall k \in \Gamma$$
(6.21)

where \hat{L}_{ij} is the estimated regional trip length to go from the current region *i* to the adjacent region j; δ_{ijk} is a dummy variable that equals 1 if trip k, with regional OD pair, crosses region *i* and goes to the adjacent *j*, or 0 otherwise.

For method 3, we have to distinguish three possible cases for the estimation of the regional trip lengths:

• the case where the regional path is composed by only one region (R = 1). The average

regional lengths are estimated as:

$$\hat{L}_{i} = \frac{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ik} l_{ik}^{OD} \alpha_{r}^{OD}}{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ik} \alpha_{r}^{OD}}, \forall k \in \Gamma$$
(6.22)

where δ_{ik} is a dummy variable that equals 1 if trip k is an internal trip to region i.

 the case where the regional path is composed by two or more regions (R ≥ 2) and for the Origin and Destination regions. The average regional lengths are estimated as:

$$\hat{L}_{ij} = \frac{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ijk} I_{ik}^{OD} \alpha_{r}^{OD}}{\sum_{O} \sum_{D} \sum_{r} \sum_{k} \delta_{ijk} \alpha_{r}^{OD}}, \text{ if } ((i = p_{1}, j = p_{2}) \lor (i = p_{R-1}, j = p_{R})) \land \forall k \in \Gamma \quad (6.23)$$

where δ_{ijk} is a dummy variable that equals 1 if trip k travels on region i and goes to j (for the Origin regions) or if trip k travels on region j coming from region i (for the Destination regions), or 0 otherwise.

 the case where the regional path is composed by two or more regions (R ≥ 2) and for the intermediate regions. The average regional lengths are estimated as:

where δ_{hijk} is a dummy variable that equals 1 if trip k, with regional OD pair, crosses the specific sequence of h - i - j regions, or 0 otherwise.

Based on Eq. 6.19 and Eq. 6.24, we investigate if: $\hat{L} \approx \overline{L}$. We estimate average regional trip length for all eight regions based on M and M^* . We define θ as the relative difference between \hat{L} and \overline{L} as:

$$\theta = \frac{\hat{L} - \overline{L}}{\overline{L}} \tag{6.25}$$

where \hat{L} is the estimated average trip length trough Eq. 6.19 to Eq. 6.24. As a benchmark and to validate this procedure, we recalculate the set of trips based on the new regional OD matrix M^* and calculate the regional trip lengths through the four methods. This allows to determine \overline{L} , to compare against the estimated regional trip lengths. In Table 6.2, we list the average relative differences $\overline{\theta}$, for each case (that is Eq. 6.19 to Eq. 6.24). We observe that Dynamic traffic assignment for multi-regional transportation systems considering different kinds of users' behavior 139

6.4. Impacts of trip-lengths estimation methods on dynamic models

region	M_1	M_2	M ₃		
1	0.060	-0.028	-0.007		
2	-0.047	-0.012	-0.001		
3	-0.008	-0.016	-0.024		
4	0.013	-0.005	-0.030		
5	-0.011	0.002	0.012		
6	0.085	0.012	0.030		
7	0.017	0.017	-0.008		
8	0.017	-0.008	0.003		

Table 6.2 – Average $\overline{\theta}$ for methods 1 to 3.

this procedure provides a good estimation of the regional trip lengths for the eight regions and the methods 1 to 3. This procedure is simple to implement and does not require a new sampling of trips. Note that, by definition, method 4 does not depend on the OD matrix and consequently one does not need to scale up the regional trip lengths for new OD matrices. This is valid when the number of od pairs that are sampled is sufficiently large, such that the trip ensure a good coverage of the city network. In our case, we made sure that the 10000 od pairs considered, are sufficient to ensure a good coverage of the city network.

6.4 Impacts of trip-lengths estimation methods on dynamic models

In this section, we show the importance of properly estimating distributions of regional trips lengths for the trip-based MFD model. We investigate how the prediction of accumulations with time are influenced by the different methods of trip lengths calculation. We also investigate the effect of traffic states and re-routing on the regional trip lengths.

6.4.1 Simulation settings

For the trip-based MFD traffic model, we consider the network and MFD functions shown in Fig. 6.3. We also consider a total simulation period of T = 10000 seconds and a demand scenario composed by 3 regional OD pairs: 1-6; 8-4; and 3-4. The regional choice set is composed by a maximum of three regional paths per each regional OD pair. The regional paths are listed in Table 6.3. Note that, the regional paths are directly obtained from Ψ , where we consider the most sampled regional paths for each regional OD pair. That is, the regional paths that have a larger number of trips associated. The demand curves for each regional OD pair are shown in Fig. 6.7. For each OD pair, we consider a demand scenario that represents a morning peak.



Fig. 6.7 – Demand scenario.

For the trip-based MFD traffic model, we consider the Deterministic User Equilibrium (DUE). The DUE is based on the Wardrop first principle (Sheffi 1985). To solve for the DUE in conjunction with the trip-based traffic simulator (Mariotte et al. 2017), we consider the Method of Successive Averages (MSA) (Sheffi 1985; Sbayti et al. 2007). The core of the MSA lies in the proper definition of the descent step α_j , where *j* is the descent iteration, that guarantees the algorithm convergence. We adopt the following and widely used definition of α_j : $\alpha_j = \frac{1}{j}$. To solve the DUE problem, users are assigned based on an all-or-nothing principle to the least cost regional path at each descent step α_j . This allows to calculate the new temporary regional path flows $Q_k^{OD,*}$, that will be used to update the new regional path flows $Q_k^{OD,j+1}$ at iteration j + 1, as:

$$Q_{k}^{OD,j+1} = Q_{k}^{OD,j} + \alpha_{j} \{ Q_{k}^{OD,*} - Q_{k}^{OD,j} \}, \forall k \in \Omega^{OD}$$
(6.26)

 Ω^{OD} is the choice set of regional paths for the OD pair; and $Q_k^{OD,j}$ represents the regional path flows at iteration *j* of the MSA. This process is repeated at every descent step of the MSA algorithm.

A commonly used convergence or stopping criterion is based on the comparison between the current and the previous descent step of the MSA that should be inferior to a given tolerance *tol*. This can represent a problem since it ensures that the algorithm terminates with a stable solution but does not guarantee that it converges to the DUE. Instead, we consider as a stopping criterion, the relative Gap (Sbayti et al. 2007):

$$Gap = \frac{\sum_{O} \sum_{D} \sum_{k \in \Omega^{OD}} Q_k^{OD} (TT_k^{OD} - \min(TT^{OD}))}{\sum_{O} \sum_{D} Q^{OD} \min(TT^{OD}))}$$
(6.27)

Ο	D	Regional path					
	6	1-2-5-6					
1		1-2-5-7-6					
2	4	3-2-4					
3		3-2-5-6-4					
0	4	8-7-6-4					
ð	4	8-7-3-5-2-4					

Table 6.3 – List of regional paths considered for the trip-based MFD traffic model and the demand scenario.

where Q^{OD} is the total demand for the regional OD pair; and TT_k^{OD} is the average travel time of regional path k; and min (TT^{OD}) is the minimum regional path travel time for the regional OD pair.

The Gap function (Eq. 6.27) represents the difference between the regional paths travel times and the equilibrium travel time. Under DUE conditions, Gap = 0 and all users choose the regional paths with the minimum travel times.

We summarize this implementation of the MSA to solve the DUE and considering a tripbased simulator in Algorithm 4.

Input the aggregated network, demand scenario and simulation duration T. Update the regional path choice set based on Γ . Perform an initial loading of the network. Set j = 1, $N_{max}^{iterations}$ and tol. while $Gap \ge tol \land j \le N_{max}^{iterations}$ do Perform an all-or-nothing assignment based on the Wardrop 1^{st} principle, on the regional paths for each OD pair. Do the trip-based MFD simulation. Obtain the regional path travel times. Update the regional path flows based on Eq. 6.26. Calculate the GAP value (Eq. 6.27). Set j = j + 1. end

Algorithm 4: Dynamic implementation of the DUE and the trip-based MFD traffic model.

6.4.2 Does trip length definition affect the simulated traffic states?

We investigate the influence of the trip length estimation methods on the traffic states based on a MFD trip based model. To solve the MFD trip based model, we follow the numerical scheme as described in Mariotte et al. (2017). The regional trip lengths are updated according

Method	Regional path	Region							
Methou		1	2	3	4	5	6	7	8
1	1-2-5-6	312	365	\sim	\sim	284	259	\sim	\sim
2	1-2-5-6	277	373	\sim	\sim	276	246	\sim	\sim
3	1-2-5-6	253	441	\sim	\sim	280	258	\sim	\sim
4	1-2-5-6	191	455	\sim	\sim	285	236	\sim	\sim
1	3-2-4	\sim	365	346	311	\sim	\sim	\sim	\sim
2	3-2-4	\sim	387	353	268	\sim	\sim	\sim	\sim
3	3-2-4	\sim	695	363	243	\sim	\sim	\sim	\sim
4	3-2-4	\sim	695	370	179	\sim	\sim	\sim	\sim
1	8-7-6-4	\sim	\sim	\sim	311	\sim	259	304	299
2	8-7-6-4	\sim	\sim	\sim	268	\sim	304	180	290
3	8-7-6-4	\sim	\sim	\sim	266	\sim	411	276	269
4	8-7-6-4	\sim	\sim	\sim	295	\sim	411	273	267

Table 6.4 – Average regional trip lengths (m) for the four methods and for the three regional paths that are used under DUE conditions.

to the new OD matrix and following the procedure described in Sect. 3.3. The evolution of the accumulation n(t) inside each region is shown in Fig. 6.8. One can clearly observe that all four methods have a clear impact on the traffic states inside the regions. In particular, methods 1 and 2 that are the most commonly used in the literature to define the regional trip lengths for the MFD-based traffic models, predict traffic states that are far away from the reference method 4 (i.e., that follows each specific sequence of crossed regions or regional path).

For the demand scenario shown in Fig. 6.7 and under DUE conditions, only one regional path for each regional OD pair is used for the four methods. This gives a total of three regional paths that are used.

The average regional trip lengths for the four methods and for these three regional paths are listed in Table 6.4. We focus our attention on the evolution of n(t) inside the origin regions 1 and 3 of regional paths 1-2-5-6 and 3-2-4, respectively. For these two regions, the maximum peak of n(t) are higher for methods 3 and 4, compared to methods 1 and 2. In fact, a larger trip length means a potential bottleneck (i.e., a reduction of the inflow capacity for this region and specific regional path) of the regional paths. But, this is not the case, as observed from the listed average regional trip lengths in Table 6.4, for regional paths 1-2-5-6 and 3-2-4. We have then to consider the next region of these two regional paths. That is region 2. Inside this region, methods 3 and 4 give larger average regional trip lengths than methods 1 and 2. Then, vehicles will take more time to cross it due to the larger

average regional trip lengths. Consequently, n(t) increases inside region 2 and it becomes a bottleneck for regional paths 1-2-5-6 and 3-2-4. This will lead to an increase of the number of vehicles that are blocked at the entries from region 1 to 2 and 3 to 2, increasing n(t)inside regions 1 and 3. This explains why the accumulation peak is larger for methods 3 and 4 despite the lower regional trip lengths compared to methods 1 and 2, inside regions 1 and 3. Also note that the propagation of congestion on regional path 1-2-5-6 inside region 2, affects the passing flow of regional path 3-2-4 inside region 2. The peak of n(t) inside region 3 appears after the peak of the accumulation n(t) inside region 1. In fact, this is observed in Fig. 6.8, where the peak of accumulation n(t) inside region 2 lasts longer for methods 3 and 4 compared to methods 1 and 2. This originates a capacity reduction from region 2 to 1 (for regional path 1-2-5-6) and from region 2 to 3 (for regional path 3-2-4). The latter explains the larger peaks of the accumulation n(t) inside regions 1 and 3, despite the lower average regional trip lengths for methods 3 and 4 compared to methods 1 and 2.

Different trip lengths at the region level means completely different traffic states. This highlights the importance of properly calculate the regional trip lengths inside the regions.

