Revisiting the Route Choice Problem: A Modeling Framework Based on Mental Representations

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Abstract

We present a new approach for modeling and analyzing route choice behavior. It is motivated by the need to reduce the complexity of the state-of-the-art choice models. It is inspired by the simplifications actually done by the travelers, using representations of their surrounding space. The proposed framework is based on elements designed to mimic the mental representations used by travelers, denoted as *Mental Representation Items* (MRIs). This paper describes how operational models based on MRIs can be derived and discusses the applications of these models to traffic assignment and route guidance systems. We report estimation results using revealed preference data to demonstrate the applicability and validity of the approach.

1 Introduction

We are interested in modeling and forecasting the route choice behavior of individuals. Route choice (RC) is one of the key questions in travel demand analysis and at the core of traffic assignment. Route choice models (RCMs) aim at predicting the route that a given traveler would take to go from the origin of her trip to the destination. A comprehensive review of the route choice modeling problem can be found in Bovy and Stern (1990) and Frejinger (2008).

Discrete choice models (DCMs) provide a powerful and flexible methodological framework, where a great deal of explanatory variables can be considered and the heterogeneity of behavior across the population can be explicitly captured. The estimation of DCMs for route choice analysis with revealed preference (RP) data involves specific challenges. The demanding requirements in data collection and processing, the combinatorial nature of the choice set, and the structural correlation due to the physical overlap of paths (Ben-Akiva and Bierlaire, 2003) are the main issues of the estimation with RP data. These issues apply to a much lesser extent to the estimation of models with stated preference (SP) data, which is therefore easier to handle.

The conventional representation of routes is based on paths that are constructed as sequences of oriented arcs on a connected graph. In addition to the above mentioned challenges for the modeler, the complexity

of the path approach is not consistent with the actual behavior of travelers (Golledge, 1999; Taylor and Tversky, 1992). The general trend in the literature is to propose more and more complex models to deal with these challenges (Fosgerau et al., 2013; Yang and Juang, 2014; Lai and Bierlaire, forthcoming; Ramos, 2015).

In this work, we are investigating in the opposite direction, i.e. we attempt to simplify the problem. This is accomplished by modeling the strategic decisions of people instead of the operational ones. The objective is to derive a modeling framework with a level of complexity consistent with the one actually handled by the travelers. To achieve this goal, we use modeling elements that capture the mental representations used by people throughout their travel in the transportation system.

The paper is organized as follows. Section 2 is a literature review about the challenges in route choice modeling. Section 3 is devoted to the methodology. In Section 4 we apply the methodological framework to a real case study. In Section 5 we illustrate the use of the MRI model for traffic assignment and for the development of route guidance systems. The last section summarizes the findings of the present study and identifies the future steps of the research.

2 Literature review

Several models have been proposed to analyze route choice. The main challenge encountered by the analysts is related to the definition of the choice set. The choice set contains the alternatives that are considered by the traveler.

Three approaches are proposed in the literature. The first one relies on heuristics to construct the choice set actually considered by the travelers (Bovy and Fiorenzo Catalano, 2007; Prato and Bekhor, 2007). Examples such as the labelling approach (Ben-Akiva et al., 1984), the link elimination approach (Azevedo et al., 1993), the link penalty approach (de la Barra et al., 1993), and the constrained k-shortest path (van der Zijpp and Fiorenzo Catalano, 2005) assume deterministic shortest paths to generate the choice set. Constrained enumeration approaches based on branch-and-bound are proposed by Friedrich et al. (2001), Hoogendoorn-Lanser (2005), and Prato and Bekhor (2006). However, Bekhor et al. (2006) showed that all methods fail to generate a set that is guaranteed to include the *observed* routes. The second approach assumes that the choice set contains all feasible paths between the origin and the destination. To make this approach operational, sampling techniques have been proposed (Frejinger et al., 2009; Flötteröd and Bierlaire, 2013). The third approach follows a technique that does not rely on sampling, while avoiding the full enumeration of paths. It has been proposed by Dial (1971) and more recently by Fosgerau et al. (2013).

The second challenge is related to the modeling of the physical overlap of paths. In the context of random utility models (RUMs), it is not possible to assume that the random utilities are independent across alternatives. The approaches proposed in the literature can be divided in two categories; those dealing with the correlation in the deterministic part of the utility function, and those dealing with it in the stochastic part. Examples of the former include the C-logit proposed by Cascetta et al. (1996) and the Path Size Logit (PSL) proposed by Ben-Akiva and Bierlaire (1999). Examples of the latter include the Multivariate Extreme Value (MEV) models, such as the Paired Combinatorial Logit and Cross Nested Logit (CNL) (Vovsha and Bekhor, 1998; Lai and Bierlaire, forthcoming), and Non-MEV models, such as the Probit (Daganzo and Sheffi, 1977) and the Logit Kernel model (Bekhor et al., 2002; Frejinger and Bierlaire, 2007).

Dealing with correlation in the stochastic part of the utility increases the model complexity and entails difficulties with respect to the estimation, especially for large networks. Frejinger and Bierlaire (2007) introduced the concept of subnetworks within a factor analytic specification of an error component model. The authors argue that they capture correlation in a behaviorally realistic way without increasing the complexity of the model. Yet, the estimation of such a model for large networks is cumbersome.

Mai et al. (2015) exploit the recursive logit (RL) model by Fosgerau et al. (2013) and extend it to the nested RL. The latter builds on the RL model, where no choice set generation is needed, and improves it to accommodate the correlation of path utilities. The first work to use a MEV model with sampling of alternatives is the one by Lai and Bierlaire (forthcoming). The authors specify a CNL model and adopt the Metropolis-Hastings algorithm proposed by Flötteröd and Bierlaire (2013) with a new expansion factor inspired by Guevara and Ben-Akiva (2013) in order to avoid the enumeration of paths.

Most models cited above are path based. The concept of path is evidently hard to handle due to the operational limitations discussed above –path generation, sampling, complex correlation– but also due to the fact that drivers do not actually make travel plans decisions based on paths (Golledge, 1999). The latter entails behavioral limitations. Hence, the state-of-the-art models are either very complex or often fail to capture observed behavior. No realistic yet simple model based on RP data has been proposed. This is where the contribution of the present study lies. We propose a simple model, which is not based on paths, and exploits RP data. It is based on mental representations actually used by the travelers.

Intuitively speaking, if we ask a traveler to describe her itinerary from home to work, we do not expect her to report sequences of links. A few attempts to use perceptual concepts in route choice analysis include the labelling approach by Ben-Akiva et al. (1984) for path generation and sampling, and the subnetworks approach by Frejinger and Bierlaire (2007) to capture correlation. Yet, the scope of these works is different and the modeling element is still a path. In this work we try to identify the strategic decisions of the travelers that are associated with their mental representations of the area of interest.

The literature of cognitive science, environmental psychology and geography, assisted in gaining insights into the representation of large-scale

environments and spatial behavior. It includes, but is not limited to, Tolman (1948), Lynch (1960), Suttles (1972), Chase (1983), Couclelis et al. (1987), Golledge (1999), Golledge and Gärling (2003), Arentze and Timmermans (2005), Hannes et al. (2008).

