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► **To cite this version:**

Humberto Gonzalez Ramirez, Ludovic Leclercq, Nicolas Chiabaut, Cécile Becarie, Jean Krug. A massively multiplayer simulation game framework to study dynamic route choice behavior. TRB's 18, 97th Annual Meeting of the Transportation Research Board, Jan 2018, Washington, United States. 16p. hal-01735364

**HAL Id: hal-01735364**

**<https://hal.science/hal-01735364v1>**

Submitted on 27 May 2021

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# 1 **A massively multiplayer simulation game framework** 2 **to study dynamic route choice behavior**

3 **Humberto González Ramírez\***

4 Univ. Lyon, ENTPE, IFSTTAR, LICIT

5 UMR\_T 9401, F-69518, LYON, France

6 Tel: +33 4 72 04 72 95

7 Email: [humberto.gonzalez@entpe.fr](mailto:humberto.gonzalez@entpe.fr)

8 **Ludovic Leclercq**

9 Univ. Lyon, ENTPE, IFSTTAR, LICIT

10 UMR\_T 9401, F-69518, LYON, France

11 Tel: +33 4 72 04 77 16

12 Email: [ludovic.leclercq@entpe.fr](mailto:ludovic.leclercq@entpe.fr)

13 **Nicolas Chiabaut**

14 Univ. Lyon, ENTPE, IFSTTAR, LICIT

15 UMR\_T 9401, F-69518, LYON, France

16 Tel: +33 4 72 04 77 58

17 Email: [nicolas.chiabaut@entpe.fr](mailto:nicolas.chiabaut@entpe.fr)

18 **Cécile Becarie**

19 Univ. Lyon, ENTPE, IFSTTAR, LICIT

20 UMR\_T 9401, F-69518, LYON, France

21 Tel: +33 4 72 04 72 92

22 Email: [cecile.becarie@entpe.fr](mailto:cecile.becarie@entpe.fr)

23 **Jean Krug**

24 Univ. Lyon, ENTPE, IFSTTAR, LICIT

25 UMR\_T 9401, F-69518, LYON, France

26 Tel: +33 4 72 04 70 64

27 Email: [jean.krug@entpe.fr](mailto:jean.krug@entpe.fr)

28 \* Corresponding author

29 Paper submitted for presentation and publication at the 97<sup>th</sup> Annual Meeting Transportation  
30 Research Board, Washington D.C., January 2018

31 Special call by ADB10 committee on “Traveller behavior and values”

32 Word count: 4985 words + 5 figure(s) × 250 + 3 table(s) × 250 + 500 (references) = 7485 words

33 August 1, 2017

1 **ABSTRACT**

2 In this work, we introduce a novel simulation game platform to study the route choice behaviour of  
3 travellers. A unique feature of this game is that it interacts with a microscopic simulator, which is  
4 in charge of reproducing the traffic conditions over real road networks, such as Lyon-Villeurbanne  
5 (36km<sup>2</sup> and 3,222 nodes). Multiple OD pairs can be assigned to players during one game session.  
6 The participants play trips changing their departure times and routes, and thus modifying the orig-  
7 inal assignment of the simulation in real-time. Thus, the simulation game permits to investigate  
8 not only the determinants of player decisions (travel time, characteristics of the alternatives, traf-  
9 fic information), but also how concomitant decisions from multiple players impact the network.  
10 The later approach is common when considering a network loading, such as a dynamic traffic  
11 assignment (DTA) problem.

12 The results of a first experiment using the simulation game are presented. The main aspect  
13 that we focus on is the influence that the travel time, the length, the number of intersections, and the  
14 provision of traffic information have on the route behaviour of travellers. The question of whether  
15 travellers are travel time minimizers is also addressed. The modelling approach that we use to  
16 investigate the route decision of the travellers is the multinomial logit model, and its predictive  
17 accuracy is assessed. We found that travellers do not behave as travel time minimizers when the  
18 travel times between the alternatives are small, and that the length and number of intersections per  
19 kilometer, did not improved the predictions of the model. A preference for peripheral route and  
20 directness was found. We discuss the possible causes of the poor predictive performance of the  
21 model in our data.

22 *Keywords:* route choice, travellers' behaviour, computer-based experiment, multinomial logit

## 1 INTRODUCTION

2 One of the several decisions that travellers make when travelling within a city is the route choice.  
3 At an aggregated level, the individual route choices of the travellers shape the states of a network.  
4 But, at the same time, the characteristics and states of the network influence the travellers decisions.  
5 This mechanism is not easy to understand because of the continuous feedback between the states of  
6 the network and the choices of travellers. Yet, understanding the route choice behaviour of travelers  
7 is fundamental to predict the states of a transportation network, and to forecast the behaviour of  
8 travellers under hypothetical scenarios. In this work, we introduce a new framework based on a  
9 simulation game to study the route choice behaviour of travellers, in particular, the motives of their  
10 choices related to the characteristics and traffic conditions of the network.

11 The study of human choices belongs to the decision theory field. Several theories of hu-  
12 man choice have been proposed, being Expected Utility Theory the starting point. Proposed first  
13 by Bernoulli (1) and later endowed with an axiomatic basis by Neumann and Morgenstern (2),  
14 EUT allows an ordering of preferences over alternatives with uncertain outcomes. Although, from  
15 an individual perspective the EUT constitutes a well defined framework for decision making, it is  
16 limited when the choices are studied by an external observer. This is because neither the utilities  
17 that individuals get from the outcomes, nor the subjective probabilities that they assign to them, can  
18 be observed by the researcher. The impossibility of observing the utilities that individuals obtain  
19 from alternatives is the assumption of Random Utility Theory (3), where the utilities are modelled  
20 as random variables. Because of their ability to relate the choices with the attributes of the individ-  
21 uals and alternatives, as well as their flexibility in allowing different distributional assumptions on  
22 the distribution of the utilities, the RUM models are broadly used in the transportation field.

23 Three methods are often found in the economic field literature to collect data on human be-  
24 havior: stated preference (SP), revealed preference (RP) and experimental economics (EE). In the  
25 SP method, choices of individuals in hypothetical situations are collected through surveys, whereas  
26 in the RP method the actual choices of individuals are observed in their natural environment (4, 5).  
27 The EE method consists in laboratory controlled experiments in which the participants are faced  
28 with simulated decision problems that resemble real-life situations. By resembling real-life situa-  
29 tions, EE exploits the advantages of the RP method. Moreover, since the researcher can control the  
30 situations in which the experiment takes place, some of the limitations of the RP are overcome. In  
31 this sense, EE experiments lie between the SP and the RP techniques.