6.4.3 Are the trip length distributions congestion dependent?

In this section, we investigate the impact of the traffic states on the regional trip lengths calculated through the four methods. For now, the regional trip lengths are calculated based on shortest-paths in distance in the city network, without considering the influence of traffic states. Hereby, we investigate the dependence of the regional trip lengths on the traffic states. For this purpose, we replace the shortest-paths in distance by shortest-paths in time when pairing city of pairs and defining trips. The goal is to see if our initial estimation of Γ based on shortest-paths in distance is stable to the evolution of traffic states or not. We consider the evolution of the mean speed as function of time, for Method 4 (Fig. 6.8), between 2000 and 5600 seconds. This interval covers the congestion period, see Fig. 6.8. Based on this, we estimate an average mean speed for each region. We refer to the set of the calculated shortest-paths in time as Υ . For the tests of this section, we only consider regional paths that are defined by more than 50 trips. This allows to eliminate dependences of the regional trip lengths calculation on the geometry of the regional (i.e., regions) network. To better explain this, we can look at regions 1, 2 and 3 (Fig. 6.3). In fact, when performing the static sampling of N_{od} pairs, the calculated trips are independent of the regional network definition (i.e., to the definition of the borders of regions). This means that, when we scale these trips from the city to the regional network, trips that departure from nodes close to the border between regions 1 and 3 are more probable to cross to region 3 rather than 2. However,

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Fig. 6.8 – Evolution of n(t) during the simulation period, considering the four methods to calculate the regional trip lengths.

for the shortest-paths calculations in time, we consider the mean speed obtained from the trip-based MFD traffic model, to calculate the travel times of the links belonging to each respective region. This induces a dependence of the calculated shortest paths in time on the regional network definition. Consider that, for example, region 2 is congested. In this case, its link travel times increase and consequently trips that begin in nodes that are more far away from the border between regions 1 and 3, will more probably cross it. Thus, we might have longer trips and more importantly, some trips can switch to different regional paths. This may lead to sampling issues when the initial regional paths were defined by only a few trips. The filtering allows to avoid the comparison of regional paths with trip sets that are not statistically significant. After the filtering, we search on Γ and Υ for the common regional paths to compare the average regional trip lengths. We refer to the regional trip lengths calculated based on the trips listed in Υ as dynamic regional trip lengths.

We first investigate the sensitivity of regional trip lengths to the traffic states, at the region level. We define a parameter α that defines the relative difference between the dynamic $(\overline{L_d})$ and static $(\overline{L_s})$ average regional trip lengths, as:

$$\alpha = \frac{\overline{L_d} - \overline{L_s}}{\overline{L_s}} \tag{6.28}$$

The relative differences α for the four methods to calculate the regional trip lengths and for the 8 regions are shown in Fig. 6.9. We clearly observe a non negligible impact of the traffic states on the regional trip lengths calculated at the region level and considering the four methods. We can observe that the relative differences α for M₃ and M₄ are on average closer to 0 than in the case of M₁. The range of α values for M₂ is also quite large, evidencing that it is also highly affected by the traffic states. The only exception is region 1, where the relative differences α are close to 0. One can also observe that the regions that are more impacted by congestion show the largest values of α , like regions 2, 4 and 5.

In summary, despite the effects of the traffic states and re-routing on the regional trip lengths are predictable, their quantification on the different aggregation methods that are discussed in this chapter is not. We observe a non-negligible influence highlighted by the relative differences α , that in some cases can go up to ~0.5. Also note that, M₄ is the one with the lower variation of α . These results show the importance of updating the trip lengths according to the traffic states. One solution is to re-calculate the shortest paths in time to define the set of trips and consequently gather the regional trip lengths. But, this is computationally expensive. Further methodologies that are computationally lighter will be



Fig. 6.9 – Relative difference α between the regional trip lengths calculated based on the time-dependent trips listed in Υ and the trips listed on Ξ . The results are listed for the four methods.

investigated in future research.

6.5 Conclusions

In this chapter, we discuss four methods to calculate distributions of regional trip lengths at the region and the regional path levels. These methods are based on the aggregation of trips in the city network and the regional network definition. We analyze the application of these methods on the 6th Lyon district network that is divided into eight regions. The analysis of the distributions of regional trip lengths are done at the region level.

First, we analyze the application of the different methods to calculate the distributions of regional trip lengths, based on a static analysis of the city and equivalent regional networks. We show that methods 3 and 4 represent better the heterogeneity of regional trip lengths inside each region, compared to methods 1 and 2. This shows that methods 3 and 4 are to be preferred to calculate the regional trip lengths for the MFD-based models. In particular, we show that the average regional trip length calculated through method 1 is not representative of all possible trip lengths of different regional paths crossing that same region calculated by method 4 (the reference method). Since the regional trip lengths depend on the regional OD matrix, we discuss a procedure to update the regional trip lengths for new regional OD matrices that does not require to re-calculate a set of trips. We show that the procedure provides good estimation results.

Second, we analyze the influence of the regional trip lengths calculated through the four methods on the traffic states. We show that methods 1 and 2, that are the most commonly used in the literature for the MFD-based models, yield evolutions of the accumulation n(t)inside the regions that are completely different than methods 3 and 4 (the reference method). We also discuss the effects of the traffic states and re-routing on the regional trip lengths. Despite these effects are predictable, their clear impact is not evident. We show that at the region level, the relative differences α are non negligible and can go up to values of ~0.5, in some cases. Thus, the regional trip lengths should be updated according to the traffic states.

As future research, we plan to extend this study in several directions. We plan to analyze the regional trip length distributions at the regional path level. More importantly, robust and computationally light methodologies to update the regional trip lengths according to the traffic states are required.
A dynamic traffic assignment framework for MFD multi-regional models

Abstract

In this chapter, we propose a regional dynamic traffic assignment for Macroscopic Fundamental Diagram (MFD) based models that explicitly accounts for trip length distributions. The proposed framework considers stochasticity on both the trip lengths and the regional mean speed. Consequently, we set four definitions of network equilibrium, depending on which terms are considered stochastic. We propose a numerical resolution scheme based on Monte Carlo simulations and the Method of Successive Averages is used to solve the network equilibrium. Based on our test scenarios, we show that the variability of trip lengths inside the regions cannot be neglected. Moreover, it is also important to consider the stochasticity on the regional mean speeds to account for correlation between regional paths. The proposed regional dynamic traffic assignment is an extension of that discussed by Yildirimoglu & Geroliminis (2014). We also discuss an implementation of the proposed dynamic traffic assignment framework on the 6th district of the Lyon network, where trip lengths are explicitly calculated. The traffic states are modeled by considering the accumulation-based MFD model. The results highlight the influence of the variability of trip lengths on the traffic states modeled.

Keywords: Regional trip lengths; Regional dynamic traffic assignment; Regional network; Macroscopic Fundamental Diagram; MFD models.

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7.1. Introduction

7.1 Introduction

Aggregated traffic models were first introduced by Godfrey (1969), Herman & Prigogine (1979) and Mahmassani et al. (1984). This approach was later revisited by the seminal works of Daganzo (2007) and Geroliminis & Daganzo (2008). The concept relies on partitioning the city network into a set of regions and then to represent flow exchanges. In Fig. 7.1 (a), we show an example of a city network. To divide the city network into regions, clustering techniques discussed in the literature can be used (e.g. Saeedmanesh & Geroliminis 2016; Lopez et al. 2017; Saeedmanesh & Geroliminis 2017; Casadei et al. 2018). The city network has to be transformed into a regional network, as shown in Fig. 7.1 (b) and Fig. 7.1 (c), to define routing options inside the regions. Let X be the set of regions. Inside each region, the traffic conditions are characterized by a well-defined Macroscopic Fundamental Diagram (MFD). An MFD is a relationship between the average circulating flow q_r ([veh/s]) and the accumulation n_r ([veh]) inside region r. The existence of this relationship was initially proved by Geroliminis & Daganzo (2008) using experimental data from Yokohama city (in Japan) and later confirmed by other authors (Geroliminis & Sun 2011a; Ambühl & Menendez 2016; Loder et al. 2017). The traffic dynamics is defined by the following conservation equation for one region *r*:

$$\frac{dn_r(t)}{dt} = Q_{in,r}(t) - Q_{out,r}(t), t > 0$$
(7.1)

where $n_r(t)$ is the accumulation of vehicles inside region r at a given instant t; $Q_{in,r}(t)$ and $Q_{out,r}(t)$ are the inflow and outflow functions, respectively.

Depending on the assumptions made on the outflow function $Q_{out,r}$, two MFD-based models can be distinguished in the literature: the accumulation-based model (Daganzo 2007; Geroliminis & Daganzo 2008); and the trip-based (Arnott 2013; Fosgerau 2015; Lamotte & Geroliminis 2016; Mariotte et al. 2017).

The literature on dynamic traffic assignment applied to regional networks and MFD based models is recent and not yet extensive. The first efforts to combine a dynamic traffic assignment framework with an MFD model were discussed by Leclercq & Geroliminis (2013) in the simplest case of parallel networks without route overlapping. Laval et al. (2017) analyzed the analytical solutions of the Dynamic User Equilibrium for a network composed of one Origin-Destination and two alternatives: one free-way with a fixed capacity; and a city street modeled by MFD dynamics. For this simple network, the authors were able to determine analytical solutions for a non-overlapping network with constant trip lengths. Yildirimoglu & Geroliminis (2014) were certainly the first to propose a framework that can be applied to

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Fig. 7.1 – (a) City network with three trips represented. The partition of the city network is also shown. (b) Regional network where the gray circles represent the regions and the gray arrows represent the connections between the different regions. (c) Partition of the city network with the respective green and blue regional paths associated with the three trips. (d) Zoom of the gray region with a well-defined MFD function and crossed by the green and blue regional paths, each with a corresponding trip length L_1 and L_2 .

multi-regional MFD models. However, their framework did not have an explicit description of trip lengths in the regional network as trip lengths were updated at each iteration of the network loading. Furthermore, the authors considered a Multinomial Logit formulation that did not account of correlations between regional paths. Yildirimoglu & Geroliminis (2014) also stressed that distributions of regional trip lengths should be considered to characterize regional paths inside each of the regions crossed.

In this chapter, we formulate a dynamic traffic assignment framework for MFD models that (i) is based on the explicit description of regional trip length distributions and (ii) accounts for the correlation between regional paths and traffic dynamics inside the regions. For point (i), we need to introduce a scaling process between the real city network and the regional one that is further described in Chapter 6. The city network (Fig. 7.1 (a)) includes all connected links corresponding to the existing roads. Local trips are defined by the sequence of links from the origin (o) to the destination (d) nodes inside the city network. The regional network is shown in Fig. 7.1 (b). A regional path is defined as the ordered sequence of regions that are crossed from the regional Origin (O) to Destination (D). Generically, a regional path p can be defined as:

$$p = (p_1, \dots, p_m, \dots, p_R), \forall m = 1, \dots, R \land m \in X$$

$$(7.2)$$

where R is the number of regions that define p; p_1 and p_R are the Origin (O) and Destination (D) regions, respectively.

In Fig. 7.1 (a), we show three examples of trips highlighted in green and blue. The corresponding regional paths are shown in Fig. 7.1 (c). As highlighted by the green trips, several trips may exist in the city network that cross the same sequence of regions and consequently define the same regional path. The latter gives an interesting property to the regional paths. As can be observed in Fig. 7.1 (a), the green trips travel different distances inside each region they cross. The green regional path is then characterized by distributions of trip lengths inside each region. Let L_{rp} be the set of trip lengths of regional path p $(\forall p \in \Omega^{OD} \land \forall (O, D) \in W)$ inside region r $(\forall r \in p)$. Ω^{OD} is the regional choice set for the OD pair and W is the set of all OD pairs of the regional network. In Chapter 6, we discuss several methods to characterize the trip length distributions of each regional path for a region, given the topology and partition of the city network. The methods differ from each other as a function of the level of aggregation of the trip length information inside regions, when scaling up the city into the regional network. As discussed in Chapter 6, a similar distribution of trip lengths can be considered for all the regional paths that cross the same region. However, the description of regional trip lengths can be refined by considering the trip length of a regional path inside a region and taking into account the successive and/or previous regions, or even the specific regional path itself. In this chapter, we will consider only the most detailed description, i.e. all regional paths have a specific trip length distribution inside each region.

An important aspect in dynamic network loading models is the correlation between paths. This dictates the sharing of information between different paths and how the path choices of different users will affect each other. In the city network, two trips are correlated if they share links in common (see for example the red links in Fig. 7.1 (a) that are shared by green

and blue trips). The correlation between regional paths is different. To better emphasize this, we zoom on the gray region crossed by the blue and green regional paths (Fig. 7.1 (d)). The traffic states inside this region are described by a single MFD, e.g. in Fig. 7.1 (d). The correlation between the blue and green regional paths occurs due to the MFD assumption of homogeneous traffic conditions inside the gray region, i.e. all vehicles traveling inside this region have the same speed. In fact, due to the MFD dynamics, a vehicle that enters the gray region will increase its accumulation n_r . This will automatically affect the region speed $v_r(n_r)$ and the travel times of all the vehicles already traveling inside this region, whatever their regional paths are.