In these research fields, and in their attempts to answer questions such as how people perceive and process information during travel in spatial networks, we come across concepts such as the *mental map*, the *mental representation*, or the *anchor point*. Each field approaches these concepts from a different perspective and defines them accordingly. Lynch (1960) decomposes the image of the city into paths, edges, districts, nodes and landmarks. Suttles (1972) defines a cognitive map as the mixture of qualitative and spatial information that allows us to make decisions in a spatial context. Golledge (1999) argues that individuals relate to anchor points in the spatial environment and that the anchors have a dual role: (i) they serve as organizing elements of peoples' mental maps, and (ii) they enable way-finding. Recent work by Hannes et al. (2008), defines the mental map as *"The whole of spatial and travel related information used and stored in memory"*.

Contrary to the research conducted in the disciplines cited above, this study does not look at how the representations of space are formed or learned. It rather exploits the intuition gained from these fields in the effort to build a flexible and operational framework for route choice analysis.

3 Methodological Framework

In this section, we outline the methodology for the definition of a route choice model based on mental representations. In addition to the mental representations themselves, four main elements need to be defined for the development of an operational random utility model: (i) the choice set $\mathcal{C}_n$, (ii) the explanatory variables, composed of the vector of attributes x_{in} of the alternatives i, such as travel time, length, etc., and the vector of socio-economic characteristics z_n of the traveler n, (iii) the specification of the deterministic part of the utility function V_{in}, and (iv) the distributional assumption for the error terms ε_{in} of the utility functions. The choice model is then

$$P_n(i \mid \mathcal{C}_n, x_n, z_n) = Pr(U_{in} \geq U_{jn} \forall j \in \mathcal{C}_n) \tag{1}$$

where $U_{in} = V_{in} + \varepsilon_{in}$.

The key feature of the present framework is the representation of routes as sequences of Mental Representation Items (MRIs). Contrary to the current state-of-the-art RCMs, the MRI framework is of greater generality. It is possible to define a MRI model that is independent of a network model. Still, the availability of a network, quite common in practice, is of great help to the modeler[1].

In what follows, we start by presenting empirical evidence of the MRI assumption and proceed with a formal definition of the MRI. Then, we describe the procedure for the specification of an operational model.

3.1 Empirical evidence

In order to investigate how mental representations could be exploited for modeling purposes, we have interviewed three drivers in the cities of Athens and Stockholm. Respondents were asked to give a description of the routes that they follow to go from home to work, or to a relative's place. We are interested in the wording they use to describe the itinerary.

All the respondents have good knowledge of the network and, if asked explicitly, they are able to describe the exact itinerary they follow in details, for instance: *"I go right in the first traffic light, continue straight*

[1]See Section 4 for the operationalization of the model using a network model.

for about 300 *meters and turn left in the third traffic light that I encounter.".* However, in their initial response to the question *Describe your itinerary from home to work*, they never give detailed itineraries. Instead, they identify two to three alternatives that they choose in rotation depending on the time of day –indicating different expectation of congestion– that are always associated with some conceivable element of the city, such as the *city center*, the *highway H*, the *neighborhood N*, the *bridge B*. These elements are used to identify alternatives. In some cases they also identify an alternative that they never choose; e.g. entering specific areas that are in the congestion pricing zone in Stockholm.

An example of a described itinerary is: *"I take E4 (major highway traversing Sweden) and then enter the city from the entrance in Solna (one of the main municipalities in Stockholm). I avoid Södermalm (district in central Stockholm) because of the tolls."*, or *"I go through Årsta (district in Stockholm) and then take the bridge to Kungsholmen (one of the islands that Stockholm comprises of)."*. The comparisons of these alternatives are described as "*longer but faster*", "*faster because of less traffic lights*", "*more pleasant*", "*more boring*", etc., meaning that not only the routes but also their attributes are perceived in an aggregated manner.

The experiments conducted in the two cities support our hypothesis that choice takes place at a higher conceptual level and that the exact sequence of links, related to the concept of path, is just the implementation of this choice. In Appendix A we present one of the interviews for the city of Athens in details. Through the interviews we get (i) insight into peoples' perception of route options, and (ii) intuition of how to define MRIs in a behaviorally realistic way. In the following sections, we use examples derived from these interviews to illustrate the ideas that we are discussing.

3.2 The Mental Representation Item

An MRI is an item characterizing the mental representation of an itinerary. It is associated with a wording that would be used in daily language to describe a route. Each MRI is characterized by a *name*, a *description*, a *geographical span*, and *representative geocoded points* (Fig. 1). The name and the description allow us to relate the MRI with the mental representation itself (conceptual components), while the span and the repre-

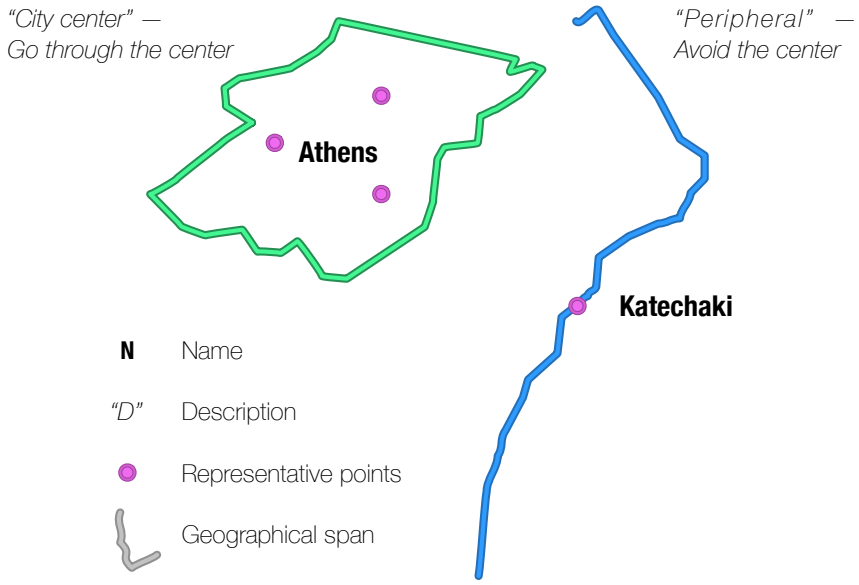


Figure 1: Examples of two MRIs and their components.

sentative points are designed to associate the MRI with a more objective representation, such as a map or a network (operational components). The representative point may be a major intersection in the city or any other point that is characteristic for the MRI, while the geographical span may be an area, a polyline, or any other shape, concave or not, that determines the boundaries of the MRIs.

A typical example of an MRI is "the city center". If we consider the example provided in Appendix A, the name of the MRI is obviously "the city center of Athens". Its description would roughly explain the boundaries of the zone, while the geographical span would describe these boundaries e.g. an area on a map or a list of nodes and links if a network model is available. The representative points may be one or few of the most important intersections in the center. Another example of a MRI would be a bridge. Considering the example of Stockholm, the most prominent feature of the city is that it spreads across 14 islands, which are connected through bridges and tunnels. The MRI name is straightforward, corresponding to a toponym, e.g. the "Centralbron"[2], that could be described as the bridge that passes by the old town (Gamla Stan). The geographical span is the

[2]Bron is the Swedish word for bridge.

span of the bridge on a map or a set of nodes and links that correspond to the span of the bridge on a network model. The representative point may be the middle point of the span.