32 EE experiments based in computer travel simulators have been extensively used to col-  
33 lect data on travellers' route choice behaviour. In these experiments, particular attention has been  
34 paid to the study of learning from experience, (6, 7, 8); the impact of advanced travel information  
35 systems (ATIS) (9, 10, 11, 12); and the effect of travel time variability and risk attitudes in the trav-  
36 ellers choices (13, 14). However, as these experiments are designed to study specific behavioural  
37 traits, they are based on simple scenarios: single OD connected by two or three routes, and a basic  
38 representation of the network and traffic information. Thus, the impact of other attributes that are  
39 believed to influence the route choice decision (15), are not investigated in this studies. Moreover,  
40 these experiments follow different methodologies. As a consequence, there is no common ground  
41 to test different modelling approaches.

42 The mobility decision game (MDG), which belongs to the EE methods, is the approach of  
43 the LICIT laboratory to investigate travellers' decisions in transportation networks at large scale.  
44 The network description in the MDG is based on the full map of a real road network, such as Lyon-  
45 Villeurbanne (36km<sup>2</sup> and 3,222 nodes) in our experiment. In the MDG, the players' decisions are

1 send to a microscopic traffic simulator environment, which is in charge of reproducing the traffic  
2 conditions in the network. Multiple OD pairs can be assigned simultaneously to players during one  
3 game session. Thus, the MDG permits to investigate not only the determinants of player decisions  
4 (travel time, network characteristics), but also how concomitant decisions from multiple players  
5 may impact the network, and the interactions between travellers. During the game, players may get  
6 traffic information from congestion map or as travel time estimates for the different route options.

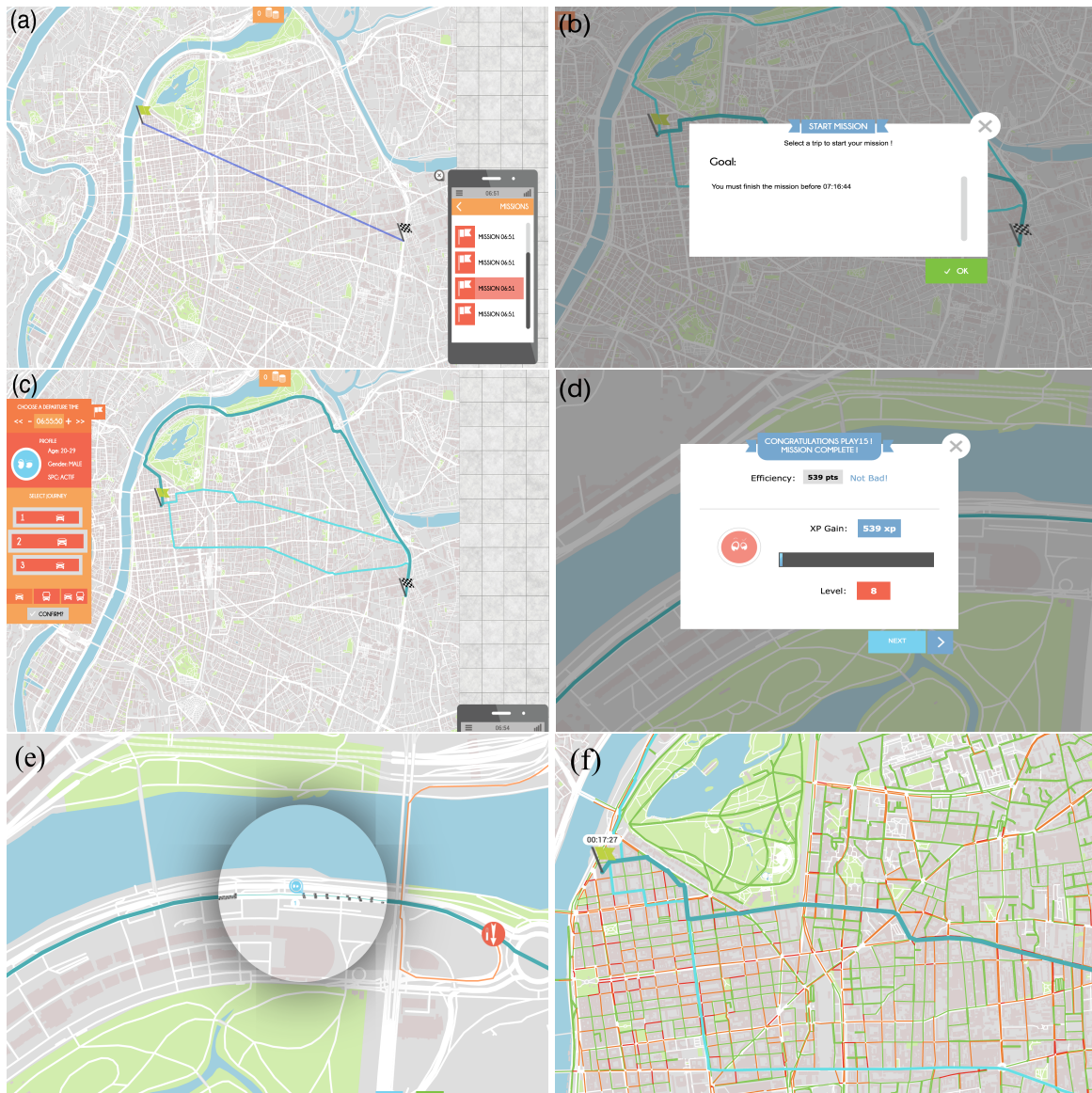
7 In this work we present the results of a first experiment using the simulation game. The  
8 objective is to gain insight into the route choice behaviour of the travellers under different traffic  
9 conditions and traffic information scenarios. In particular, we are interested in the role that (i)  
10 the travel time, (ii) the characteristics of the alternative set, and (iii) the traffic information have  
11 in explaining the decisions of the travellers. The question of whether travellers are travel time  
12 minimizers is central in our investigation. This is possible because with the MDG we can define  
13 routes connecting the origins and destinations of different OD pairs with distinct characteristics;  
14 provide traffic information (in the form of congestion maps and travel times) during a session, and,  
15 since the traffic conditions in the scenarios are generated by a microscopic simulator, it is possible  
16 to study the decision of travellers in a dynamically changing scenario. The modelling approach  
17 that we adopt to investigate points (i) and (ii) is the multinomial logit model, as it represents the  
18 starting point in our investigation. The three exogenous variables that we consider for this model  
19 are the travel time, the length of the route, and the number of intersection per kilometer. The  
20 adequacy of the model is assessed by means of its prediction accuracy in subsamples of the data.