In short, two important variables influence vehicles' travel times in the regional network: the trip length distributions of regional paths and the evolution of mean speed inside each region. The first element stems from the spatial distribution of local trips that are gathered to form a single regional path inside each region. The second element is related to the temporal distribution of regional speed over the assignment period, i.e. the period of time when regional path flow distributions are maintained constant. The framework proposed in this chapter explicitly accounts for these two factors by defining different utility functions. In practice, only the more detailed utility function accounts for both factors simultaneously. The other definitions are set for the purposes of comparison and precisely assess the influence of these two factors. Network equilibrium is calculated through the Method of Successive Averages. Monte Carlo simulations are used to accommodate the regional path trip length distributions and the regional mean speed evolution over time. The methodology is described in more detail in Sect. 7.2. In Sect. 7.3, two simple test cases with one and two regions are presented to analyze in detail the components of the utility function definitions and to assess the importance of considering trip length and mean speed distributions. In Sect. 7.4, we then investigate the application of the proposed regional dynamic traffic assignment framework on the 6th district of the Lyon network (France), where the trip lengths are explicitly scaled from the city network in accordance with the methodology discussed in Chapter 6. In Sect. 7.5, we outline the conclusions of this chapter.

7.2 Regional dynamic traffic assignment: methodological framework

In this section, we describe the methodological framework of the dynamic traffic assignment for multi-regional MFD models.

In the city network, users classically evaluate their trip choices based on the perceived travel times U_k^{od} :

7.2. Regional dynamic traffic assignment: methodological framework

$$U_k^{od} = \overline{TT_k^{od}} + \epsilon_k^{od}, \forall k \in \Omega^{od} \land \forall (o, d) \in \Xi$$
(7.3)

where $\overline{TT_k^{od}}$ is the average travel time over the assignment period on the local trip k for od pair; Ω^{od} is the route choice set for the od pair; Ξ is the set of all od pairs; and ϵ_k^{od} is the error term that accounts for the travel time uncertainty.

The travel times evolve with the changes of the traffic conditions in each link of the city network. In regional networks, travel times are not only influenced by changes of the traffic conditions inside regions, but also by the trip length distributions. We notice here a clear difference with the city network, where link lengths are constant and similar for all paths that take the same link. Not only do the regional paths that cross the same region have different mean trip lengths, they also have different trip length distributions. Therefore, the travel time of a *p* of regional OD pair, TT_p^{OD} , can be calculated as:

$$TT_{p}^{OD} = \sum_{r \in X} \left(\frac{L_{rp}}{v_{r}(n_{r})} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.4)

where δ_{rp} is a dummy variable that equals 1 if regional path *p* crosses region *r*, or 0 otherwise. We consider that the following two terms can be distributed:

- the empirical set of trip lengths $\{L_{rp}\}$, for each region r that defines p.
- the time varying speed-MFD set $v_r(n_r)$ of each region r that defines p.

Depending on which distributions are considered, four utility functions can be defined to describe all regional path alternatives for each OD pair. In this chapter, we target the User Equilibrium, considering different formulations of the utility function. They are defined based on a first order Taylor expansion of Eq. 7.4 around the mean values of $\overline{L_{rp}}$ and $\overline{v_r}$ as well as on which terms we consider to be distributed. Then, we define the four following utility functions:

• Utility 1: neither the set of trip lengths L_{rp} nor the set of mean speeds $v_r(n_r)$ are considered distributed. The perceived cost U_p^{OD} is:

$$U_{\rho}^{OD} = \sum_{r \in X} \left(\frac{\overline{L_{rp}}}{\overline{v_r}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.5)

where $\overline{L_{rp}}$ is the average trip length of regional path *p* inside region *r*; and $\overline{v_r}$ is the mean speed of region *r*.

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• *Utility 2:* only the set of trip lengths L_{rp} is considered distributed. The perceived cost U_p^{OD} is:

$$U_{p}^{OD} = \sum_{r \in X} \left(\frac{\overline{L_{rp}}}{\overline{v_{r}}} + \frac{1}{\overline{v_{r}}} (L_{rp} - \overline{L_{rp}}) \right) \delta_{rp}$$
$$= \sum_{r \in X} \left(\frac{L_{rp}}{\overline{v_{r}}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.6)

• *Utility 3:* only the set of mean speed $v_r(n_r)$ is considered distributed. The perceived cost U_p^{OD} is:

$$U_{p}^{OD} = \sum_{r \in X} \left(\frac{\overline{L_{rp}}}{\overline{v_{r}}} + \frac{\overline{L_{rp}}}{\overline{v_{r}}^{2}} (v_{r} - \overline{v_{r}}) \right) \delta_{rp}$$
$$= \sum_{r \in X} \left(\frac{\overline{L_{rp}} v_{r}}{\overline{v_{r}}^{2}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.7)

• Utility 4: both the sets of trip lengths L_{rp} and mean speeds $v_r(n_r)$ are considered distributed. The perceived cost U_p^{OD} is:

$$U_{p}^{OD} = \sum_{r \in X} \left(\frac{\overline{L_{rp}}}{\overline{v_{r}}} + \frac{1}{\overline{v_{r}}} (L_{rp} - \overline{L_{rp}}) + \frac{\overline{L_{rp}}}{\overline{v_{r}}^{2}} (v_{r} - \overline{v_{r}}) \right) \delta_{rp}$$
$$= \sum_{r \in X} \left(\frac{L_{rp}}{\overline{v_{r}}} + \frac{\overline{L_{rp}} v_{r}}{\overline{v_{r}}^{2}} - \frac{\overline{L_{rp}}}{\overline{v_{r}}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.8)

where v_r is a conditional distribution of L_{rp} during the simulation period. Nevertheless, after the simulation period the variance of v_r should be independent of the one of L_{rp} . This is assumption is investigated in more detail in Sect. 7.3.5.

These four utility function definitions, defined by Eq. 7.5 to Eq. 7.8, allow calculating different network equilibria. Hereafter, we refer to the network equilibrium related to the utility definitions from Eq. 7.5 to Eq. 7.8 as *Equilibrium 1* to *Equilibrium 4*, respectively. In this chapter, we consider *Equilibrium 4* as the reference because it accounts for distributions of the two key elements mentioned in the introduction.

To calculate the regional network equilibrium defined by any of the utility functions Eq. 7.5 to Eq. 7.8, we consider the Method of Successive Averages (MSA). The MSA is based on a descent step finding procedure. The new regional path flows $Q_p^{OD,j+1}$, at descent step j + 1,

are updated according to the regional path flows $Q_p^{OD,j}$, at descent step j, and to the new temporary regional path flows $Q_p^{OD,*}, \forall (O, D) \in W$, as:

$$Q_p^{OD,j+1} = Q_p^{OD,j} + \alpha_j \{Q_p^{OD,*} - Q_p^{OD,j}\}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.9)

The question is how to determine the new temporary regional path flows $Q_p^{OD,*}$, considering the utility functions defined in Eq. 7.5 to Eq. 7.8. This is done by performing Monte Carlo simulations. From the sets $\{L_{rp}\}$ and $v_r(n_r)$, we gather samples L_{rp}^l and v_r^h , respectively, depending on the specificities of each utility function definition. Note that $v_r(n_r)$ time series is given considering the simulation time-step of 1 second. Moreover, $v_r(n_r)$ is a conditional distribution given the distribution of trip lengths $\{L_{rp}\}$ throughout the simulation period. The dynamic network loading is performed given trip length distributions for regional paths, directly influencing $v_r(n_r)$. For each Monte Carlo trial and each OD pair, we calculate the regional path utilities and assign users based on an all-or-nothing procedure to the regional path with the minimal utility. Let L_{rp}^l be a trip length sample *l* gathered from the set $\{L_{rp}\}$ and v_r^h be a mean speed sample *h* gathered from the set $v_r(n_r)$. The new temporary regional path flows $Q_p^{OD,*}$ are updated by averaging all the users' choices over all Monte Carlo samples. In more detail for each regional network equilibrium:

- Equilibrium 1: For each regional OD pair, we calculate the mean speed $\overline{v_r}$ and mean trip length $\overline{L_{rp}}$ and then the regional path utilities following Eq. 7.5. The temporary regional path flows, $Q_p^{OD,*}$, are updated as $Q_p^{OD,*} = 1$, if $V_p^{OD} = \min(\overrightarrow{V^{OD}})$, $\forall p \in \Omega^{OD} \land \forall (O, D) \in W$.
- Equilibrium 2: For each regional path, we uniformly draw trip length samples L_{rp}^{l} from $\{L_{rp}\}$. Let $N_{L_{rp}}^{MC}$ be the total number of samples considered for the trip lengths. We also calculate the mean speed $\overline{v_r}$ for each region. The trip length distribution L_{rp} in Eq. 7.6 is discretized into the L_{rp}^{l} samples. From Eq. 7.6, the regional path utility U_p^{l} is calculated as:

$$U'_{p} = \sum_{r \in X} \left(\frac{L'_{rp}}{\overline{v_{r}}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.10)

• Equilibrium 3: For each regional path, we uniformly draw mean speed samples v_r^h from $v_r(n_r)$ time series. Let $N_{v_r}^{MC}$ be the total number of samples for the mean speed $v_r(n_r)$ set. We calculate the mean speed $\overline{v_r}$ for each region and the average trip lengths of each regional path p inside region r. The mean speed distribution $v_r(n_r)$ in Eq. 7.7 is

discretized into the v_r^h samples. From Eq. 7.7, the regional path utility U_p^h is calculated as:

$$U_{p}^{h} = \sum_{r \in \mathcal{X}} \left(\frac{\overline{L_{rp}} v_{r}^{h}}{\overline{v_{r}}^{2}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.11)

• Equilibrium 4: For each regional path, we independently draw uniform trip length samples L_{rp}^{l} from $\{L_{rp}\}$ and mean speed samples v_{r}^{h} from $v_{r}(n_{r})$. The mean speed $\overline{v_{r}}$ for each region and the average trip lengths of each regional path p inside region r are also calculated. In Eq. 7.8, both the L_{rp} and $v_{r}(n_{r})$ distributions are discretized into the L_{rp}^{l} and v_{r}^{h} samples, respectively. From Eq. 7.8, the regional path utility U_{p}^{lh} is calculated as:

$$U_{p}^{lh} = \sum_{r \in X} \left(\frac{L_{rp}^{l}}{\overline{v_{r}}} + \frac{\overline{L_{rp}}v_{r}^{h}}{\overline{v_{r}}^{2}} - \frac{\overline{L_{rp}}}{\overline{v_{r}}} \right) \delta_{rp}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(7.12)

For the MSA implementation, we also have to define the descent step α_j , where j is the descent iteration, to ensure good convergence properties. In this chapter, we consider that $\alpha_j = \frac{1}{j}$. On the other hand, we must also define the convergence criteria of the MSA algorithm. To do this, we follow the work of Sbayti et al. (2007) and consider:

• the relative Gap:

$$Gap = \frac{\sum_{O} \sum_{D} \sum_{p \in \Omega^{OD}} Q_p^{OD}(V_p^{OD} - \min(\overrightarrow{V^{OD}}))}{\sum_{O} \sum_{D} Q^{OD} \min(\overrightarrow{V^{OD}}))}$$
(7.13)

where $\overrightarrow{V^{OD}} = \{V_p^{OD}\}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$. The Gap function is also an indicator of the network equilibrium quality that indicates how far we are from the User Equilibrium. We consider that the network equilibrium is achieved if $Gap \leq tol$, where tol is a pre-defined tolerance.

- the number of violations $N(\lambda)$. It consists in comparing the regional path flows at descent iteration j+1, $Q_p^{OD,j+1}$, with those at descent iteration j, $Q_p^{OD,j}$. $N(\lambda)$ represents the number of cases where $|Q_p^{OD,j+1} Q_p^{OD,j}|$ is higher than a pre-defined threshold Φ (Sbayti et al. 2007), where Φ is an upper bound. Convergence is achieved if $N(\lambda) \leq \Phi$.
- a maximum number of iterations N_{max} .