The exact definition of the MRI is context dependent. It must be designed such that (i) it has a meaningful behavioral interpretation and (ii) its level of aggregation is high enough for the model to be simple and operational yet low enough for the model to be useful. A process that takes into consideration the characteristics of the city and fusing information from surveys where people talk about their itineraries is a recommended approach for the definition of the MRI in a given context.

A concept akin to that of an MRI is the one of the *subnetwork*, proposed by Frejinger and Bierlaire (2007). The concept of subnetwork is used to capture perceptual correlation without increasing the model complexity. The authors define a subnetwork component as a *"sequence of links corresponding to a part of the network which can be easily labeled and is behaviorally meaningful in actual route descriptions"*. Hence, even paths that do not physically overlap are assumed to be correlated. As an example, *"paths going through the city center may share unobserved attributes, even if they do not share any link"* (Frejinger and Bierlaire, 2007). The motivation of this work is similar, but extend the idea of incorporating perceptual elements in route choice to the choice set itself. We aim at deriving a model where the mental representation actually used by the travelers to describe their routes are the main modeling elements.

3.3 Definition of the alternatives

Following the definition of the MRI, a route consists of either one-MRI or sequence-of-several-MRIs. Figure 2 illustrates a few examples of MRI sequences in the city of Stockholm. Three alternatives, as identified by one of the interviewed drivers (see Section 3.1), are depicted. Two of the alternatives first cross the district of Årsta and then entail a bridge choice either through Essingeleden, or through Liljeholmensbron, while the third alternative passes by the Gullmarsplan square (metro station), traverses the Söderledstunneln and then goes through the city center.

An advantage of the alternatives generated on the basis of MRI sequences is that they have a much simpler correlation structure than the

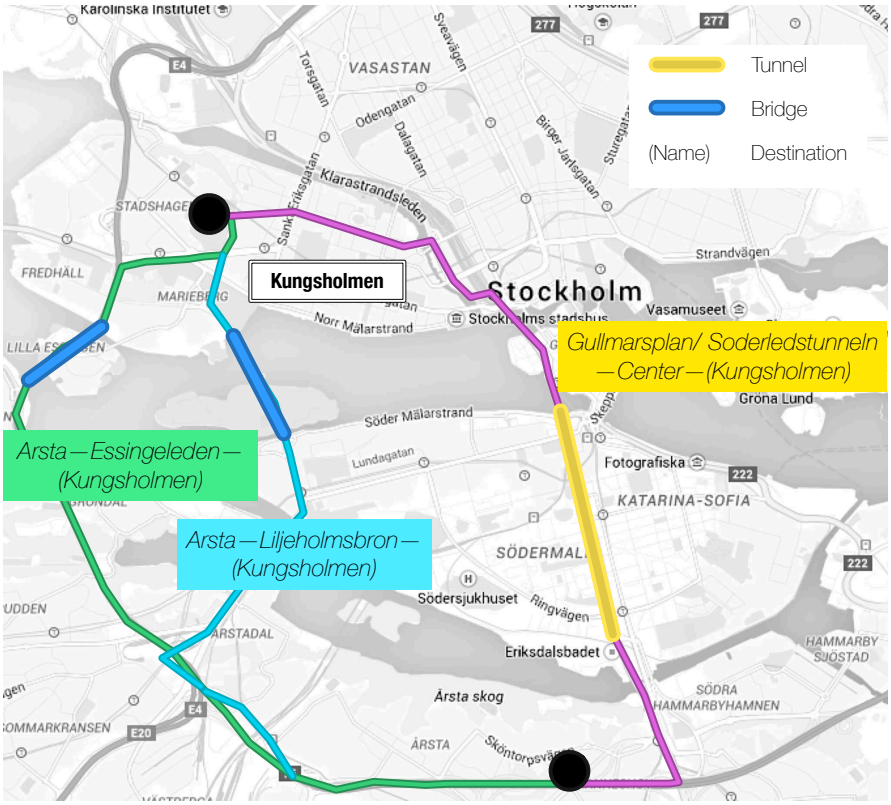


Figure 2: Examples of MRI sequences in the case of Stockholm.

path alternatives. It is important that the number of MRIs is kept low so that the number of MRI sequences is also low and can be enumerated to characterize the choice set. The case study presented in Section 4 deals with the simplest possible case, where each route is described by a single MRI and there is a common choice set for all individuals.

3.4 Specification of the model

As soon as the MRIs are defined and the choice set is determined, we are able to specify a route choice model and define the choice probabilities for each MRI alternative. Each MRI alternative is associated with a utility which is a function of the attributes of the alternatives x_{in} and the characteristics of the individual z_n.

As mentioned above, it is intended that the number of alternatives is kept low in order to keep the model as simple as possible. As the MRI alter-

natives have a simple correlation structure they may actually be assumed to be independent. In this case, we can assume that the error terms ε_{in} are independently and identically (i.i.d.) extreme value distributed across i and n, so that we obtain the logit model

$$P_n(i \mid \mathcal{C}_n) = \frac{e^{V_{in}}}{\sum_{j \in \mathcal{C}_n} e^{V_{jn}}}. \tag{2}$$

Other types of models can be investigated. When the alternatives are sequences of MRIs, the possible correlation structure can be captured by a cross-nested logit model, where each MRI is a nest, and an alternative i belongs to a nest m if MRI m appears in the sequence i. This model specification is similar to the link nested model by Vovsha and Bekhor (1998) and Lai and Bierlaire (forthcoming), but the level of complexity is not comparable[3], and fully under the control of the modeler.

The issues that arise are (i) how to relate the available data to MRI alternatives (Section 3.4.1) and (ii) how to specify the utility functions for the abstract items and assign attributes to the alternatives (Section 3.4.2) in order to render the specification operational.

3.4.1 From data to MRIs

Collecting route choice data for a MRI model is relatively easy using interviews and surveys, as the level of aggregation of the data is similar to the level of the model. Reported itineraries are the ideal data source as the analyst gets direct feedback about the mental representations of the users, which assists the definition of the MRIs. Nowadays, route choice data coming from GPS devices or smartphones are more and more available. In the same way that the classical path-based models require some map-matching procedures, we need in the case of such a data source to relate the MRI alternatives with the reported locations or the GPS data.

To estimate an MRI choice model, a measurement equation is needed that captures the contribution of each piece of data to the likelihood function. Let i be an alternative of the MRI model and y be an observation –it can be a reported sequence of places in a survey, or a GPS trace. Its contribution to the likelihood function is then

[3]Note that Ramming (2002) estimated this model for a network of 34,000 links, where the estimation of nest-specific coefficients was impossible.

$$\sum_{i \in \mathcal{C}_n} P(y \mid i) P(i|\mathcal{C}_n, x_{in}, z_n) \tag{3}$$

where $P(y \mid i)$ is the likelihood to observe y if i is the alternative actually chosen by the traveler. It is defined on the basis of the MRI' s *geographical span* (Section 3.2). If a network model is available the span may be defined as a list of links. In the opposite case, it can be defined as a geomarked area on a map. In some circumstances, it is convenient to associate each piece of data to a single alternative, so that $P(y|i)$ has values 1 –if the observation y traverses the geographical span of the MRI– and 0 –otherwise. For more complex measurement models, we refer the reader to Bierlaire and Frejinger (2008) and to Chen and Bierlaire (2013).