21 Section 2 presents the DMG tool and the experimental set-up. The general results of the  
22 experiment, including an statistical analysis of the impact of ATIS, travel time minimization, and  
23 relation of attributes with the route choices are presented in section 3. In section 4, we fit a multi-  
24 nomial logit model to our data, and its prediction accuracy is assessed. We discuss the possible  
25 causes of the poor performance of the model in our data at the end of this section. Finally, we  
26 discuss our findings and the next steps in section 5.

## 27 **MOBILITY DECISION GAME**

28 From the users' point of view, the MDG consists in playing *missions*, which corresponds to trips  
29 with a given purpose. When a player selects a mission, the target arrival time of the trip is dis-  
30 played. Then, the player chooses the departure time and route to complete the trip. Once the  
31 trip has started, the participants can re-route at predefined points. A mission is finished when the  
32 destination is reached before the target arrival time or when the target arrival time is not accom-  
33 plished. After a mission is finished, the participants may play another one. In figure 1, we show  
34 the gameplay of the DMG.

35 To generate the scenarios in which the missions are placed, the MDG interacts in real-time  
36 with a microscopic simulator, which is in charge of generating all the trips that populate the net-  
37 work. The trips on predefined OD pairs are those that the participants can play as missions, chang-  
38 ing their departure times and routes, and thus modifying the original assignment of the simulation.  
39 Since multiple players play in the same simulation, their decisions affect the others. Moreover,  
40 in the MDG all the trips are clearly identified, i.e., the position of all vehicles can be known at  
41 any time, thus, the correlations between the different routes at a link level can be computed. This,  
42 together with the fact that the MDG can be configured so that multiple OD pairs can be played  
43 simultaneously, will allow us in the future to calibrate and test different assignment models. In  
44 addition to the real-time interaction with a microscopic simulator, the MDG can be configured to



**FIGURE 1 MDG gameplay. (a) selection of a mission; (b) the objective of the mission is informed; (c) the route and travel time choice; (d) the score earned after a mission is finished; (e) re-route point; and (f) congestion map and travel time.**

1 simulate traffic conditions with different demand levels, and to show traffic information in the form  
 2 of congestion maps and/or travel time estimates.

### 3 Case study

4 A first experiment with the MDG consisted in 202 participants that were divided in four groups of  
 5 approximately 50 people. Two sessions, one with 2 OD pairs and one with 3 OD pairs, were as-  
 6 signed to each group and the participants were assigned into three different information treatments.  
 7 In total, 8 sessions, each lasting 20 minutes were played. The sessions were placed in a simulated  
 8 environment of the city of Lyon-Villeurbanne (36km<sup>2</sup> and 3,222 nodes), between 7:00 and 8:00 in

1 the morning. The purpose of all the missions in the game was *commuting to work*, and the objec-  
 2 tive was to complete the trip before a given time. After a mission is selected, participants choose  
 3 among three alternative routes to complete the trip, and once the trip has started, participants were  
 4 be able to re-route at predefined points (see figure 1). The demand levels, the OD pairs, and the  
 5 information that the participants received are detailed in the rest of this section. A total number of  
 6 724 choices from the participants were recorded.

#### 7 *Demand level*

8 Two demand scenarios were considered for the simulation game sessions,  $D_1$  and  $D_2$ . In  $D_1$ , the  
 9 global demand in the network is maintained constant,  $d_1 = 5770veh/h$ , during the first part of the  
 10 experiment; then, at 7:20am, it rises its level to  $d_2 = 6950veh/h$ . In  $D_2$  the demand starts at level  
 11  $d_2 = 6950veh/h$  and then decreases to  $d_1 = 5770veh/h$  at 7:20am. Note that when the global  
 12 demand level is increased (or decreased) during a simulation, a transition period is needed for the  
 13 network to reach its new traffic state. These transition period allow us to investigate the travellers  
 14 choices under different traffic conditions.

#### 15 *OD pairs and routes*

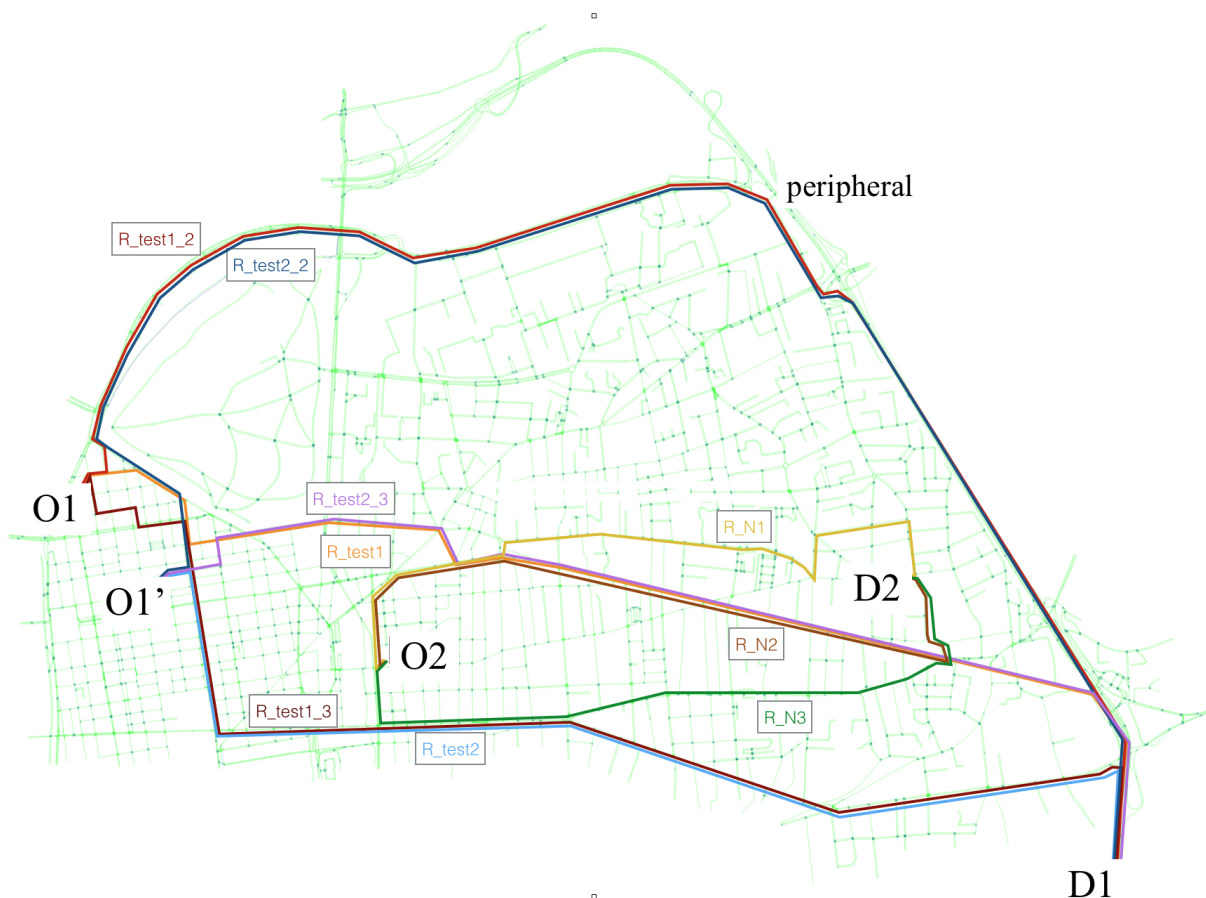
16 Each group of participants plays two sessions that differ in the number of OD pairs where missions  
 17 are assigned. Two OD pairs considered in the first session of each group have the same destination,  
 18 but have a slightly different origin. Paths from this origins to this destination share most of their  
 19 links. We denote these two OD pairs as  $OD_1$  and  $OD'_1$  (see figure 2). In the second session played  
 20 by each group a third OD is added, denoted by  $OD_2$ . The corresponding number of missions for  
 21 each of the three OD pairs,  $OD_1$ ,  $OD'_1$  and  $OD_2$ , was 260, 258, and 206, respectively. The three  
 22 OD pairs, as well as the routes connecting them are shown in figure 2. Their characteristics are  
 23 shown in table 1.