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Input the regional choice set Ω^{OD} , $\forall (O, D) \in W$, the set of trip lengths L_{rp} , $\forall p \in \Psi \land \forall r \in X$. Input the demand scenario and simulation duration T. Initialize j = 1, $\alpha_{j=1} = 1$, tol, ϕ and N_{max} . if Equilibrium 2, 3 or 4 then Initialize $N_{L_{rp}}^{MC}$ and $N_{v_r}^{MC}$. end Initialize the route flows $Q_{0}^{OD,j=1} = 0, \forall k \in \Omega^{OD} \land \forall (O, D) \in W.$ Perform an initial network loading. while $Gap \ge tol \operatorname{and}/\operatorname{or} N(\lambda) \ge \Phi \operatorname{and} j \le N_{max}$ do Set $Q_p^{OD,j} = Q_p^{OD,j+1}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W.$ if j=1 then For all regions $r \in X$, the mean speed $\overline{v_r}$ corresponds to the free-flow speed. else For all regions $r \in X$, calculate the average mean speed $\overline{v_r}$ based on v_r . end if Equilibrium 1 then Calculate U_p^{OD} , $\forall p \in \Omega^{OD} \land \forall (O, D) \in W$ according to Eq. 7.5. For each $(O, D) \in W$, users are assigned based on an all-or-nothing procedure to the regional route p with the minimal U_p^{OD} . Update the new route $Q_p^{OD,*}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$. end if Equilibrium 2 then for l=1 to $N_{L_{rp}}^{MC}$ do For each region $r \in p \land \forall p \in \Omega^{OD}$, draw one trip length sample L_{pr}^{l} from $L_{rp}, \forall r \in p \land \forall p \in \Omega^{OD} \land \forall (O, D) \in W.$ Calculate U_p^l according to Eq. 7.10 $\forall p \in \Omega^{OD} \land \forall (O, D) \in W$. For each $(O, D) \in W$, assign users based on an all-or-nothing procedure to the regional path p with the minimal perceived utility. end end if Equilibrium 3 then for h=1 to $N_{v_r}^{MC}$ do For each region $r \in p \land \forall p \in \Omega^{OD}$, draw one a mean speed sample v_r^h from $v_r, \forall r \in p \land \forall p \in \Omega^{OD} \land \forall (O, D) \in W.$ Calculate U_p^h according to Eq. 7.11 $\forall p \in \Omega^{OD} \land \forall (O, D) \in W$. For each $(O, D) \in W$, assign users based on an all-or-nothing procedure to the regional path p with the minimal perceived utility. end end if Equilibrium 4 then for I=1 to $N_{L_{rp}}^{MC}$ do for h=1 to $N_{v_r}^{MC}$ do For each region $r \in p \land \forall p \in \Omega^{OD}$, draw one trip length sample L_{pr}^{l} from L_{rp} and one mean speed sample v_r^h from v_r , $\forall r \in p \land \forall p \in \Omega^{OD} \land \forall (O, D) \in W$. Calculate U_p^{lh} according to Eq. 7.12 $\forall p \in \Omega^{OD} \land \forall (O, D) \in W$. For each $(O, D) \in W$, assign users based on an all-or-nothing procedure to the regional path p with the minimal perceived utility. end end Update the new temporary regional path flows $Q_{o}^{D,*}$ by averaging all the users' choices over all Monte Carlo samples end Update the route flows based on $Q_p^{OD,j+1}$ based on Eq. 7.9. Run the MFD-based model (either the accumulation- or trip-based MFD model). Update $v_r, \forall r \in X$, based on the traffic states resulting from the MFD-based model. Calculate Gap (Eq. 7.13) and $N(\lambda)$. Update $\alpha_j = \frac{1}{j}$. Set j = j + 1. end Save the route flows: $Q_p^{OD,j+1}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$.

Algorithm 5: Regional dynamic traffic assignment framework for MFD-based models.

The MSA loop is repeated until the convergence criteria are satisfied. Algorithm 5 summarizes the MSA loop and Monte Carlo implementations for the four utility functions.

7.3 Analysis of the regional dynamic traffic assignment framework on simple regional networks

In this section, we analyze the implementation of the regional dynamic traffic assignment framework discussed in the previous section, in two simple regional networks: one region and one regional OD pair (Sect. 7.3.2); and two regions and two regional OD pairs (Sect. 7.3.3). In Sect. 7.3.4, we investigate if the proposed framework handles the correlation between regional paths. In Sect. 7.3.5, we verify that the variance of the regional mean speed σ_{v_r} does not depend on the variance of the trip length distributions σ_L in our simulations.

7.3.1 Test scenarios definition

For the first test scenario, we consider a regional network consisting of one region and one regional OD pair connected by two regional paths. We show the regional network in Fig. 7.2, where the two regional paths are highlighted in orange. Let L_1 and L_2 be the distributions of trip lengths inside the region. We consider a bi-parabolic MFD function with: critical jam accumulation $n_{jam} = 1000$ veh; critical production $P_{critical} = 3000$ veh.m/s; and free-flow speed u = 15 m/s.



Fig. 7.2 – *Left:* Regional network. One regional OD pair is shown, with two regional paths with distributions of regional trip lengths L_1 and L_2 . *Right:* The demand scenario for the OD pair and for the tests of Sect. 7.3.2 and Sect. 7.3.4.

For the second test scenario, we consider a regional network consisting of two regions and two regional OD pairs connected by two regional paths each. We show the regional network in Fig. 7.3. Let: L_1 and L_2 be the regional trip length distributions for the orange regional paths; and L_3 and L_4 be the regional trip length distributions for the green regional paths. The traffic states inside each of the two regions are defined by a parabolic MFD function

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Fig. 7.3 – *Left:* Regional network consisting of two regions labeled R_1 and R_2 . Two DO pairs are shown with two regional paths connecting each one. *Right:* Demand scenarios for the two OD pairs and for the tests of: (a) Sect. 7.3.3 and Sect. 7.3.4; (b) Sect. 7.3.5.

with: critical jam accumulation $n_{jam} = 1000$ veh; critical production $P_{critical} = 2000$ veh.m/s; and free-flow speed u = 15 m/s.

For all the MFD simulations performed in this section, we consider a simulation period of T = 800 seconds. For the network equilibrium convergence, we set a maximum number of violations of $\Phi = 0$ and/or a Gap tolerance $tol \leq 0.01$ and a maximum of descent step iterations of $N_{max} = 100$. For the Monte Carlo simulations, we consider $N_{L_{rp}}^{MC} = N_{v_r}^{MC} = 10000$ samples.

7.3.2 Analysis of the regional path flows at equilibrium: 1-region test case

We analyze the regional path flows calculated for the four network equilibrium definitions (i.e. defined Eq. 7.5 and Eq. 7.8). We investigate how different the regional path flows for the reference Equilibrium 4 are in comparison to the other three network equilibria. The trip lengths for the two regional paths are sampled according to a normal distribution with: a fixed mean $\overline{L_2} = 1500$ [m] for regional path 2; and a varying mean values between 1300 to 1700 [m] increasing step size by 25 [m] for regional path 1. We consider three values of the standard deviation $\sigma_L = 50, 100, 200$ [m], similar for both regional paths.

In Fig. 7.4, we show the regional path flows for the four network equilibria as a function of $\overline{L_1}$ and the three values of σ_L .

Equilibrium 1 is purely deterministic since we consider that neither the L_{rp} nor v_r are distributed. For this equilibrium, since the MFD dynamics is the same for both regional paths,

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Fig. 7.4 – Regional path flows for the four network equilibria as function of $\overline{L_1}$ and for the 1 region network (Fig. 7.2). For Equilibrium 2 and 4, three values of σ_L are considered.



Fig. 7.5 – Evolution of the speed v_r [m/s] as a function of the simulation time t [s] for Equilibrium 3 and four values of $\overline{L_1} = 1300, 1400, 1500, 1600$ [m].



Fig. 7.6 – Evolution of the mean speed $\overline{v_1}$ [m/s] (left panel) and of the standard deviation σ_{v_1} [m] (right panel) as a function of the average trip length $\overline{L_1}$ [m], for Equilibrium 3.

only the average trip lengths $\overline{L_1}$ and $\overline{L_2}$ modify the perceived utility functions. When $\overline{L_1} < \overline{L_2}$, implying $U_1 < U_2$, all vehicles choose the minimum utility that corresponds to regional path 1. For $\overline{L_1} = \overline{L_2} = 1500$ [m], implying $U_1 = U_2$, vehicles equally choose regional paths 1 and 2. For $\overline{L_1} > \overline{L_2}$, implying $U_1 > U_2$, all vehicles choose regional path 2. The evolution of the regional path flows as a function of the increase of $\overline{L_1}$ is completely different to those obtained by our reference, i.e. Equilibrium 4.

For Equilibrium 3, the regional path flows at equilibrium depend on the average trip lengths $\overline{L_1}$ and $\overline{L_2}$ and on the mean speed distribution $v_r(n_r)$ (see Eq. 7.7). This definition of the network equilibrium is independent of σ_L . Consequently, only one evolution of the regional path flows is shown by the dashed black line in Fig. 7.4. In Fig. 7.5, we show the evolution of the speed v_r [m/s] for Equilibrium 3 and four values of $\overline{L_1}$ [m]. In Fig. 7.6, we show the evolution of the mean speed $\overline{v_1}$ and of the standard deviation σ_{v_1} as a function of the $\overline{L_1}$ increase. In Fig. 7.7, we show the distributions of the regional path utilities $U_1^{OD_1}$ and $U_2^{OD_1}$. We also set a criterion α that defines the normalized difference between the regional path utilities:

$$\alpha = \frac{U_2^{OD_1} - U_1^{OD_1}}{U_2^{OD_1}} \tag{7.14}$$

The α criterion allows predicting the route flow distributions. If $\alpha > 0$, the vehicles choose regional path 2 for these Monte Carlo trials. The distributions of α directly gives an immediate overview of the flow distribution between the two regional paths. The distributions of the α criterion are also shown in Fig. 7.7, for four values of $\overline{L_1}$ [m]. In Fig. 7.7, we observe the presence of two peaks for the regional path utilities $U_1^{OD_1}$ and $U_2^{OD_1}$. These peaks correspond to the fluid and congested regimes of the traffic states inside the region. This is also observed in the evolution of the speed v_1 in Fig. 7.5. In Fig. 7.6, we observe that both the mean speed $\overline{v_1}$ and the standard deviation σ_{v_1} do not vary greatly as $\overline{L_1}$ increases. Moreover, σ_{v_1} is small. The regional path flows at equilibrium will then be more dependent on how close the average trip lengths are $\overline{L_1}$ and $\overline{L_2}$. We depict this in more detail, analyzing the regional path utility distributions shown in Fig. 7.7. For $\overline{L_1} = 1300$ [m], σ_{ν_1} is not sufficiently large to compensate the distance between $\overline{L_1}$ and $\overline{L_2}$. From the Monte Carlo trials, we obtain $U_2^{OD_1} > U_1^{OD_1}$ for all the samples, as shown by the α distribution in Fig. 7.7. Thus, all vehicles choose regional path 1, since $\alpha < 0$. The average trip length for $\overline{L_1} = 1400$ [m] is closer to $\overline{L_2} = 1500$ [m] and the effect of σ_{v_1} has an impact on the regional path flows. $U_2^{OD_1}$ is perceived as the minimal one for several Monte Carlo samples, as evidenced by the overlap between the regional path utility distributions and the α criterion. Hence, some vehicles choose regional



Fig. 7.7 – *Left:* Distributions of the regional path utilities $U_1^{OD_1}$ and $U_2^{OD_1}$. *Right:* α criterion distribution. The results are shown for Equilibrium 3 and four values of $\overline{L_1}$ [m]. The vertical red dashed line represents the value at $\alpha = 0$.

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Fig. 7.8 – Regional path utility distributions $U_1^{OD_1}$ and $U_2^{OD_1}$, for Equilibrium 2 (left) and 4 (right) and $\overline{L_1} = 1600$ [m]. The results are shown for the three values of σ_L .