3.4.2 Specification of the utility function

The specification of the utility functions for the MRI model is probably the most challenging part from a modeling point of view. Indeed, as the main modeling element is a mental representation, the alternatives and their attributes are in general latent, that is based more on perceptions than on objective measurements. In this paper, our objective is to obtain a model that is simple to develop and to use. Therefore, we propose below two heuristics to generate attributes for each alternative. The second does not require a network model. Clearly, more advanced specifications, exploiting the literature on perceptions, could be investigated as well.

A deterministic approach with representative paths Given a network model of the area of interest, a unique representative path is associated with each alternative (Fig. 3). For example, it can be the path connecting the origin, one of the geocoded representative points of each MRI in the sequence, and the destination, following the shortest (or the fastest) path. The procedure consists of the following steps prior to the estimation of the model:

1. For each MRI, determine a representative node r in the network model.

2. For each alternative, consider the sequence of nodes associated with the sequence of MRIs, proceeded by the origin of the trip and followed

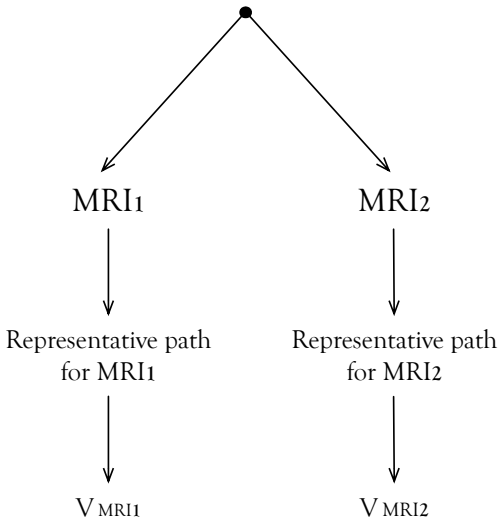


Figure 3: Schematic representation of the specification of utility functions through representative paths.

by the destination.

3. Generate the path connecting the nodes in the sequence, where two successive nodes are connected by the shortest path (according to a given metric, such as length, travel time, or a combination of both).

4. The attributes and the utility function of the alternative are defined as the attributes and the utility function of the representative path.

If socio-economic characteristics of the travelers are available, they should be incorporated in the utility functions. Note that we have chosen to present here a very simple technique, as our objective is to obtain a simple model. We show later that it generates meaningful results. The power of this framework is that the modeler is flexible and may choose the desired level of complexity to achieve his objectives.

In the first step of the above procedure, the choice of the representative node requires also some modeling assumptions. Most importantly, the specific representative node of an MRI may vary from observation to observation, as a function of the origin and destination of the trip. For example, considering the MRI "avoid the city center", trips that cross it from north

to south, and trips that cross it from east to west may use different representative nodes, so that the generated path makes sense. This is why the definition of the MRI involves more than one representative points.

The process outlined above is based on a shortest path approach where the link cost tables may include the lengths, the travel times or any other attribute. Our experience shows that this approach, although quite simple, may provide meaningful results, and allows to keep the complexity of the model low. We present its implementation in Section 4.

Network-free approach The main advantage of the MRI framework is its flexibility and greater generality in comparison to the current state-of-the-art models. A network model and paths are neither necessary to generate the choice set, as already discussed above, nor to specify utility functions for the MRI model. As soon as the MRIs are identified and defined on the basis of the geographical span, it is possible to define aggregate attributes for each item. These can be for example (i) the level of service (LOS), through congestion indices or average speed limits, and (ii) the density of landmarks or points of interest, through land use data. Using such measures to describe the MRIs has the advantage of being coherent with the level of aggregation of the modeling elements. In addition, it enables the specification of the utility functions without the link additive attributes in a network- and path-free approach. In such a context, the availability of reported itineraries along with the travelers' estimation or perception of the attributes of each item is the ideal source of data.

4 Case Study

The objective of this case study is to demonstrate that the model is indeed applicable with real data. We focus here on a case where only GPS data is available, and we show that, despite the need to use heuristics that may sound arbitrary in the first place, sensible results can be obtained. For this purpose, we use the network of Borlänge in Sweden (Fig. 4). The network consists of 3077 nodes and 7459 unidirectional links. The estimation results presented in this section are based on real GPS data collected from private vehicles in the city of Borlänge. The data had been previously processed to obtain map-matched trajectories useful for route choice analysis[4]. Each observation consists in a sequence of links from the origin to the destination node.

In what follows, we present one possible way to operationalize the model, according to what was discussed in Section 3, taking advantage of the available network model. Note that, consistently with the objective of this research, we have tried on purpose to keep the modeling as simple as possible.

Figure 4: Borlänge road network where the city center is highlighted by the shaded area.

[4]We refer to Frejinger and Bierlaire, 2007 and Axhausen et al., 2003 for a description of the Borlänge GPS dataset.

Figure 5: National roads, R50 and R.70, in Borlänge encircling the city center.

4.1 Definition the choice problem

In lack of survey data where people talk about their itineraries, we merely rely on examining the network of Borlänge for the definition of the MRIs.

The center of the city (shaded area in Fig. 4) is the first distinct element in the network of Borlänge. It is characterized by higher density of small streets in comparison with the rest of the network. This core is encircled by the national roads (R.50 and R.70) that are highlighted in Fig. 5. In most of their parts, the national roads have four lanes –two in each direction– and the pavement is divided by guard-rails. These features signify higher operating speeds, as well as higher convenience, in comparison with the rest of the streets that have at most one lane per direction, lower speed limits, and are less direct.

Figures 6 and 7 show the output of Google Maps Directions API for route options given two arbitrarily selected OD pairs. After investigating options proposed by Google Maps for several OD pairs, it seems that three high level possibilities appear: (i) going through the city center, (ii) following orbital routes around the city center and along its boundaries, and

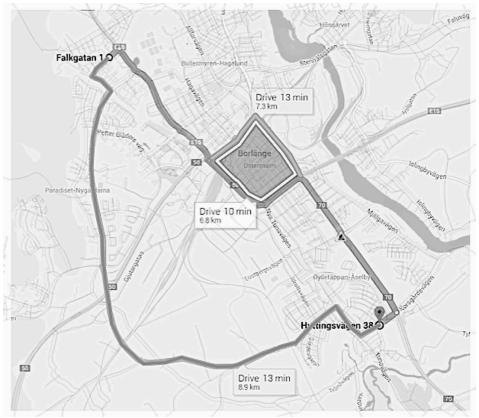


Figure 6: Example of route options provided by Google Maps Directions.

(iii) avoiding the city center. Examples of each option are provided in Fig. 6 and 7. These patterns have also been observed in the dataset.

Consequently, we identify three major elements: the *"city center"*, the *"perimeter of the city center"*, and the *"avoid the city center"*[5]. We further separate the *"perimeter of the city center"* in two elements: (i) *"clockwise movement"*, and (ii) *"counter-clockwise movement"*, indicating left and right turn accordingly. These are two clear options for travelers as they approach the center. Therefore, we obtain four MRIs. We label them as CC, CL, CO and AV, equivalently for the *"city center"*, the *"clockwise movement"*, the *"counter-clockwise movement"* and the *"avoid the city center"*.