OD	Route	Length	No. intersections / km
$OD_1$	R_test1_2	5,562	12.40
	R_test1	7,589	5.54
	R_test1_3	6,160	12.01
$OD'_1$	R_test2_2	8,110	6.41
	R_test2_3	5,140	12.26
	R_test2	5,398	11.86
$OD_2$	R_N1	3,237	13.60
	R_N2	3,123	14.09
	R_N3	3,248	14.47

**TABLE 1** Attributes of the routes in the OD pairs.

#### 24 *Information treatments*

25 The participants in the experiment are divided into treatment groups according to the travel time  
 26 information that they can consult. Three information treatments are considered in the experiment:  
 27 not informed (NI), congestion map information (CMI) and travel time information (TTI). The num-  
 28 ber of missions played in each treatment was 211 in the NI treatment, 188 in the CMI treatment,  
 29 and 325 in the TTI treatment. A description of the treatment groups is presented below.



**FIGURE 2 OD pairs and routes considered for players in the experiment.**

- 1 • *Not informed treatment (NI)*. These participants don't receive any kind of information  
 2 regarding the traffic conditions. This group acts as a control group.
- 3 • *Congestion map information (CMI)*. The congestion map information is provided as  
 4 printed maps with colors depicting the congestion in the network roads for periods of 30  
 5 minutes. No travel time information is provided. The congestion maps in this treatment  
 6 are obtained from a prior simulation of the network. Therefore, the traffic information  
 7 depicted in the maps is not exact.
- 8 • *Travel time information (TTI)*. This treatment receives real-time information, computed  
 9 in the last 15 minutes of the current game. The information provided consists in a con-  
 10 gestion map and the travel time estimation, both accessed through the interface of the  
 11 game.

## 12 GLOBAL ANALYSIS OF THE MDG RESULTS

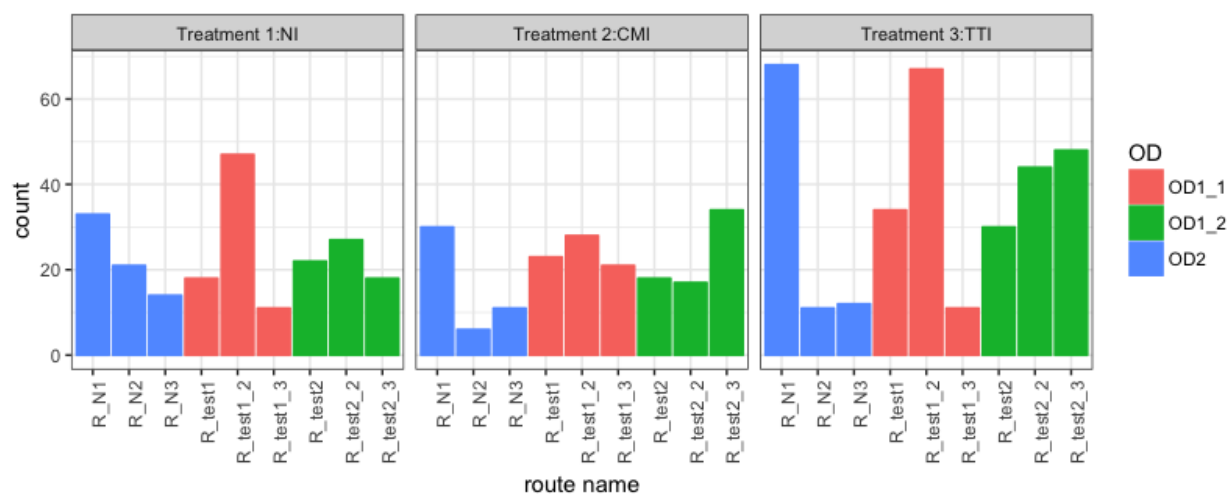
13 In this section, we analyze the results of a first route choice experiment using the MDG. First, we  
 14 show the route choice distributions and provide a qualitative analysis of the results. Second, we  
 15 study the impact of the traffic information by comparing the choice distributions between the three



1 information treatments. Third, we investigate if participants behave as travel time minimizers, and  
 2 if traffic information help them to minimize their travel times.

### 3 **Route choice distributions**

4 In figure 3, it can be seen that for  $OD_1$  and treatment NI, the participants have a strong preference  
 5 for the R\_test1\_2 route; which is the peripheral route and also the longest in distance. Apparently,  
 6 travellers perceive the peripheral routes, which are often longer in distance, to be faster; avoiding  
 7 the inter-urban routes. However, this preference for the peripheral route is less evident for the  $OD_1$ ,  
 8 where R\_test2\_2 is similar to R\_test1\_2, except in the initial part. The change in preference, due  
 9 to a small change in the origin, might be explained because in R\_test2\_2 one must move away  
 10 from the destination in order to take the peripheral route, making it less preferable (see figure 2).  
 11 The same conduct can also explain the low preference for the R\_N3 route in  $OD_2$ , which is only  
 12 12 meters longer than the most preferred one, R\_N1. This behaviour can be observed in the three  
 information treatments.