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Fig. 7.9 – α distributions for Equilibrium 2 (left) and 4 (right), $\overline{L_1} = 1600$ [m] and three values of $\sigma_L = 50, 100$ and 200 [m]. The vertical red dashed line represents the value at $\alpha = 0$.

path 2 (see Fig. 7.4). For $\overline{L_1} \in [1375, 1475]$ [m], the regional paths are approximately similar because the intersection between the regional path utilities is relatively small. This is due to the fact that σ_{v_1} is approximately constant as a function of $\overline{L_1}$ (see Fig. 7.6). Since all the demand of the OD pair can cross only this region, the evolutions of the traffic states are approximately similar. As $\overline{L_1}$ increases, vehicles switch from regional path 1 to 2. This offsets the evolution of the speed v_1 inside the region. For $\overline{L_1} = \overline{L_2} = 1500$ [m], both regional path utility distributions are equal and vehicles choose both regional paths equally as shown in Fig. 7.4. For $\overline{L_1} = 1600$ [m], the distribution of $U_1^{OD_1}$ is shifted towards larger values compared to $U_2^{OD_1}$ due to the increase of $\overline{L_1}$. As $\overline{L_1}$ increases, vehicles that choose regional path 1 need more time to complete their trips inside the region, reducing the speed v_1 . This shifts the distribution of $U_1^{OD_1}$ towards higher values compared to the distribution of $U_2^{OD_1}$. Thus, around 80% of the vehicles choose regional path 2. For larger values of $\overline{L_1} \ge 1700 \text{ [m]}$ all vehicles choose regional path 2 since $U_1^{OD_1} > U_2^{OD_1}$. The evolution of the regional path flows as $\overline{L_1}$ increases for Equilibrium 3 is completely different from that of Equilibrium 4 for the three σ_L values considered (see Fig. 7.4). This enhances the importance of taking into account the trip length distributions, when calculating the regional path flows distributions.

Equilibrium 2 considers that only the trip lengths L_{rp} are distributed. Equilibrium 2 and 4 give similar regional path flows for larger values of $\sigma_L = 200$. This is because the influence of σ_{v_1} becomes less significant for large σ_L values. For the three σ_L values and for $\overline{L}_1 =$ $\overline{L}_2 = 1500$ [m], the regional path utilities of Equilibrium 2 and 4 are similar. Consequently, vehicles choose both regional paths equally. To investigate the similarities and differences between Equilibrium 2 and 4 in more detail, we fix $\overline{L}_1 = 1600$ [m] and analyze the regional path utility distributions (Fig. 7.8) for the three values of σ_L . We also consider the respective distributions of α (Fig. 7.9). The similarities between both network equilibria depend on the standard deviation σ_L and on the position of the two peaks of the regional path utilities for Equilibrium 3 compared to those of Equilibrium 2 (see e.g. Fig. 7.8). This is because the reference Equilibrium 4 is a convolution of Equilibrium 2 and 3 regional path utilities (see Eq. 7.8). For $\sigma_L = 50$ [m], the convolution between the regional path utilities of Equilibria 2 and 3, leads to a bi-variate shape for the regional path utilities of Equilibrium 4 (Fig. 7.8). The latter occurs since the σ_L value is not sufficiently large to offset the distance between the two peaks of the regional path utilities of Equilibrium 3, i.e. the effect due to σ_{v_1} . For larger $\sigma_L = 200 \text{ [m]}$ values, the σ_L offsets the influence of σ_{v_1} and the regional path flows between Equilibrium 2 and 4 are similar. These two effects offset each other and lead to a similar regional path flows between Equilibria 2 and 4, as also shown by the α criterion. For larger $\sigma_L = 100, 200 \text{ [m]}$ values, these two peaks vanish from the regional path utilities as observed

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in Fig. 7.8. Nevertheless, after convolution, they still control where the largest fraction of the regional path utilities for Equilibrium 4 will be located. For the case shown in Fig. 7.8, the overlap between $U_1^{OD_1}$ and $U_2^{OD_1}$ is similar for both Equilibrium 2 and the reference Equilibrium 4. Therefore, as also evidenced by the α criterion, the regional path flows are similar between both regional paths.

Equilibrium 2 gives the regional path flow distributions closest to those of Equilibrium 4, but the differences become more significant for lower values of σ_L , showing the importance of also considering that v_r is distributed. Despite the regional path flows between Equilibrium 2 and 4 are similar for this test case and larger values of $\sigma_L = 200$ [m], this might not be true when there are also interactions between different regional OD pairs. This is investigated in the next section. In brief, we cannot neglect the variability of trip lengths and traffic states inside the region. If we do so, we may obtain regional path flows that are very different from those given by the reference Equilibrium 4.

7.3.3 Analysis of the regional path flows at equilibrium: the 2-region test case

In this section, we investigate how different the regional path flows calculated for the reference Equilibrium 4 are compared to the other three network equilibria for a more complex two-region test case. The trip lengths for the four regional paths are also sampled according to a normal distribution with: fixed mean lengths $\overline{L_1} = 1400$, $\overline{L_2} = 1500$ and $\overline{L_4} = 1700$ [m] for regional paths 1, 2 and 4, respectively; and an increasing mean trip length $\overline{L_3}$ between 1200 and 2200 [m] varying stepwise by 25 [m]. We also consider three values of the standard deviation $\sigma_L = 50, 100, 200$ [m].

We focus our analysis on the regional OD_2 pair since it is the most interesting one. In this test setting, all the demand of the regional OD_1 passes through region R_1 . This influences the regional path flows of OD_2 , since regional path 3 passes through region R_1 .

In Fig. 7.10, we show the path flows as a function of $\overline{L_3}$, for regional paths 3 and 4 and the four network equilibria. First, it can be observed that the flows of regional paths 3 and 4 are not equally distributed when $\overline{L_3} = \overline{L_4} = 1700$ [m], due to the interaction with the OD_1 . The regional path flows are equally distributed for different values of $\overline{L_3}$, depending on the network equilibrium. Second, the regional path flows for Equilibria 1 and 3 are those that differ most in comparison to the reference Equilibrium 4. We start by analyzing Equilibrium 1 in more detail. Vehicles switch from regional path 3 to 4 as $\overline{L_3}$ increases, such that the condition $U_3^{OD_2} = U_4^{OD_2} \Rightarrow \frac{\overline{L_3}}{\overline{L_4}} = \frac{\overline{Y_1}}{\overline{Y_2}}$ is satisfied. To analyze the differences and similarities between Equilibria 2 and 3 compared to the reference Equilibrium 4, we analyze the regional path flows for a fixed value of $\overline{L_3} = 1850$ [m]. To do this, we consider the distributions of the

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Fig. 7.10 – Path flows as function of $\overline{L_3}$, for regional paths 3 and 4 that connect the OD_2 pair. For Equilibria 2 and 4, three values of σ_L are considered.

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Fig. 7.11 – Distributions of the regional path utilities $U_3^{OD_2}$ and $U_4^{OD_2}$ for Equilibrium 2 to 4. The results are shown for $\overline{L_3} = 1850$ [m]. For Equilibrium 2 and 4, two values of $\sigma_L = 50, 100$ [m] are considered.

regional path utilities $U_3^{OD_2}$ and $U_4^{OD_2}$ for $\overline{L_3} = 1850$ [m]. The results are shown in Fig. 7.11.

As with the analysis of the previous section test case, the shape and overlap between $U_3^{OD_2}$ and $U_4^{OD_2}$ for the reference Equilibrium 4 depend on the position of the distribution peaks for Equilibrium 3 compared to the positions of the distributions for Equilibrium 2, and on the standard deviation σ_L . We first consider the case of $\sigma_L = 50$ [m], in Fig. 7.11. The convolution between the regional path utility distributions of Equilibria 2 and 3 leads to a bivariate distribution for Equilibrium 4. The closeness between the two peaks of different regional path utility distributions for Equilibrium 3, induces a large overlap between $U_3^{OD_2}$ and $U_4^{OD_2}$ for Equilibrium 4. Since this overlap is larger for the reference Equilibrium 4 compared

to Equilibrium 2, the regional path utility $U_3^{OD_2}$ might be perceived as the minimal one for a larger number of Monte Carlo trials. Consequently, for $\overline{L_3} = 1850$ [m], the path flow of regional path 3 is slightly larger for the reference Equilibrium 4 than for Equilibrium 2. But the effects of the convolution between the regional paths utility distributions of Equilibria 2 and 3 are offset for larger values of σ_L . For Equilibrium 3, the regional path utility distributions are similar for $\sigma_L = 50$ and $\sigma_L = 100$, since they do not depend on σ_L . But for larger values of σ_L and for Equilibrium 2, the intersection between $U_3^{OD_2}$ and $U_4^{OD_2}$ increases. This increases the chance that $U_3^{OD_2}$ is perceived as the minimal utility for a larger number of Monte Carlo trials. In this case, it leads to an approach between the regional path flows calculated for Equilibria 2 and 4. In brief, Equilibrium 2 is that which gives the regional path flows closest to the reference Equilibrium 4. However, it is difficult to predict in which circumstances this will occur. This backs the conclusion of the previous section, where we should take into account the effects of the trip length variability as well as the time-evolution of regional traffic states.

7.3.4 The effect of the correlation between regional paths on the network equilibrium

In this section, we show that the framework proposed takes into account the correlation between regional paths, thanks to the Monte Carlo trials performed at the region level. To this end, we compare the regional path flows calculated for Equilibria 2 and 4 with the Multinomial Logit (MNL) model. The MNL assumes that the distribution of travel times over paths are independent and identically Gumbel distributed, with a scale parameter θ . Following Chen et al. (2012), the scale parameter is defined at the origin-destination od level, in city networks. In this chapter, use the regional OD level as baseline, i.e. θ^{OD} . The MNL model has the advantage of having a closed form for the calculation of the regional paths' choice probability. However, the MNL is not able to handle the correlation between regional paths due to the θ^{OD} assumption.

We consider two test scenarios. The first test scenario corresponds to the 1-region network and demand scenario shown in Fig. 7.2. The trip lengths are sampled according to a normal distribution with a fixed mean $\overline{L_2} = 1500$ [m] for regional path 2; and a mean value varying between 1300 to 1700 [m], increasing the step size by 25 [m] for regional path 1. The standard deviations for both regional paths are fixed at $\sigma_L = 50, 100, 200$ [m]. The second test scenario corresponds to the 2-region network and demand scenario shown in Fig. 7.3 (a). The trip lengths are sampled according to a normal distribution with: fixed mean lengths $\overline{L_1} = 1400, \overline{L_2} = 1500$ and $\overline{L_4} = 1700$ [m] for regional paths 1, 2 and 4, respectively; and an increasing mean trip length $\overline{L_3}$ between 1200 and 2200 [m] varying stepwise by 25 [m]. The standard deviations for the four regional paths are fixed at $\sigma_L = 50, 100, 200$ [m].



Fig. 7.12 – *Top:* Regional path flows at equilibrium as a function of $\overline{L_1}$, for the first test scenario. *Bottom:* Regional path flows at equilibrium as a function of $\overline{L_3}$, for the second test scenario.

The scale parameter of the MNL, θ^{OD} , is calibrated according to the previous values of σ_L [m], as:

$$\theta^{OD} = \sqrt{\frac{\pi^2 \overline{v}_r^2}{6\sigma_L^2}} \tag{7.15}$$

In Fig. 7.12, we show the regional path flows for both test scenarios, for Equilibria 2 and 4, and for the MNL. For the first test scenario, we observe that the regional path flows for Equilibrium 2 are similar to those of the MNL. This occurs because we consider an independent sampling of trip lengths, with a similar σ_L value for both regional paths. Moreover, the utility function defined in Eq. 7.6 to calculate Equilibrium 2 does not consider that the regional mean speed set $v_r(n_r)$ is distributed and that the average mean speed \overline{v}_r is the same for both regional paths. On the other hand, the calculation of Equilibrium 4 considers that both

the mean speed and trip lengths are distributed, capturing the correlation between the two regional paths. This is demonstrated by the different regional path flows for Equilibrium 4 and the MNL shown in Fig. 7.12. For large σ_L values, the influence of σ_v is offset. Therefore, the regional path flows are similar for Equilibrium 2 and 4 and the MNL. Whilst, for low σ_L values, σ_v plays an important role and the regional path flows for Equilibrium 2 and the MNL are different than those of the reference Equilibrium 4. For the second test scenario, it can be seen that Equilibrium 2 gives regional path flows different from those of the MNL. This occurs because in this test scenario, we have a correlation between regional paths connecting different regional OD pairs. The latter influences the calculation of the mean speed $\overline{\nu}_r$ for this region and directly influences the utility function defined in Eq. 7.6. On the other hand, the scaling of the θ^{OD} of the MNL is not sensitive to the mean speed $\overline{\nu}_r$, $\forall r = 1, 2$.

In brief, we show the importance of considering the effect of the traffic states in the calculation of the network equilibrium, to capture the correlation between regional paths. Moreover, we show that the reference Equilibrium 4 represents an extension of the dynamic traffic assignment framework for regional networks proposed by Yildirimoglu & Geroliminis (2014). First, our framework accounts for distributions of trip lengths that are explicitly calculated, while Yildirimoglu & Geroliminis (2014) calculated them in an iterative process, as discussed in the introduction. Second, we do not assume any prior statistical distribution for the regional path travel times. Yildirimoglu & Geroliminis (2014) assumed that these terms are identically and independently distributed Gumbel variables and made use of the MNL formulation. Third, our framework captures the correlation between regional paths, while the MNL formulation does not.