For the CC the name obviously corresponds to the "city center of Borlänge". The description would correspond to a sentence equivalent to "go through the center". For the CL and CO the name corresponds to the name of the streets defining the perimeter; these are the Backaviadukten (south half of the perimeter), Siljansvägen (north-east part of the perimeter), and Ovanbrogatan (north-west part of the perimeter). The description would correspond to "turning left or right", respectively for clockwise and counter-clockwise, as approaching the city center. Finally, for the AV the name may correspond to the name of any street that can be used to avoid the center. What is important in this case is the description. It would correspond to a sentence equivalent to "take the peripheral X to avoid the city center".

[5]Note that there is the river on the east side of the city. In the present work we do not consider trips between the two sides of the river.

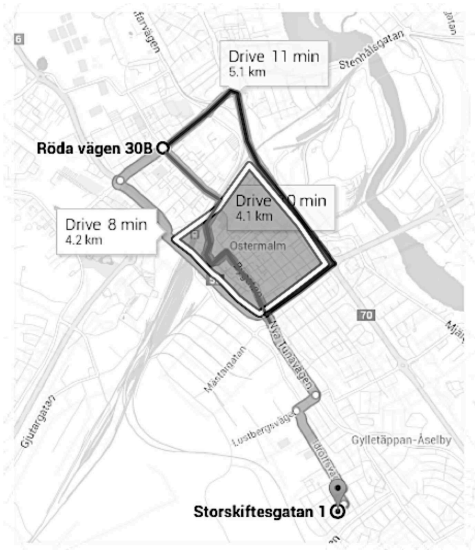


Figure 7: Example of route options provided by Google Maps Directions.

We now need to characterize the four MRIs. Following Section 3.2, we determine the *geographical span* and one or more *representative points for each* MRI. The geographical span of the CC alternative is the list of all links of the network that are inside the perimeter that defines the boundaries of the center. The representative points are two nodes that roughly correspond to the middle points of the two main streets in the center (Fig. 8). The geographical span of the CL and the CO alternatives is the list of all links on the perimeter defining the boundaries of the center, while the representative points are the three nodes that roughly correspond to the middle points of the three streets. Finally, the geographical span of the AV alternative is the list of all the remaining links, excluding the ones inside and on the perimeter of the center. The representative points are the two nodes that correspond to the two main peripherals that can be used to avoid the center, depending on the origin and destination of the trip. Figure 9 depicts the representative points of the four MRIs.

Once the MRIs are identified, the choice set must be built. We consider the most simple case: each alternative involves exactly one MRI. Moreover, the choice set is the same for every individual in the population that we consider. Therefore, we have $\mathcal{C}_n = \{\text{CC, CL, CO, AV}\}$, for all n.

Figure 8: The two main streets in the city center.

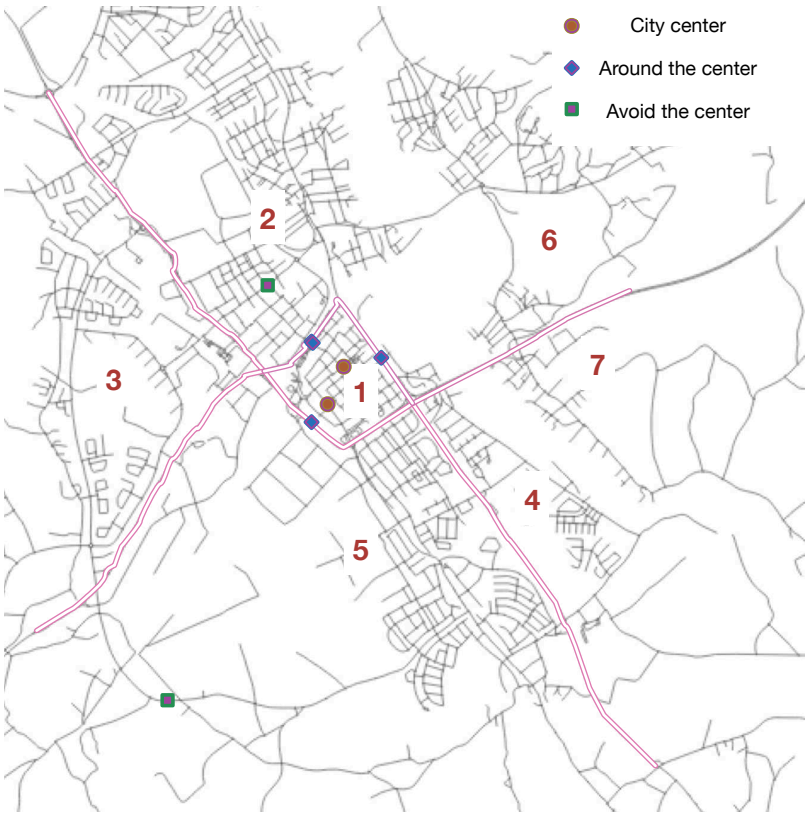


Figure 9: Representative points of the MRIs.

4.2 Model specification

The fact that the MRIs consist of physically disjoint network elements justifies the use of a logit model. We compare two different specifications. The first specification includes travel times and the second one lengths. Tables 1 and 2 show the specification of Model 1 and Model 2, respectively. We include the variables *number of left turns* (LEFT) and *number of intersections* (IS) in both specifications. As the choice set size is four it is possible to estimate ASCs. These specifications have been obtained after testing various specifications.

4.3 Data processing and measurement model

The available dataset of GPS map-matched trajectories needs to be transformed into a dataset consistent with the model specification. In this case, the measurement model defined in (3) is deterministic, and each observation is replaced by one alternative of the MRI model, according to the definition of the geographical span (see Section 4.1). More precisely, $P(y|i) = 1$, if the observed path traverses the geographical span of the MRI, and *zero* otherwise. Note that in this application, each observation traverses exactly one MRI. Examples of observed routes, and the MRI that they correspond to, are provided in Fig. B1a-e. This step was initially done manually in order to gain insight into the data and develop the rules to automate the procedure.

The network is divided in 7 zones but for this case study we only use 5 zones. We ignore trips where either the origin or the destination of the trip is located in the other side of the river (zones 6 and 7). We obtain a sample of 139 observations for the estimation of the model.

For the network model of Borlänge the available information includes the link lengths, the turning angles between each pair of links and the in- and out-degree of each node, allowing us to identify intersections. The travel time of each link is computed as the ratio of the link length divided by an average speed, the latter being the average observed speed over all observations and all links with the same speed limit.

We use the heuristic described in Section 3.4.2 for the specification of the utility functions. The *representative path* for each MRI is the fastest path. A representative example of the four alternatives in the MRI choice set, as generated by this process, is depicted in Fig. 10.