**FIGURE 3** Route choice distribution for each OD pair disaggregated by treatment.

13

### 14 **Influence of traffic information in route choice**

15 Since the traffic information received by the participants in the experiment differs across the treat-  
 16 ments, we expect the choices to be different as well. To corroborate this hypothesis, we performed  
 17 chi-square tests to the choice distributions of the treatments NI vs CMI, NI vs TTI, and CMI vs  
 18 TTI, reporting p-values of 0.0057, 0.0178, and 0.0148, respectively. From these results we can  
 19 conclude that there is strong evidence that points towards the expected result: the choice distribu-  
 20 tions are different across treatments. Furthermore, the fact that the choice distributions are not the  
 21 same for the informed treatments, CMI and TTI, implies that the manner in which traffic infor-  
 22 mation is presented leads to different route choices. This is evident in the case of the R\_test1\_2  
 23 route, which is the preferred in both NI and TTI treatments, but that in treatment CMI is not more  
 24 preferred to the rest of the alternatives: the choice distribution of  $OD_1$  in the CMI treatment is  
 25 not significantly different from a uniform distribution (chi-squared test with p-value of 0.7676).  
 26 This can be explained because in the congestion maps a large contiguous section of the peripheral  
 27 route is shown as congested; however, the congested sections in the rest of the alternatives, while

1 representing a larger portion of the total length, are not contiguous. This may be perceived by  
 2 participants as *bad* traffic conditions on the route and, thus, they tend to avoid it.

### 3 **Travel time minimization**

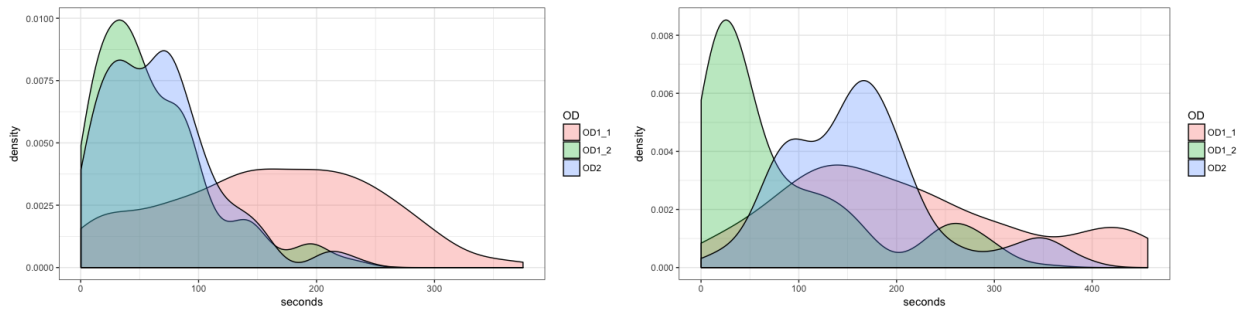
4 To see if the information leads to better choices, in terms of travel time, we investigate the travel  
 5 time minimization rate of participants, i.e., the proportion of times in which the fastest route was  
 6 chosen. Since the experiment is dynamic, the travel time on each route depends on the demand  
 7 level, as well as on the decisions of other participants. Thus, the fastest alternative (in mean travel  
 8 time) is not always the same during a session. Therefore, we restrict the computation of the mean  
 9 travel time for the alternative  $j$  at the moment in which decision  $i$  was made. If we let  $t_i$  be the  
 10 moment at which decision  $i$  was made, then the mean travel time of  $j$  is the mean travel time of all  
 11 trips in  $j$  that started in the time interval  $[t_i - h, t_i)$ . We denote the mean travel time obtained in this  
 12 manner as  $\bar{tt}_j^i$ . For each decision  $i$ , we can now order the three alternatives according to  $\bar{tt}_j^i$ , and  
 13 obtain the proportion of times that the fastest, second fastest and slow alternatives were chosen.  
 The results are presented in table 2.

OD	Treat	No. Total	Perc. Fast	Perc. Med	Perc. Slow
$OD_1$	NI	76	0.539	0.316	0.145
	CMI	72	0.417	0.292	0.292
	TTI	112	0.607	0.277	0.116
$OD'_1$	NI	67	0.284	0.493	0.224
	CMI	69	0.319	0.319	0.362
	TTI	122	0.352	0.361	0.287
$OD_2$	NI	68	0.368	0.324	0.309
	CMI	47	0.404	0.468	0.128
	TTI	91	0.418	0.462	0.121

**TABLE 2 Proportion of times that the fastest, medium and slowest routes were chosen.**

14  
 15 The results show that the travel time minimization rate depends on both the OD pair and  
 16 the information that the participants received. Between treatments, we observe that the participants  
 17 in the TTI treatment were better in identifying the fastest alternative; behaviour expected from  
 18 the most informed treatment. However, within the TTI treatment, we observe that for the  $OD'_1$   
 19 and  $OD_2$ , the second fastest route was chosen more. This result is not in agreement with the  
 20 expected behaviour that travellers are travel time minimizers. To further investigate this unexpected  
 21 behaviour, we compute the difference  $\bar{tt}_{(1)}^i - \bar{tt}_{(2)}^i$  and  $\bar{tt}_{(2)}^i - \bar{tt}_{(3)}^i$ , i.e., the difference of the mean  
 22 travel times between the fastest and the second fastest alternatives, and the difference of mean  
 23 travel times between the second fastest and the slow alternatives (see figure 4). We observe that in  
 24 the case of the  $OD'_1$  and  $OD_2$ , the mean travel time difference is small compared to that of  $OD_1$ :  
 25 62 and 67 seconds for  $OD'_1$  and  $OD_2$ , and 160 seconds for  $OD_1$ . A similar result can be found for  
 26 the difference in mean travel times of the second fastest and the slow alternatives in  $OD'_1$ , which  
 27 explains the more uniform choices of fastest, second fastest and slow routes in the TTI treatment  
 28 group. This is not the case in  $OD_2$ , where the difference between the second fastest and the slow  
 29 routes is not as small as for the fastest and second fastest routes and, thus, the slow route is chosen  
 30 less. We conjecture that the travellers are indifferent between alternatives with similar travel times,

1 and thus other route attributes weight more in the route choice. We will investigate this conjecture  
 2 in section 4, where a multinomial logit model is fitted considering not only the travel time, but also  
 the length of the route and the number of intersections per kilometer.