7.3.5 Investigating the independence between σ_{v_r} and σ_L

The mean speed distribution $v_r(n_r)$ is a conditional distribution of σ_L , as explained when describing the utility functions in the methodology section (Sect. 7.2). The framework is conditioning the mean speed time series to the trip length distributions. But, after the simulation the variance of the mean speed should be independent of the variance of the trip length distributions. This is investigated in this section and to this end we analyze the standard deviation of the mean speed, σ_{v_r} , for different values of the mean trip length L_3 , σ_L and demand peak for regional OD_1 pair. We consider the regional network shown in Fig. 7.3 and focus on σ_{v_1} for region R_1 . The trip lengths for the four regional paths are sampled according to a normal distribution. For regional paths 1, 2 and 4, we consider fixed mean trip lengths $\overline{L_1} = 1400$, $\overline{L_2} = 1600$ and $\overline{L_4} = 1700$ [m], respectively. For regional path 3, we consider four values for the mean trip length $\overline{L_3} = 1500$, 1600, 1700, 1800 [m]. We consider

the demand scenario shown in Fig. 7.3 (b), where the peak for the OD_2 is increased from 0.4 to 1.5. We vary σ_L between 0 and 100 [m] increasing step size by 10 [m].

In Fig. 7.13, we show the contour plots of σ_{v_1} for region R_1 , for the four values of $\overline{L_3}$. We observe that for a fixed value of the demand peak, σ_{v_1} does not significantly vary across the different values of σ_L . This shows that σ_{v_1} is independent of σ_L after the simulation. Not considering joint correlations when performing the trials of σ_L and σ_{v_1} for Equilibrium 4 is justified because σ_{v_1} is clearly a condition observation since σ_L is known during the simulation period.

7.4 Application to a real test case: the 6th district of the Lyon network

In this section, we demonstrate the importance of considering σ_L and σ_{v_r} in the definition of the utility function for a real setting related to a real city network. The traffic states are simulated through an accumulation-based MFD model (Daganzo 2007; Geroliminis & Daganzo 2008) for the 6th district of the Lyon network (Fig. 7.14 (a)). This network has 757 links and 431 nodes and is divided into 8 regions. The MFD functions (Fig. 7.14 (b)) have been fitted considering microscopic simulations from Symuvia (Leclercq 2007) on the same network, where the demand scenario mimics a morning peak. We further assume a bi-parabolic shape to fit the simulated data.

To explicitly calculate the regional choice set Ω^{OD} and the sets of trip lengths L_{rp} , we consider the formulation discussed in Chapter 6. This framework is based on a set of trips Γ and on the border definition of the regions composing the regional network. We obtain Γ , by sampling $N_{od} = 10000$ od pairs on the 6th district Lyon network and calculating the shortest-paths in distance for each pair. These trips define a total of 205 regional paths. The regional paths are listed with different levels of significance, i.e. different regional paths are defined by a different number of aggregated trips. We define the most significant regional paths for one OD pair as those that are defined by the largest number of trips. In this test scenario, we consider 6 regional paths per each OD pair. This yields a total of 17 regional paths. We explicitly calculate the trip length distributions based on Γ and follow the method discussed in Chapter 6, which considers the related regional path *p*. It consists in filtering the trips by their regional associated path. The set of trip lengths of regional path *p* inside region *r* is calculated as:

$$L_{rp} = \{\delta^{p}_{rk} | _{rk} \}, \forall k \in \Gamma$$

$$(7.16)$$

7.4. Application to a real test case: the 6^{th} district of the Lyon network



Fig. 7.13 – Contour plots of the σ_{v_1} as a function of the demand peak for regional OD_1 pair and σ_L . The results are shown for four mean trip lengths $\overline{L_3} = 1500, 16001700, 1800$ [m].

where I_{rk} is the length of trip k inside region r; and δ_{rk}^{p} is a dummy variable that equals 1 if trip k crosses region r and is associated to regional path p, or 0 otherwise.

We also consider the demand scenario as shown in Fig. 7.14 (c) for the six regional OD pairs. The total simulation period is set to T = 8000 seconds and is divided into 32 assignment periods of 250 seconds each. The network equilibrium is calculated for each period. For the convergence criteria, we consider a maximum number of violations of $\Phi = 0$ and/or a Gap tolerance $tol \leq 0.01$ and a maximum of descent step iterations of $N_{max} = 100$. For the Monte Carlo simulations, we consider $N_{L_{rp}}^{MC} = N_{v_r}^{MC} = 10000$ samples.

In Fig. 7.15, we show the evolution of the mean speed $\overline{v}(t)$ as a function of the simulation time t for the eight regions and the four network equilibria. To investigate the influence of σ_{v_r} on the network equilibrium, we compare the evolution of $\overline{v}(t)$ between Equilibria 1 and 3 as well as of Equilibria 2 and 4. It can be seen that for regions 1 to 3, the evolution of $\overline{v}(t)$ does not show significant differences between the four network equilibria. In fact, the demand scenario is set such that the accumulation of vehicles inside these three regions is low. But for the other five regions, significant differences can be seen between the four network equilibria. A similar evolution trend of $\overline{v}(t)$ for both Equilibria 1 and 3 for regions 4 to 8 can be discerned. Some differences are observed due to the system's dynamics. In general, Equilibrium 3 gives an evolution of $\overline{v}(t)$ similar to that of Equilibrium 1 because σ_{v_r} is small over the period of 250 seconds. Note that for low values of σ_{v_r} , the values in the set $\{v_r(n_r)\}$ are close to \overline{v}_r . Therefore Eq. 7.7 is similar to Eq. 7.5, i.e. $U_p^{OD} \sim \sum_{r \in X} \left(\frac{\overline{L}_{rp}}{\overline{v}_r} \right) \delta_{rp}$. The effect of σ_{v_r} is more significant for the charging and discharging periods of the regions, where it has a larger value. This induces differences in the evolution of $\overline{v}(t)$ that can be observed in regions 6 to 8. On the other hand, for low σ_{v_r} values, Eq. 7.8 reduces to $U_p^{OD} \sim \sum_{r \in X} \sum_{r \in X} \left(\frac{L_{rp}}{\overline{v}_r} \right) \delta_{rp}$, which is similar to the regional path cost defined for Equilibrium 2, i.e. Eq. 7.6. This also explains the similar evolution trends of $\overline{v}(t)$ for Equilibria 2 and 4 and all eight regions. Differences between these two network equilibria can be observed in the charging and discharging periods of the regions, where σ_{v_r} is more significant. To investigate the influence of σ_L on the network equilibrium, we compare the evolution of $\overline{v}(t)$ between Equilibrium 3 and 4. One can observe that the introduction of σ_L completely changes the dynamics of the system. This can be observed in particular for the evolutions of $\overline{v}(t)$ between \sim 3000 and \sim 5000 seconds, for Equilibria 3 and 4 inside regions 4, 6, 7 and 8. These results also highlight the importance of considering that both the trip lengths $\{L_{rp}\}$ and regional mean speeds $v_r(n_r)$ are distributed.

7.4. Application to a real test case: the 6^{th} district of the Lyon network



Fig. 7.14 – (a) Lyon 6^{th} district network divided into 8 regions. (b) MFD function of each region. (c) Demand scenario.

7.4. Application to a real test case: the 6^{th} district of the Lyon network



Fig. 7.15 – Evolution of the mean speed $\overline{v(t)}$ as a function of the simulation time t for the eight regions and the four network equilibria.

7.5. Conclusions

7.5 Conclusions

In this chapter, we propose a regional dynamic traffic assignment framework for MFD-based models that explicitly account for trip length distributions L_{rp} and the evolution of the regional mean speed $v_r(n_r)$. We set four formulations of the network equilibrium, based on which terms are considered distributed. We show that Equilibrium 4, which considers that both trip lengths and regional mean speed are distributed, should be preferred. The results shown in this chapter confirm that we cannot neglect the variability of trip lengths inside the regions. In addition, we showed the importance of considering that the regional mean speed is also distributed, in order to account for the correlation between regional paths. The proposed regional dynamic traffic assignment in the MFD context is an extension of the framework discussed by Yildirimoglu & Geroliminis (2014). First, our framework explicitly accounts for multiple trip lengths inside the regions that are explicitly calculated. Second, we do not assume any prior statistical distribution for the regional path travel times, whereas Yildirimoglu & Geroliminis (2014) considered that they are independent and identically distributed variables. Moreover, the authors used the MNL formulation to calculate the network equilibrium. Instead, we considered the distributions of trip lengths and regional mean speed and used Monte Carlo simulations to calculate the network equilibrium. Contrary to the MNL formulation, our framework was able to capture the correlation between regional paths. We also analyzed the implementation of our framework on the 6th district of the Lyon network, where the trip lengths are explicitly calculated following the specific regional path, as proposed in the previous Chapter 6. Since we calculated the network equilibrium for small simulation periods, the mean speed did not vary greatly and σ_{v_r} was low. In this case, σ_L dominated in the calculation of the utility functions and was responsible for the changes in the system dynamics observed.

In the next Section 7, this regional traffic assignment framework is extended to account for different kinds of users' behavior. In particular, we aim to introduce bounded rational and regret-averse users.

Overview of Part II: Regional dynamic traffic assignment with different behavioral rules

In the following, the outline of this second part of the thesis is provided, summarizing the proposed dynamic traffic assignment framework for multi-regional MFD systems that is discussed in the three previous chapters. To finalize the discussion of this second part, the extension of Equilibrium 4 to different kinds of users behavior is discussed in Sect. II.1. For this purpose, the bounded rational and regret-aversion behavior discussed in the first part of the thesis are considered. In Sect. II.2, a schematic overview of the full regional dynamic traffic assignment framework is given.

II.1 Extension of the regional network equilibrium to different kinds of user's behavior

In this section, the extension of Equilibrium 4 to different kinds of users behavior is discussed. In Part I of the thesis, the influence of different kinds of the users' behavior on the traffic city network performance is investigated. The latter includes the (i) risk-aversion and risk-seeking users' behavior modeled by Prospect Theory (Chapter 3); (ii) users' bounded rationality (Chapter 4); and (iii) regret-averse users (Sect. I.1). The extension of Equilibrium 4 discussed hereafter takes into account bounded rational and regret-averse users. The users risk-aversion and risk-seeking behavior modeled by Prospect Theory is not considered, since they are more likely to behave with a perfect rationality in a choice scenario with few alternatives, as shown in Chapter 3. For this extension, the numerical resolution scheme is in all similar to the one discussed for Equilibrium 4 in Chapter 7. Monte Carlo simulations are used to model the distributions of trip lengths L_{rp} and mean speeds $v_r(n_r)$. The method of Successive Averages is used to calculate the regional network equilibrium. The only difference between the calculation of Equilibrium 4 and the extensions discussed hereafter is that users are assigned based on different rules to the regional paths.

As discussed in Chapter 4, bounded rational users have a *satisficing* behavior and an indifference preference for their regional path choice. Following the methodological framework proposed in that chapter, it is necessary to identify the set of satisficing paths ω^{OD} . For a regional path *p* to be *satisficing*, its utility U_p needs to satisfy the following condition:

$$U_{p} \leq AL^{OD}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(II.1)

where U_p is given by Eq. 7.8; and the aspiration level AL^{OD} depends on the indifference band Δ^{OD} :

$$AL^{OD} = (1 + \Delta^{OD})\min\left(\sum_{r \in X} \left(\frac{\overline{L_{rp}}}{\overline{v_r}}\right) \delta_{rp}, \forall p \in \Omega^{OD}\right), \forall (O, D) \in W$$
(II.2)

The probability of choosing a regional path p given that it is perceived as *satisficing*, is defined by Eq. 4.5. One needs now to calculate the two terms of this equation. First, following the indifference preference rule discussed in Chapter 4:

$$P(\text{choosing regional path } p \setminus U_p \le AL^{OD''}) = \frac{1}{|\omega^{OD}|}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(II.3)

where |.| is the number of *satisficing* regional paths listed in ω^{OD} .

The other probability term $P(U_p \leq AL^{OD})$ is solved by Monte Carlo simulations following the same resolution scheme as discussed for Equilibrium 4 in Chapter 7.