Table 1: Specification table of Model 1 with piecewise linear travel time

Parameter	CC	CL	CO	AV
ASC_{CC}	0	0	0	0
$ASC_{CL,CO}$	0	1	1	0
ASC_{AV}	0	0	0	1
$\beta TIME_{CC}$	TT (min)	0	0	0
$\beta TIME_{CL,CO}^{(0-10min)}$	0	TT (min) ≤ 10	TT (min) ≤ 10	0
$\beta TIME_{CL,CO}^{(>10min)}$	0	TT (min) > 10	TT (min) > 10	0
$\beta TIME_{AV}$	0	0	0	TT (min)
$\beta LEFT$	# left turns	# left turns	# left turns	# left turns
βIS	# IS	# IS	# IS	# IS

Table 2: Specification table of Model 2 with the length formulation

Parameter	CC	CL	CO	AV
ASC_{CC}	0	0	0	0
$ASC_{CL,CO}$	0	1	1	0
ASC_{AV}	0	0	0	1
$\beta LENGTH_{CC}$	Length (km)	0	0	0
$\beta LENGTH_{CL,CO,AV}$	0	Length (km)	Length (km)	Length (km)
$\beta LEFT$	# left turns	# left turns	# left turns	# left turns
βIS	# IS	# IS	# IS	# IS

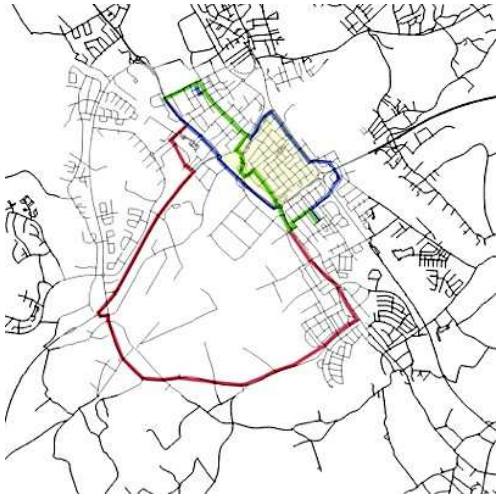


Figure 10: Illustration of a MRI choice set with the representative paths.

We underline once again that the determination of the representative node for each MRI is OD dependent. To facilitate the determination of the representative node r for each observation a simple zoning system is assumed (Fig. 9). As an example, avoiding the center usually corresponds to a long detour (Fig. B1e). Indeed, for people traveling from south to north, and vice versa, this is the only way to avoid the center (through Paradisvägen, a rural street). Only for trips between the zones 2 and 3 it is possible to avoid the center through other streets. For these trips we define a second representative node[6].

Statistics on the attributes of the MRI alternatives are provided in Table 3. Table 4 shows the number of times that each MRI is chosen. Figure 11 shows the distribution of the travel times of the four MRI alternatives.

4.4 Model estimation

The parameter estimates[7] are presented in Table 5. All the parameters have the expected signs.

The estimates of travel time indicate that the users are more sensitive to travel time when they have to go through the center, in comparison with

[6]An additional MRI alternative could be considered in this case, but due to the low number of observations we did not proceed with this demarcation.

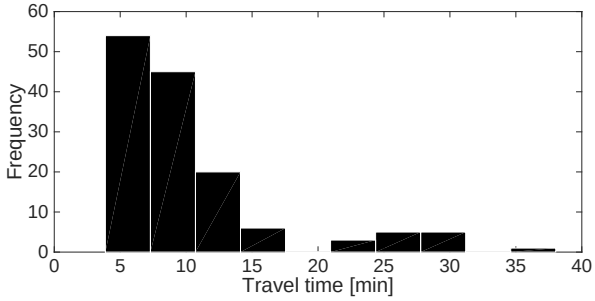
[7]The models are estimated using *Biogeme*, an open source software for discrete choice models (Bierlaire, 2003).

Table 3: Descriptive statistics on attributes

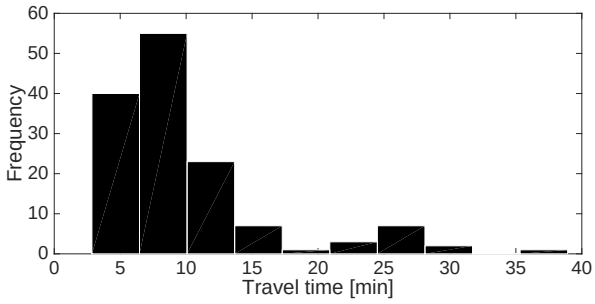
	mean	**median**	**min**	**max**	**std. dev**
TT_CC (min)	10.18	8.38	3.88	38.03	6.41
TT_CL (min)	9.98	8.18	2.86	38.93	6.32
TT_CO (min)	10.21	8.37	3.81	36.47	6.23
TT_AV (min)	11.80	13.12	2.66	38.58	11.81
L_CC (km)	7.65	5.21	1.88	42.91	7.39
L_CL (km)	7.84	5.47	1.57	43.82	7.30
L_CO (km)	7.95	5.48	2.33	42.62	7.23
L_AV (km)	9.18	9.04	1.54	42.29	8.90
IS_CC (#)	27	26	9	51	9
IS_CL (#)	25	24	6	58	10
IS_CO (#)	26	26	4	48	11
IS_AV (#)	34	37	10	75	15
LT_CC (#)	2	2	0	8	2
LT_CL (#)	2	2	0	5	1
LT_CO (#)	2	2	0	4	1
LT_AV (#)	3	3	0	9	2

Table 4: Frequency of the chosen alternatives

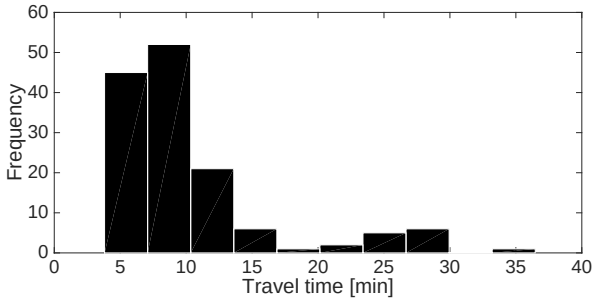
Choice	**# times chosen**
CC	13
CL	53
CO	51
AV	22
Total	139



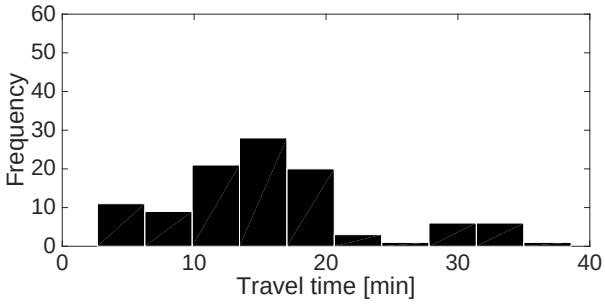
(a) CC



(b) CL



(c) CO



(d) AV

Figure 11: Distribution of travel time for the four MRIs.

the other alternatives. This is also reflected in the length coefficient of the second model, where length is penalized more in the utility of the *through the CC* alternative, compared with the generic coefficient for the other three alternatives. The piecewise specification of the travel time coefficients for the *around* alternatives reveals that users are less sensitive when the travel times are short (shorter than 10 minutes) and more sensitive when the travel time becomes longer.

Looking at the two models, the parameter estimates for the number of left turns and the number of intersections are of equivalent magnitude.