**FIGURE 4** Difference in mean travel times between the fastest and second fastest alternatives (left), and the second fastest and slow alternatives (right).

3

#### 4 MULTINOMIAL LOGIT MODELLING

5 In this section, we expand the analysis of Section 3.3 by fitting two multinomial logit models  
 6 to each of the OD pairs. First, we investigate the route choice as a response to the mean travel  
 7 time and the information treatment, formalizing the analysis in the previous section. Then, in a  
 8 tentative to investigate if other route attributes can explain that the participants are not travel time  
 9 minimizers, we include the length and the number of intersections per kilometer in our analysis.

#### 10 Route choice as a response to the mean travel time and information treatments

11 We fit a multinomial logit model to each of the OD pairs. The specification of the model is

$$\text{MODEL 1: } V_{ij} = \sum_{T \in \{NI, CMI, TTI\}} \left[ \alpha_j^T + \beta^T \bar{t}_j^i \right] \mathbb{I}_T(TREAT_i), \quad (1)$$

12 where  $\bar{t}_j^i$  is the mean travel time in route  $j$  at the moment of the decision  $i$  (obtained as in section  
 13 3.3),  $TREAT_i$  is the treatment to which the decision maker  $i$  belongs, and  $\mathbb{I}_T$  is the indicator function  
 14 that takes the value 1 when  $TREAT_i = T$ .

15 The estimated coefficients of this model are shown in the Table 3. In the case of the  $OD_1$ ,  
 16 the estimated coefficient  $\hat{\beta}^T$  is significant only for the TTI treatment. This result is expected,  
 17 because the participants in the TTI treatment were the only ones with information about the travel  
 18 time. Moreover,  $\hat{\beta}^{TTI} < 0$ , which means that the higher the travel time, the less desirable the route  
 19 is. For the NI treatment  $\hat{\alpha}_j^{NI}$  is significant only for  $j = R\_test1\_2$ , which is the peripheral route.  
 20 The fact that  $\hat{\alpha}_j^{NI}$  is significant for this route, and that the coefficient for the travel time is not,  
 21 implies that the preference for the peripheral route in this treatment is not related to the travel time.  
 22 Moreover,  $\hat{\alpha}_j^{TTI}$  for the same route,  $R\_test1\_2$ , is significant and has the same magnitude, but with  
 23 contrary sign (-0.8532), meaning that in the TTI treatment the preference for the peripheral route  
 24 comes from the travel times estimates that the participants received. In the case of the of the  $OD'_1$ ,  
 25 the estimated coefficient  $\hat{\beta}^T$  is significant only for the NI treatment. This result is contradictory, as  
 26 these participants received no information regarding the travel time; we regard it as an artefact in

1 the experiment. The peripheral route in this case has estimated coefficients that are not significant.  
 2 Finally, in the case of the  $OD_2$ , none of the estimated coefficients of the travel time are significant.  
 3 The estimated constant terms  $\hat{\alpha}_j^{NI}$  and  $\hat{\alpha}_j^{TTI}$  of the R\_N3 route are significant and negative, which  
 4 shows a dislike for this route.

### 5 **Route choice as a response to the mean travel time, the length of the route and the number** 6 **of intersections per kilometer**

7 The specification of the multinomial logit model that we use in this section is

$$\text{MODEL 2: } V_{ij} = \beta_1 LEN_j + \beta_2 INTER_j + \beta_3 \bar{tt}_j^i, \quad (2)$$

8 where  $LEN_j$  and  $INTER_j$  are the length and the number of intersections per kilometer, and  $\bar{tt}_j^i$  is  
 9 the mean travel time in route  $j$  at the moment of the decision  $i$  (see section 3.3).

10 The model was estimated for the three OD pairs considering only participants in the TTI  
 11 treatment. We focus only on participants in the TTI treatment, assuming that they are the most  
 12 responsive to travel times. The estimated coefficients are exhibited in the table 3. The results  
 13 show that for  $OD_1$  the  $\bar{tt}_j^i$  is the only significant variable, with estimated coefficient  $\hat{\beta}_3 < 0$ , which  
 14 implies that the more the mean travel time, the less desirable the route is. For the rest of the  
 15 OD pairs,  $OD'_1$  and  $OD_2$ , the opposite is found:  $\bar{tt}_j^i$  is not significant, whereas  $LEN_j$  and  $INTER_j$   
 16 are. This result points in the same direction of our previous conjecture, that when the differences in  
 17 mean travel time are small, the route choices of the travellers are driven by other factors, rather than  
 18 the travel time. The estimated coefficient for the  $INTER_j$  variable,  $\hat{\beta}_2$ , is negative for both  $OD'_1$   
 19 and  $OD_2$ , which implies that attractiveness for a route decreases with the number of intersections  
 20 per kilometer. However, the estimated coefficient of the length of the route,  $\hat{\beta}_1$  is negative in the  
 21 case of the  $OD'_1$ , but positive in the case of  $OD_2$ .

22 The prediction accuracy of the models, removing the not significant explanatory variables,  
 23 was assessed by means of bootstrapping, leaving out at each iteration 20% of the data in the fitting  
 24 process. In each iteration, the choice probabilities of the held out sample were predicted, and their  
 25 mean compared, using the chi-square distance, to the actual choice distribution. This distance is a  
 26 measure of the prediction error and it is a measure of how well the model generalizes to scenarios  
 27 that have not been seen. In this work, the bootstrapping was iterated 1,000 times and the mean of  
 28 the predicted errors reported and compared to that of the null model. For the  $OD_1$ , the prediction  
 29 mean error of the null model is 0.1233, while the mean error including the  $\bar{tt}_j^i$  variable is 0.1001.  
 30 This represents an improvement of 18.8%. In the case of the  $OD'_1$  and  $OD_2$ , both the null model  
 31 and the model including the  $LEN_j$  and  $INTER_j$  variables have the same prediction errors: 0.1220  
 32 for  $OD'_1$  and 0.1581 for  $OD_2$ . Meaning no improvement.