In the case of regret-averse users, they aim to minimize their own regret with respect to the unselected regional paths, as discussed in Sect. I.1. Considering that both the trip lengths L_{rp} and mean speeds $v_r(n_r)$ are distributed, the perceived regret H_p^{OD} of regional path p is:

$$H_{p}^{OD} = \sum_{r \in X} \left(\frac{L_{rp}^{l}}{\overline{v_{r}}} + \frac{\overline{L_{rp}}v_{r}^{h}}{\overline{v_{r}}^{2}} - \frac{\overline{L_{rp}}}{\overline{v_{r}}} \right) \delta_{rp} - R(y) = U_{p}^{lh} - R(y), \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(II.4)

The regret-aversion function R(y) is:

$$R(y) = 1 - e^{-\delta^{OD}y}, \forall p \in \Omega^{OD} \land \forall (O, D) \in W$$
(II.5)

where $y = \min(U_{\rho}^{lh}, \forall p \in \Omega^{OD}) - U_{\rho}^{lh}, \forall (O, D) \in W.$

The methodology adopted to calculate the network equilibrium, considering regret-averse users is in all similar to the one discussed for Equilibrium 4 in Chapter 7. There are only two differences. First, one needs to consider the perceived regret as defined in Eq. II.4 instead of the perceived utility as defined in Eq. 7.8. Second, for each Monte Carlo trial, users are assigned based on an all-or-nothing procedure to the minimal regret regional path instead of the minimal travel time one.

The influence of the users bounded rational and regret-aversion behavior on the evolution of the traffic states, compared against Equilibrium 4 is now investigated. The traffic states are simulated through an accumulation-based MFD model (Daganzo 2007; Geroliminis & Daganzo 2008) for the Villeurbarnne and the 3^{rd} and 6^{th} districts of Lyon network (Fig. II.1 (a)). This network is composed by 3127 nodes and 3363 links and is divided into seven regions. The MFD functions are shown in Fig. II.1 (b) and have been fitted considering microscopic simulations from Symuvia (Leclercq 2007) on the same network. A bi-parabolic shape is further assumed to fit the simulated data. A total of seven OD pairs are considered: 1 to 5; 2 to 7; 4 to 2; 4 to 6; 5 to 2; 6 to 1; and 7 to 3. The regional paths are calculated based on Method 1 discussed in Chapter 5, for all models. A total of 3000000 trips in the city network are calculated to define Γ and ensure a good graph coverage. A maximum of three regional paths per OD pair are considered. The latter yields a total of 21 regional paths that are considered for all the assignment scenarios, including Equilibrium 4 and the different bounded rationality and regret-aversion models settings. Based on the set of trips Γ previously defined, the distributions trip lengths for these regional paths are calculated through Method 4, discussed in Chapter 6. The regional paths and calculated trip lengths L_{rp} are listed in Table II.1. The demand scenario considered is shown in Fig. II.1 (c) for the seven OD pairs. The total simulation period is set to T = 10000 seconds. The latter is divided into 40 assignment periods of 250 seconds each. For the MSA convergence, the $tol = 10^{-2}$, $\Phi = 0$ and $N_{max} = 100$ are set. For the Monte Carlo simulations, $N_{L_{rp}}^{MC} = N_{v_r}^{MC} = 10000$ samples are fixed. Three values of the indifference band $\Delta^{OD} = 0, 1, 100$ and regret-aversion parameter $\delta^{OD} = 0, 1, 10$ are set.

Fig. II.2 shows the evolution of the vehicles accumulation n(t) for Equilibrium 4 as well as for the three settings of the indifference band (Δ^{OD}) and regret-aversion (δ^{OD}) parameters. One can observe that setting $\Delta^{OD} = 0$, the bounded rational framework reduces to the


Fig. II.1 – (a) Villeurbarnne and the 3^{rd} and 6^{th} districts of Lyon (France) traffic network, divided into seven regions. (b) MFD function of each region. (c) Demand scenario.

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				Trip lengths L_{rp} [m]						
Ο	D	Reg. Path	Path ID	Region						
				1	2	3	4	5	6	7
1	5	[1,2,3,5]	1	442	958	715	0	1351	0	0
1	5	[1,2,6,7,5]	2	566	1118	0	0	211	1403	1229
1	5	[1,3,5]	3	933	0	1194	0	1096	0	0
2	7	[2,3,5,7]	4	0	525	733	0	1032	0	1139
2	7	[2,6,3,5,7]	5	0	105	603	0	1032	257	1050
2	7	[2,6,7]	6	0	751	0	0	0	1418	798
4	2	[4,1,2]	7	2761	335	0	2227	0	0	0
4	2	[4,3,2]	8	0	708	1049	1191	0	0	0
4	2	[4,3,6,2]	9	0	333	1160	791	0	340	0
4	6	[4,3,5,6]	10	0	0	1121	768	358	679	0
4	6	[4,5,6]	11	0	0	0	778	1026	620	0
4	6	[4,5,7,6]	12	0	0	0	2226	2011	301	1301
5	2	[5,3,2]	13	0	637	765	0	1309	0	0
5	2	[5,4,3,2]	14	0	650	984	1391	444	0	0
5	2	[5,4,1,2]	15	2778	368	0	2924	594	0	0
6	1	[6,5,3,1]	16	924	0	1655	0	461	603	0
6	1	[6,5,3,2,1]	17	952	452	789	0	465	604	0
6	1	[6,3,2,1]	18	963	450	739	0	0	532	0
7	3	[7,5,3]	19	0	0	763	0	1249	0	955
7	3	[7,6,5,3]	20	0	0	708	0	965	1094	90
7	3	[7,5,4,3]	21	0	0	313	3285	2731	0	585

Table II.1 – Regional paths for the seven OD pairs and their respective trip lengths L_{rp} listed in meters [m]. Each regional path has an associated identification number as listed in the table.

Equilibrium 4 as evidenced by the similar evolution of n(t) shown in Fig. II.2. Similarly for the Regret Theory implementation when $\delta^{OD} = 0$. Let's first focus on the analysis on how the increase of the users indifference, i.e. increase of Δ^{OD} , influences the traffic states inside the regions. The evolution of the accumulation n(t) shows, in general, a similar trend when comparing the settings of $\Delta^{OD} = 1,100$ against Equilibrium 4. However, the accumulation peaks increase in general, as observed in Fig. II.2 for regions 1, 4 and 7. The increase of Δ^{OD} , increases the users indifference for their regional path choice. As discussed in Chapter 4, when $\Delta^{OD} \to \infty \implies Q_p^{OD} \to \frac{1}{|\Omega^{OD}|}$, where |.| represents the number of regional paths listed in the regional choice set Ω^{OD} . The increase of Δ^{OD} allows users to choose regional paths with higher travel times, explaining the increase of the accumulation n(t) verified for regions 1, 4, 5 and 7 (see Fig. II.2).

To better understand how the bounded rational behavior affects the traffic states inside

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Fig. II.2 – Evolution of the accumulation n(t) of vehicles in each region during the simulation period, for Equilibrium 4 and the three settings of the indifference band Δ^{OD} and of the regret-aversion parameter δ^{OD} .

the regions, let's investigate the evolution of the accumulation $n_p(t)$ for all regional paths p that are crossing regions 1, 4 and 6. Fig. II.5 shows the evolution of the accumulation of all regional paths p, that cross the previously mentioned regions. Note that, the labeling of the regional paths follows Table II.1.

II.1. Extension of the regional network equilibrium to different kinds of user's behavior



Fig. II.3 – Evolution of the accumulation $n_p(t)$ of all regional paths p that cross regions 1, 4, 6 and 7, respectively. The results are shown for Equilibrium 4 and the two settings of the indifference band $\Delta^{OD} = 1, 100$.

One can observe that for region 1, as Δ^{OD} increases other regional paths like 2, 7 and 15 start to be chosen (see Fig. II.5). The increase of the accumulation on these regional paths explain why the total accumulation inside region 1 also increases with Δ^{OD} . In particular, the peak in $n_p(t)$ that is observed for regional path 7 around ~ 4000 seconds explains the one observed around the same simulation time in region 1 (see Fig. II.2). In the case of region 4, the accumulation of regional paths 9 and 11 decreases while for regional paths 7 and 12

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increases, as Δ^{OD} increases. Regional paths 7 and 9 connect the regional OD pair 4-2 (see Table II.1). For $\Delta^{OD} = 100$, the total demand of this regional OD pair will be equally assigned on the three regional paths. Since the average trip length inside region 4 for the regional path 7 is higher than the one of regional path 9, users take more time to complete their travel inside this region. This increases the accumulation $n_p(t)$ of regional path 7. Regional paths 11 and 12 connect the regional OD pair 4-6. The average trip length inside region 4 is higher for regional path 12 compared to 11. Then, vehicles need more time to complete their trips inside region 4, when traveling on regional path 12. This increases the accumulation $n_p(t)$ of this regional path, as observed in Fig. II.5. Consequently, the total accumulation n(t)inside region 4 increases as Δ^{OD} also does. In the case of region 6, the accumulation n(t)decreases as Δ^{OD} increases. For $\Delta^{OD} = 100$, users are equally assigned on all regional paths that connect all the seven regional OD pairs considered. In the case of Equilibrium 4 (or $\Delta^{OD} = 0$), the regional paths 6, 11 and 21 have the larger accumulations $n_p(t)$. Regional path 2 starts to be chosen when $\Delta^{OD} = 1$, showing a significant accumulation peak. Note that regional paths 2, 6 and 20 have the largest average trip lengths inside region 6. Since less users choose regional paths 2, 6 and 20 as Δ^{OD} increases, the accumulation $n_p(t)$ of these regional paths decreases. The total accumulation n(t) of region 6 consequently decreases, as the other regional paths crossing this region do not show a significant increase of $n_p(t)$.

Let's focus now on the analysis on how the increase of the users regret, i.e. δ^{OD} , influences the traffic states inside the regions. Note that, as δ^{OD} increases, users switch to the regional paths with the minimal travel times (i.e. when $\delta^{OD} \rightarrow \infty$ in Eq. II.4). As one can observe in Fig. II.2, the evolution of the traffic states for the two settings of $\delta^{OD} = 1,100$ show, in general, a similar evolution trend as Equilibrium 4. In some regions, the accumulation peaks increase as δ^{OD} also does. For example, the case the accumulation peaks inside regions 1 and 3 that occur around 2000 and 3000 seconds, respectively. The two main differences in the evolution of the traffic states are verified inside regions 2 and 7. To better analyze these differences, let's investigate the evolution of the accumulation $n_p(t)$ for all regional paths p that cross region 7. Fig. II.4 shows the evolution of the accumulation $n_p(t)$ of all regional paths that cross this region. As one can observe, the accumulation peaks that appear around \sim 3000 and 4000 seconds for regional paths 19 and 6, respectively, decrease as δ^{OD} increases. On the other hand, the other regional paths crossing this region 7 become more congested around ~ 3000 seconds when $\delta^{OD} = 100$, because users switched to the regional paths with minimal travel times. This increases the total accumulation inside region 7 for $\delta^{OD} = 100$ as observed in Fig. II.2.

In this section, the extension of the regional dynamic traffic assignment framework to

II.2. Synthesis of Part II



Fig. II.4 – Same as in Fig. II.5, but for regions 1, 2, 6 and 7 as well as the two settings of the regret-aversion parameter $\delta^{OD} = 1,100$.

account for bounded rational and regret-averse users is discussed and tested. The results show that the increase of the users indifference for their regional path choice, increases in general the accumulation inside the regions. The latter is because users are allowed to choose longer regional paths as their indifference level increases. The increase of the users regret for their route choice can change the traffic conditions inside the regions, as observed in this test case for regions 2 and 7. The increase the regret level, leads users to switch to the regional paths with the minimal travel times and this might increase the congestion level inside some regions (e.g., region 7).

II.2 Synthesis of Part II

In this Part II of this thesis, a dynamic traffic assignment framework for multi-regional MFD based models is proposed. A flowchart that summarizes this framework, with the connection to the different chapters in this Part II, is presented in Fig. II.5. This DTA framework is flexible for both accumulation- and trip-based MFD models and both of them are considered in the tests discussed in this Part. In Chapter 5 to Chapter 7, the test network is the 6th district Lyon (France) network, that is divided into eight regions. In the previous Sect. II.1, the extension of the proposed DTA framework to bounded rational and regret-averse users is discussed. The test network includes the city of Villeurbarnne as well as the 3rd and 6th districts of Lyon network (France).