Table 5: Estimation results

Parameters	**Model 1** Value (Rob. t-test 0)	**Model 2** Value (Rob. t-test 0)
$ASC_{CL,CO}$	-2.110 (-1.47)	-0.975 (-0.58)
ASC_{AV}	1.870 (0.89)	0.307 (0.18)
$\beta TIME_{CC}$	-0.772 (-2.82)	
$\beta TIME_{CL,CO}^{(0-10min)}$	-0.286 (-1.74)	
$\beta TIME_{CL,CO}^{(>10min)}$	-0.616 (-2.86)	
$\beta TIME_{AV}$	-0.583 (-3.11)	
$\beta LENGTH_{CC}$		-1.480 (-2.99)
$\beta LENGTH_{CL,CO,AV}$		-0.871 (-5.03)
$\beta LEFT$	-0.288 (2.22)	-0.270 (-1.89)
βIS	-0.047 (-2.16)	-0.063 (-3.42)
Number of observations	139	139
Number of parameters	8	6
$\overline{\rho}^2$	0.375	0.416
$\mathcal{L}(0)$	-183.201	-183.201
$\mathcal{L}(\hat{\beta})$	-106.563	-101.064

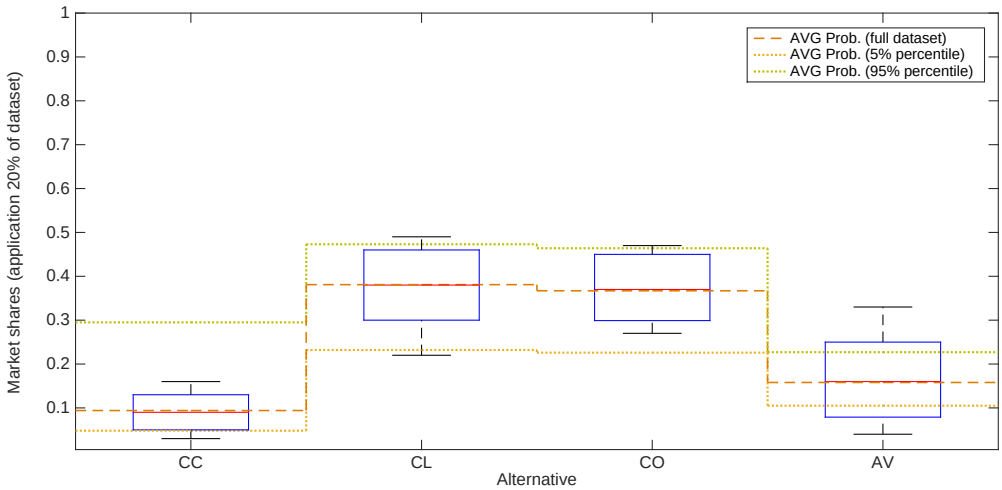


Figure 12: Box plot of the market shares from the application in 20% of the data against the confidence intervals from the estimation on the full dataset.

Intuitively, the CL and CO alternatives may share unobserved attributes, and if this is the case they should be nested. Hence, a nested logit formulation, assuming a nest with the CL and CO alternatives, was also tested and rejected by the likelihood ratio test against the logit model.

4.5 Forecasting results & validation

In order to validate the model and test its performance with respect to the predicted choice probabilities, we adopt a cross-validation approach. The procedure is outlined below:

1. Randomly select 80% of the data for estimation.
2. Use the estimated model to predict the remaining 20%.
3. Repeat 100 times.

The results are summarized in the box plot in Fig. 12, where we present the resulting sample shares for each alternative. In the same plot, we overlay the sample shares from the estimation on the full dataset (average probability), as well as their 5% and 95% percentiles. The result is quite satisfying as it appears that the level of precision for the forecast, using the

point estimates of the parameters, is consistent with the confidence interval of the full model considering the distribution of the estimators.

5 Model Application

It is important to ensure the feasibility of the use of the proposed model in practical applications. Two applications we expect the model to be useful for are: (i) traffic assignment and (ii) design of route guidance systems. In this section, we discuss operational aspects of using the model in these contexts, and we demonstrate its applicability using the Borlänge case study.

5.1 Traffic assignment

Let us consider the assignment of a single traveler n with known origin and destination. We are interested in the probability $P(a \mid \mathcal{C}_n)$ that traveler n crosses any network link a, given her MRI choice set $\mathcal{C}_n$. This probability is written as

$$P(a \mid \mathcal{C}_n) = \sum_{i \in \mathcal{C}_n} P(a \mid i) \cdot P(i \mid \mathcal{C}_n) \tag{4}$$

where $P(a \mid i)$ is the probability of using link a given that MRI i is chosen. It is expressed by

$$P(a \mid i) = \sum_{p} \mathbf{1}(a \in p) \cdot P(p \mid i) \tag{5}$$

where $\mathbf{1}(a \in p)$ is the zero/ one indicator of path p containing link a and $P(p \mid i)$ is the probability of traveling along path p given that MRI i is chosen. $P(p \mid i)$ can be seen as the operational component, that is the implementation of decision i, while $P(i \mid \mathcal{C}_n)$ is the behavioral component represented by the MRI choice model. For the sake of illustration, a simple model specification is subsequently described.

Let s_v^i be a real number representing the consistency of node v with MRI i. The determination of s_v^i reflects the definition of the MRIs on the basis of the geographical span and the representative points. In particular, if a node is contained in the MRI's geographical span it has a consistency equal to 1, and 0 otherwise. The nodes corresponding to the representative points of an MRI may receive a consistency value higher than 1.

Each path p consists in a sequence of nodes. We can then compute the score $s_p^i = \sum_{v \in p} s_v^i$ of each path for every MRI $i \in \mathcal{C}_n$, where $\sum_{v \in p} \cdot$

represents the sum over all nodes v contained in path p. s_p^i denotes the consistency of a path p with an MRI i.

The path choice probability from the universal path choice set given a MRI i is then, apart from normalization, specified as

$$P(p \mid i) \sim \exp\left(\alpha \frac{s_p^i}{\sum_{j \in \mathcal{C}_n} s_p^j} + \beta t_p\right) \tag{6}$$

where $\sum_{j \in \mathcal{C}_n} \cdot$ spans over all MRIs in $\mathcal{C}_n$, t_p is the travel time on path p, and $\alpha > 0$, $\beta < 0$ are real-valued coefficients. The consistency sum favors paths that have relatively high node overlap with MRI i. It represents, at the path level, the traveler's operational decisions leading at the link-by-link level to an implementation of MRI i. The second factor favors paths that are faster. Some cost-dependency of this type is needed because otherwise it becomes more important to stay in the MRI than to reach the destination.