33 We investigate the possible causes of the failure of the multinomial logit model to predict  
 34 the behaviour of the participants in the case of the  $OD'_1$  and  $OD_2$ . In section 3.3 we conjectured  
 35 that the travellers are indifferent between alternatives with similar travel times and, thus, other  
 36 route attributes weight more in the route choice. However, in the results of the above analysis,  
 37 the length of the route and the number of intersections are not explaining the choice of travellers  
 38 either. This result suggests that there may be other variables, that we are not observing, but that  
 39 participants rely on when making their decisions. If this is the case, a violation of the IIA as-  
 40 sumption could explain the poor performance of the above models. To show this, note that if two  
 41 alternatives,  $j$  and  $k$  have similar attributes, then their systematic part of the utility will be similar,

1 i.e.,  $V(X_j, \theta_i) \approx V(X_k, \theta_i)$ . Because of the IIA assumption in the multinomial logit models, this  
2 implies that the probability of individual  $i$  choosing either of the alternatives,  $j$  or  $k$ , will also be  
3 similar:  $P_i(C = j|X_j, \theta_i) \approx P_i(C = k|X_k, \theta_i)$ . Therefore, the aggregated observations will also be  
4  $\mathbb{E}_{\Theta} [P_i(C = j|X_j, \theta_i)] \approx \mathbb{E}_{\Theta} [P_i(C = k|X_k, \theta_i)]$ . However, this is not the case for the  $OD_2$ , in which  
5 the alternatives R\_N1 and R\_N3 have similar length, number of intersections per kilometer, and  
6 travel time, but still a strong preference towards the route R\_N1 is observed. The aggregated prob-  
7 ability for the former being equal to 0.7473 and for the later 0.1319 (see figure 3). In the case of  
8 the  $OD'_1$ , the travel time, the length and the number of intersections are similar for the R\_test2 and  
9 R\_test2\_3 routes. Their aggregated probabilities are, respectively, 0.2458 and 0.3814. The result  
10 is not as extreme as for the case of  $OD_2$ , but may have the same explanation.

Model	OD	Coefficients	Estimate	Std. Error	t-value	Pr(>  t )
MODEL 1	OD <sub>1</sub>	$\alpha_j^{NI}, j = R\_test1\_2$ (intercept)	0.8602	0.4054	2.1216	0.0339 *
		$\alpha_j^{NI}, j = R\_test1\_3$ (intercept)	-0.3686	0.5728	-0.6435	0.5199
		$\alpha_j^{CMI}, j = R\_test1\_2$	-0.5470 (+0.8602)	0.5428	-1.0078	0.3135
		$\alpha_j^{CMI}, j = R\_test1\_3$	0.1145 (-0.3686)	0.7224	0.1585	0.8741
		$\alpha_j^{TTI}, j = R\_test1\_2$	-0.8532 (+0.8602)	0.5095	-1.6744	0.0940 .
		$\alpha_j^{TTI}, j = R\_test1\_3$	0.1537 (-0.3686)	0.7278	0.2113	0.8327
		$\hat{\beta}^{NI}$	-0.0441	0.1132	-0.3893	0.6971
		$\hat{\beta}^{CMI}$	0.0509	0.0990	0.5143	0.6070
		$\hat{\beta}^{TTI}$	-0.2839	0.0960	-2.9571	0.0031 **
	Log-Likelihood: -239.59					
	OD' <sub>1</sub>	$\alpha_j^{NI}, j = R\_test1\_2$ (intercept)	-0.0373	0.3264	-0.1143	0.9090
		$\alpha_j^{NI}, j = R\_test1\_3$ (intercept)	-0.4640	0.3550	-1.3071	0.1912
		$\alpha_j^{CMI}, j = R\_test1\_2$	0.1062 (-0.0373)	0.4807	0.2209	0.8252
		$\alpha_j^{CMI}, j = R\_test1\_3$	1.1834 (-0.4640)	0.4762	2.4850	0.0130 *
		$\alpha_j^{TTI}, j = R\_test1\_2$	0.4615 (-0.0373)	0.4051	1.1394	0.2545
		$\alpha_j^{TTI}, j = R\_test1\_3$	0.8686 (-0.4640)	0.4300	2.0199	0.0434 *
		$\hat{\beta}^{NI}$	-0.2893	0.1152	-2.5115	0.0120 *
		$\hat{\beta}^{CMI}$	0.0984	0.1030	0.9554	0.3394
		$\hat{\beta}^{TTI}$	-0.0609	0.0855	-0.7121	0.4764
	Log-Likelihood: -257.16					
	OD <sub>2</sub>	$\alpha_j^{NI}, j = R\_N2$ (intercept)	0.2814	0.6411	0.4389	0.6607
		$\alpha_j^{NI}, j = R\_N3$ (intercept)	-0.8416	0.3207	-2.6246	0.0087 **
		$\alpha_j^{CMI}, j = R\_N2$	-2.1969 (0.2814)	1.0642	-2.0644	0.0390 *
		$\alpha_j^{CMI}, j = R\_N3$	-0.1828 (-0.8416)	0.4805	-0.3805	0.7036
$\alpha_j^{TTI}, j = R\_N2$		-2.3707 (0.2814)	0.9236	-2.5669	0.0103 *	
$\alpha_j^{TTI}, j = R\_N3$		-0.9149 (-0.8416)	0.4519	-2.0246	0.0430 *	
$\hat{\beta}^{NI}$		-0.2172	0.1728	-1.2564	0.2090	
$\hat{\beta}^{CMI}$		0.0963	0.2251	0.4277	0.6688	
$\hat{\beta}^{TTI}$		0.0780	0.1670	0.4672	0.6404	
Log-Likelihood: -178.81						
MODEL 2	OD <sub>1</sub>	$\hat{\beta}_1$	-0.0005	0.0010	-0.4751	0.6347
		$\hat{\beta}_2$	-0.1327	0.2922	-0.4542	0.6497
		$\hat{\beta}_3$	-0.2839	0.0960	-2.9571	0.0031**
	Log-Likelihood: -95.804					
	OD' <sub>1</sub>	$\hat{\beta}_1$	-0.0075	0.0043	-1.7199	0.0855 .
		$\hat{\beta}_2$	-3.7883	2.1853	-1.7335	0.0830 .
		$\hat{\beta}_3$	-0.0609	0.0855	-0.7121	0.4764
	Log-Likelihood: -127.23					
	OD <sub>2</sub>	$\hat{\beta}_1$	0.0092	0.0054	1.6970	0.0897 .
$\hat{\beta}_2$		-2.1247	0.3670	-5.7897	7.049e-09 ***	
$\hat{\beta}_3$		0.0780	0.1670	0.4672	0.6404	
Log-Likelihood: -67.2583						
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