The core of this DTA framework is the definition of regional and internal paths as highlighted in Chapter 5. Moreover, note that in this thesis the partitioning of the city network is assumed to be well defined and given as an input. In Chapter 5, three methods are proDynamic traffic assignment for multi-regional transportation systems considering different kinds of users' behavior 190

II.2. Synthesis of Part II



Fig. II.5 – Flowchart that summarizes the dynamic traffic assignment framework for multi-regional systems MFD based models.

posed to gather the regional paths based on the trips in the city network as well as on its partitioning. In this thesis, the Method 1 proposed in this chapter is used to calculate the regional paths and define the regional choice sets for the regional OD pairs. The regional paths are characterized by distributions of trip lengths inside each region they cross as shown in Chapter 6. Four methods are then proposed to calculate these distributions of trip lengths, also based on a set of trips and on the city network partitioning. The most detailed method, i.e. that filters the trips by their related regional path, is the one that yields the largest heterogeneity of trip length distributions. This method is then used in the follow-up of this thesis. In Chapter 7, four different regional network equilibrium definitions are discussed, given the distributions of trips lengths and the evolution of the traffic states in the regions modeled by the MFD. The definition of Equilibrium 4, that considers both trip lengths L_{rp} and regional mean speeds $v_r(n_r)$ to be distributed, is to be preferred. The definition of Equilibrium 4 in Chapter 7, assumes that users are utility minimizers. In the previous Sect. II.1, the extension of this framework to account for bounded rational and regret-averse users is discussed.

The DTA framework proposed in this second part of the thesis, is the first that investigates the connections between the city and regional networks for a multi-regional traffic assignment. First, it considers dedicated methods to calculate the regional paths and trip length distributions, based on the scale-up of the city network. Second, the dynamic network loading model accounts for explicitly calculated trip length distributions and evolution of the regional mean speeds. Third, it is able to account for different kinds of the users behavior.



Conclusions

This thesis focused on the (i) investigation of the influence of users behavior on the traffic city network performance and (ii) on the development of a dynamic traffic assignment for multi-regional MFD based models considering different kinds of users behavior. This is addressed in different papers that are part of several chapters of this thesis. In this chapter, an overview of the main contributions and some future research directions are also outlined. In Fig. 8.1, a schematic overview of the connections between the different parts and chapters of the thesis as well as the future perspectives is presented.

This thesis starts with a literature review (Chapter 2) about traffic assignment models. This allows to identify different model frameworks that account for different kinds of users behavior as well as users heterogeneity. The different kinds of users behavior include risk-seeking and risk-aversion, bounded rationality and regret-aversion. In terms of the users heterogeneity, two model frameworks that include the Value of Time (VOT) and Value of Reliability (VOR) are identified. The follow-up of the thesis focuses on the investigation of the users behavior influence on the city network performance. The latter is evaluated with reference to the DUE and SUE models (i.e. the benchmark models). In Chapter 3, a framework considering the risk-seeking and risk-aversion behavior modeled by Prospect Theory and distribution of route travel times is designed. The users risk-seeking and risk-aversion behavior is also balancing the uncertainties of the travel times and they are more likely to behave as perfect rationalizers. In Chapter 4, a new bounded rational framework that considers indifferent and strict users preferences as well as distributions of travel times is introduced. This framework reduces to the DUE or SUE when users have indifferent



Fig. 8.1 – Schematic overview of the connections between the different components of this thesis and perspectives.

preferences and the indifference band is set to $\Delta^{od} = 0$. It also extends the work of Zhao & Huang (2016) to a dynamic context considering the setting of Δ^{od} . The users indifferent preference clearly influences the network internal and outflow capacities, that are reduced as the level of bounded rationality increases (i.e. as Δ^{od} increases). While, for the users strict preferences, the network internal and outflow capacities are similar for the different Δ^{od} settings. To finalize the discussion of Part I of the thesis, the influence of the regret-aversion behavior on the network performance is also investigated (Sect. I.1). The network internal capacity increases with the increase of the users regret-aversion (i.e. δ^{od}) compared to the SUE. The mean speed is inferior to the DUE, independent of the level of regret-aversion.

In the second part of the thesis, an innovative dynamic traffic assignment framework for multi-regional systems MFD-based models is proposed. It is flexible for both accumulationand trip-based MFD models and both are considered in the tests. In this thesis, the city network partitioning is assumed to be well-defined and given as an input. This dynamic traffic assignment framework is tested on the 6th Lyon (France) district network, divided into eight regions. It considers the concept of regional path as introduced by Yildirimoglu & Geroliminis (2014). The first step consists in identifying these regional paths based on information of the city network. In Chapter 5, three methods are proposed to gather the regional paths based on trips in the city network and its partitioning. Two of the methods are based on an exhaustive search on the city network. A third method based on shortest-paths calculations directly on the regional network is also discussed. The first two methods require a good city network coverage (i.e. related to the setting of N_{od}). These two methods require a large computational for large city networks. The third method shows to be a good alternative as evidenced by the similarity and strict similarity criteria. Regional paths are characterized by distributions of trip lengths inside each region they cross as shown in Chapter 6. Four methods are proposed to calculate these trip length distributions based on a set of trip in the city network and its partitioning. These methods are: (i) no prior information regarding the regional Origin and Destination of the trips; (ii) the next adjacent region to be traveled by the trips; (iii) the previous and next adjacent regions to be traveled by the trips; and (iv) the related regional path to each trip, that is set as the reference. The reference method represents better the heterogeneity of trip lengths inside a region than the method that considers no prior information about the trips. A procedure to update the trip lengths when the OD matrix changes is discussed and tested. One solution is the recalculation of the trips set, but this is time consuming especially for large city networks. The new estimated trip lengths show a good agreement with the ground truth (i.e. when a new set of trips is recalculated). The importance of properly estimating the trip lengths is highlighted since they clearly influence

the simulated traffic states by an MFD model. The distributions of trip lengths depend on the traffic states inside the regions as shown at the end of this chapter. They should then be updated accordingly. In Chapter 7, taking into account the distributions of trip lengths and evolution of the regional mean speeds, four regional network equilibria are formulated. The difference between these network equilibrium definition rely on which of the two previous terms are considered to be distributed. The variability of trip lengths inside the regions of the regional network cannot be neglected for the regional dynamic traffic assignment in the MFD context. The correlation between regional paths is captured by considering the variability of the regional mean speeds in the dynamic network loading.

In summary, the proposed dynamic traffic assignment in this Part II of the thesis, is the first that investigates the connections between the city and regional networks and proposes systematic scaling-up methods to define regional paths and calculate distributions of trip lengths. Moreover, this framework accounts for trip length distributions that are explicitly calculated and it does not assume any prior distribution for the regional path travel times. Instead, the distributions of trip lengths explicitly calculated and the evolution of regional mean speeds are considered and Monte Carlo simulations are used to calculate the regional network equilibrium. This framework is flexible to account for different kinds of users behavior, such as bounded rational and regret-aversion that were investigated in the first Part I of the thesis, as discussed in Sect. II.1.

The dynamic traffic assignment framework for multi-regional MFD-based models proposed in this thesis is tested using synthetic benchmark data. A validation with real data is currently under research as it is one of the tasks of the ERC MAGnUM project.

The research presented in this thesis can be extended in several directions, as indicated in Fig. 8.1. First, the dynamic traffic assignment for multi-regional MFD models proposed in this thesis is foreseen to be extended to heterogeneous users that value the travel time and reliability differently. This includes the VOT and VOR models discussed in the literature review in Part I. This extension includes different transportation modes such as buses and a metro system. While, the extension to consider the metro in this DTA framework and MFD model is straightforward. The other one that accounts for buses requires the inclusion of the 3D MFD (Geroliminis et al. 2014; Castrillon & Laval 2017; Loder et al. 2017) in the simulator. Second, the study presented in Chapter 5 is planned to be investigated on the whole Lyon network (France) and further testing the proposed method that directly calculates the regional paths in the regional network. Third, as highlighted in Chapter 6, light methodologies to update the distributions of trip lengths according to congestion should be further investigated. Fourth, the extension of the proposed DTA framework to a re-assignment procedure where both

regional paths and distribution of trip lengths can be updated with a light computational cost is required. In line with this, the third method proposed in Chapter 5 to calculate the regional paths directly in the regional network might be a good starting point to update the set of regional paths with a light computational power required. As also previously mentioned, in this thesis, the city network partition is assumed to be well-defined and given as an input parameter. As shown by Saeedmanesh & Geroliminis (2016), Saeedmanesh & Geroliminis (2017), Lopez et al. (2017) and Casadei et al. (2018), this also represent a stand alone research subject. Further research in the partitioning of a city network into regions as well as the optimal number of regions to be considered for an MFD simulation is also required.

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FOLIO ADMINISTRATIF

THÈSE SOUTENUE DEVANT L'ÉCOLE NATIONALE DES TRAVAUX PUBLICS DE L'ÉTAT

NOM : ASSUNÇÃO BATISTA

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Prénoms : Sérgio Filipe

TITRE : Affectation dynamique des usagers sur les grands réseaux des transports considérant différents types de comportements des usagers

École doctorale : Mécanique, Énergétique, Génie civil, Acoustique (MEGA)

NATURE : Doctorat

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Spécialité : Génie civil

RÉSUMÉ :

La croissance démographique dans les zones urbaines représente un problème pour la planification des transports. La surcharge des systèmes de transport urbains entraîne des coûts monétaires importants et des problèmes environnementaux. Des mesures politiques sont alors nécessaires pour réduire le niveau de congestion et accroître l'efficacité des systèmes de transport. À court terme, les simulateurs de trafic pourraient constituer un outil puissant pour la conception de solutions innovantes. Mais les simulateurs de trafic classiques sont exigeants sur le plan informatique pour les applications à grande échelle. De plus, la mise en place du scénario de simulation est complexe. Une modélisation de trafic agrégée pourrait être une bonne solution (Daganzo 2007; Geroliminis & Daganzo 2008). Le réseau routier des villes est divisé en régions, où un diagramme fondamental macroscopique bien défini (MFD) régule les conditions de circulation à l'intérieur de chacune. Le MFD concerne le débit et la densité de trafic moyens dans une région. Malgré que l'idée d'agréger le réseau de la ville soit simple, il soulève plusieurs défis qui n'ont pas encore été abordés. Jusqu'à aujourd'hui, seule Yildirimoglu & Geroliminis (2014) propose un cadre d'affectation dynamique du trafic pour les réseaux régionaux et les modèles MFD. Ce cadre est basé sur le modèle Logit multinomial et ne traite pas explicitement des distributions de longueurs de parcours. De plus, leur structure ne considère pas que les utilisateurs sont différents les uns des autres et ont des objectifs et des préférences différents pour leurs voyages.

L'objectif de cette thèse est double. Tout d'abord, l'influence du comportement des utilisateurs sur la performance globale du réseau routier d'une ville est étudiée. Cette analyse se concentre sur la vitesse moyenne du réseau et ses capacités internes et de sortie, en comparant différents modèles tenant compte des différents types de comportement des utilisateurs par rapport à l'équilibre utilisateur déterministe et stochastique. En second lieu, un cadre innovant et complet d'affectation dynamique du trafic pour les modèles multi-régionaux basés sur le MFD est proposé. Ce cadre est divisé en plusieurs étapes et repose sur les connexions entre la ville et les réseaux régionaux. Dans un premier temps, des méthodes systématiques de mise à l'échelle sont proposées pour rassembler les voies régionales. Dans un deuxième temps, quatre méthodes sont discutées pour calculer les distributions de longueurs de parcours pour caractériser ces chemins régionaux. Dans la troisième étape, un modèle de chargement de réseau qui considère les distributions de longueurs de parcours explicitement calculées et l'évolution des vitesses moyennes régionales est proposé. Enfin, ce cadre d'affectation dynamique du trafic est étendu pour prendre en compte les usager qui ont une aversion au regret ou une rationalité imparfaite.

Mots-Clés : Affectation dynamique du trafic, Comportement des usagers, Réseaux régionaux, Chemins régionaux, Diagramme fondamental macroscopique.

Laboratoire(s) de recherche : Laboratoire d'Ingénierie Circulation Transport (LICIT)

Directeur de thèse : Ludovic Leclercq

Président de jury : Christine SOLNON (Université de Lyon)

Composition du jury :

Prof. Jorge LAVAL (Georgia Tech), Rapporteur

Prof. Francesco VITI (Université du Luxembourg), Rapporteur

Prof. Kay AXHAUSEN (ETH, Zurich), Examinateur

Prof. Margarida COELHO (Université d'Aveiro), Examinatrice

Prof. Christine SOLNON (INSA, Université de Lyon), Président de jury

Prof. Ludovic LECLERCQ (Université de Lyon), Directeur de thèse