**TABLE 3 Estimated coefficients for the multinomial logit models MODEL 1 and MODEL 2.**

1 **DISCUSSION AND FUTURE WORK**

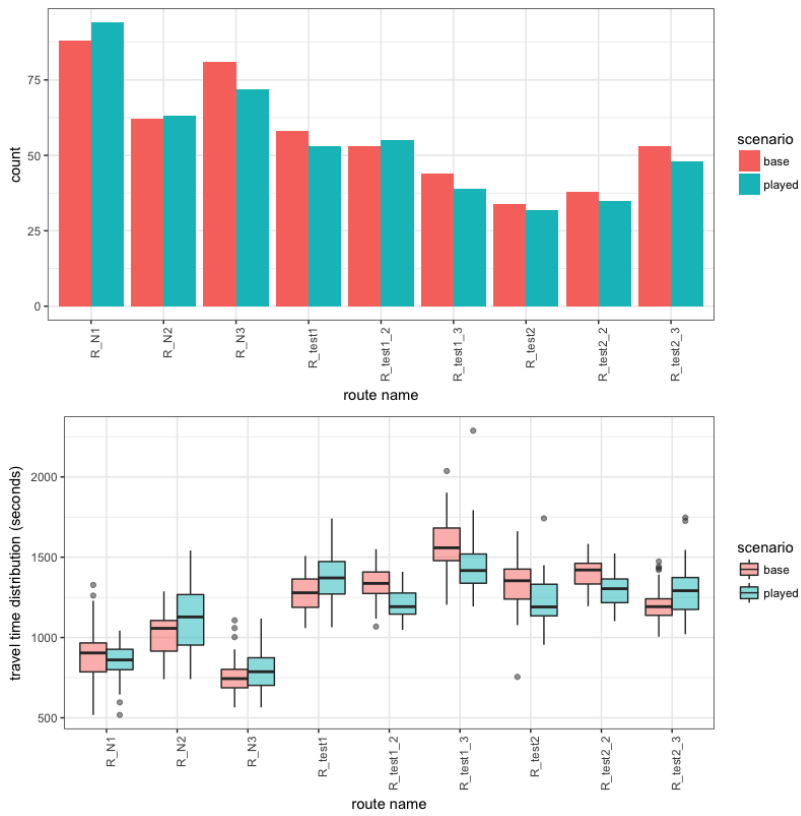
2 In this paper, we introduced the mobility decision game platform that is being developed in the  
 3 LICIT laboratory to study the behaviour of travellers at a network level. The platform was used in  
 4 a first case study about route choice behaviour, and the relevance of the multinomial logit model  
 5 to predict the observed route choices was assessed. In the results of the experiment, we found  
 6 that participants are not travel time minimizers. In the two OD pairs in which participants were  
 7 not travel time minimizers, OD'<sub>1</sub> and OD<sub>2</sub>, the difference in mean travel time between the fastest  
 8 and second fastest route was small. We conjectured that, when travel times are close, other route  
 9 attributes weight more in the route decision. Two route attributes, the length and the number of

1 intersections per kilometer, were included in a multinomial logit model to test this conjecture.  
2 However, adding this two attributes in the model did not produce significantly better results. We  
3 found that the reason of the poor performance of the multinomial logit model in predicting the route  
4 choices is that the IIA property is not satisfied: in our data we observe routes with similar measured  
5 attributes having different choice probabilities. This implies that there are other attributes that we  
6 have not yet identified, but that participants took into account when making their decisions. We  
7 speculate that the directness of the route may be one of the attributes responsible of this behaviour.  
8 Nonetheless, we also found that travellers preferred the peripheral route. This observation is in  
9 line with the results in Lotan (10), where travellers that are unfamiliar with the network showed  
10 a preference for the freeway, which is a peripheral route. A preference for the peripheral route,  
11 which resulted to be amongst the least reliable, is also found in a RP experiment in Ramos (16),  
12 but in the later, the travellers were familiar with the network. As peripheral routes are often longer  
13 and less direct, they may not be comparable with the inter-city alternatives. This suggests that  
14 peripheral routes should be treated as a different category in the modelling. A nested logit model  
15 is suitable for this kind of data.

16 In this paper we focused on the individual route choices of travellers one OD pair at a  
17 time. Thus, path flow estimation is done using a partially myopic vision of the interaction between  
18 players at the network level. Interactions are considered through the consequences of travellers'  
19 decisions in terms of travel time over the different alternatives, but not as a joint process over all  
20 OD pairs. The later approach is common when considering a network loading, such as a dynamic  
21 traffic assignment (DTA) problem. A promising property of the MDG platform is that it allows to  
22 study the impact of individual decisions at the network level. This can be done because in the MDG  
23 the position of all trips at a certain time are known, thus the relation between the travel times and  
24 the flows, as well as the correlations between the flows in different routes can be computed. The  
25 MDG can thus be used to calibrate or design new DTA models based on behavioural observations  
26 and not an equilibrium statement. Figure 5 shows a premise of what can be observed with the  
27 DMG in this sense.

28 Figure 5 depicts the aggregated flows and travel time distributions on the played routes in  
29 one of the experiment sessions. The path flows and travel times of the played session are compared  
30 with a base scenario, which is a simulation without players. Compared to the base scenario, the  
31 route choices of the participants changed the flow and, as a consequence, the travel times. If  
32 analysis were done at an OD level, we would expect an increase (decrease) in the flow path on one  
33 route to cause an increase (decrease) in the travel times in that route. However, this is not what we  
34 observe in the figure 5, where the routes R\_N1 and R\_test1\_2 increased their flow in the played  
35 session, but have smaller travel times. The reason of this behaviour is because the interactions with  
36 the routes in other OD pairs are not being considered. This shows how the MDG can be used for  
37 the research on the global analysis of a transportation network.

38 Although the findings on travellers route choices in this paper are not new, they reinforce  
39 our confidence in the MDG as a reliable tool for data collection on travellers behaviour. Moreover,  
40 the findings provide a path for the design of forthcoming experiments. Future plans include new  
41 experiments to investigate other route attributes that may influence the decisions of travellers; the  
42 comparison between different choice models in predicting the route decisions; and the study of the  
43 relevance of different DTA models to reproduce the flow patterns obtained with the MDG.



**FIGURE 5 Path flows (top), and travel time distributions (bottom) in the played routes.**



## 1 ACKNOWLEDGEMENTS

2 This project has received funding from the European Research Council (ERC) under the Euro-  
3 pean Union's Horizon 2020 research and innovation programme (grant agreement No 646592 –  
4 MAGnUM project).

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