Now, the link choice probabilities defined in (4) need to be computed. The number of paths with nonzero probability of being selected given that MRI i was chosen may be too high to be enumerated and used in the traffic assignment context. We propose to use the Metropolis-Hastings Algorithm of Flötteröd and Bierlaire (2013) to draw, for each MRI i, a large number of Q_i paths from the un-normalized distribution (6). Letting p_i^q be the qth path drawn for MRI i, $P(a \mid i)$ is then approximated by

$$\hat{P}(a \mid i) = \frac{1}{Q_i} \sum_{q=1}^{Q_i} \mathbf{1}(a \in p_i^q). \tag{7}$$

This is, for a given MRI i, the ratio of the number of times link a is contained in a sampled path divided by the total number of sampled paths. The MRI-unconditional link choice probabilities (4) are then approximated through

$$\hat{P}(a \mid C_n) = \sum_{i \in \mathcal{C}_n} \hat{P}(a \mid i) \cdot P(i \mid C_n). \tag{8}$$

5.1.1 Application to Borlänge case study

We now use the network of Borlänge to apply the methodology described above. We take into account one OD pair of a person traveling from the

south to the north of the city. The MRI choice probability $P(i \mid C_n)$ follows the specification given in Section 4. For the OD pair of interest we obtain:

$$P(AV \mid \mathcal{C}) = 0.002$$
$$P(CC \mid \mathcal{C}) = 0.084$$
$$P(CL \mid \mathcal{C}) = 0.247$$
$$P(CO \mid \mathcal{C}) = 0.667$$

Finally, for the specification of $P(p \mid i)$ we have chosen $\alpha = 25$ and $\beta = -2.5$. Figure 13 depicts for each link a of the network, the probability –as defined in (4) and approximated by (8)– that a single traveler executing a single trip passes through that link. On this figure one can identify the links where congestion might occur. Figures 14 to 17 show the link choice probabilities –as defined in (5) and approximated by (7)– conditional on the choice of the indicated MRI. On these figures one can identify the most attractive links for each MRI.

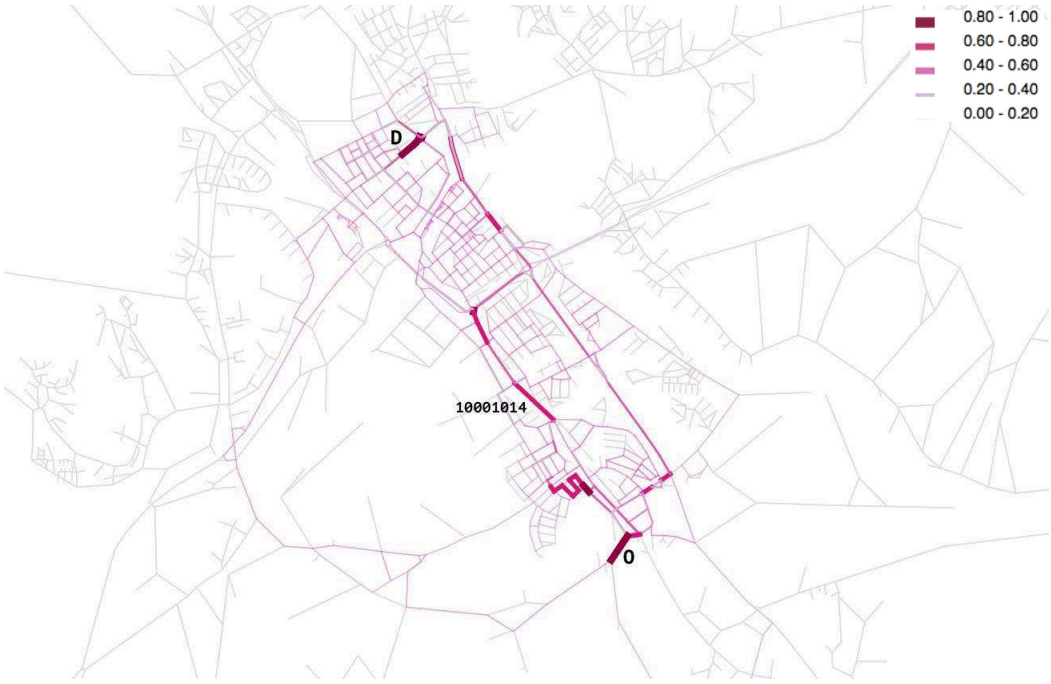


Figure 13: Link choice probabilities given the MRI choice set.

Figure 14: Link choice probabilities conditional on the choice of the avoid the CC alternative.

Figure 15: Link choice probabilities conditional on the choice of going through the CC alternative.

Figure 16: Link choice probabilities conditional on the choice of going around and clockwise the CC alternative.

Figure 17: Link choice probabilities conditional on the choice of going around and counter-clockwise the CC alternative.

5.2 Route guidance

The proposed approach is particularly relevant in the context of route guidance systems. The nature of the MRI makes it a natural way to provide information and guidance directly to users, without the necessity to use a navigation system. Variable Message Signs (VMS), radio announcements, oral instructions can easily benefit from the output of the model. Still, the models can be used for navigation systems using the same decomposition as described earlier. At the behavioral level, a recommendation of the sequence of MRIs is provided. Given that recommendation, a specific path to follow may be calculated, for instance the shortest path consistent with the MRI. The role of the representative geocoded points is particularly important here. Note that current navigation systems already work with this concept: if one provides as a destination the name of a city, without being more specific, the system itself selects a specific location in the city center and leads one there.

With the help of the MRI based behavioral model, in-vehicle navigation systems could be adjusted according to the needs of the driver. As an example, drivers with good knowledge of the network do not always need step-by-step instructions to reach their destination, rather suggestions that would help them to avoid congestion in specific parts of the network (e.g. avoid the city center). In this context, the navigation systems could provide the option to choose between detailed itineraries in case of new destinations, or aggregate route suggestions in case of everyday trips, such as the trip to work, according to the current traffic conditions.

5.2.1 Illustration for the Borlänge case study

Assuming a population of more than one traveler, and maintaining the simplification of a single OD pari, Figure 13 suggests that congestion may arise on link $a = 10001014$. Guiding travelers to MRIs that avoid link a may hence be an advisable route guidance strategy. For this, the probability $P(i \mid a)$ that a randomly selected individual moving through a has chosen MRI i is helpful to compute

$$P(i \mid a) = \frac{P(a \mid i)P(i)}{\sum_{j \in \mathcal{C}_n} P(a \mid j)P(j)}. \tag{9}$$

Using the $P(a \mid i)$ values from the previous example and the MRI choice

probabilities $P(i)$ reported in Section 5.1.1, one obtains $P(AV \mid a) = 0.0$, $P(CC \mid a) = 0.069$, $P(CL \mid a) = 0.186$ and $P(CO \mid a) = 0.745$. This means that the MRI CO contributes most and the MRI AV contributes least to the congestion. A useful guidance message, for people traveling from the south to the north of the city (in accordance with the OD used in this example), could then be:

> "Avoid the city center (i.e. use AV), and in particular do not travel through Backaviadukten (i.e. avoid CO)."

6 Conclusion

In this paper, we present a new approach for route choice analysis that is designed to be flexible and simple. It explicitly separates the high level decisions, associated with mental representations, from the operational decisions resulting in explicit paths. The framework has to be adapted on a case by case basis. We have shown here, using a real case study with RP data, that the use of simple heuristics leads to a meaningful model that can be estimated and used in practice.

The proposed framework opens the door to more modeling opportunities. The MRI concept is sufficiently general to capture a great deal of behaviorally meaningful aspects of route choice, yet sufficiently specific to yield operational models. It also motivates new approaches to data collection. In particular, it would suggest to conduct specific surveys that would help the modeler in defining the MRIs and the perception of the performance of each alternative. New possibilities for the use of route choice models have been identified as well. Namely, the concept of MRI may be particularly relevant for travel information and guidance.

A great deal of future research is anticipated with this novel framework. Other case studies and model specifications should be investigated. In addition, we plan to extend the framework using a multiple-level representation. Depending on the level of detail in the data, the topology of the network, and the interviews of travelers, different characterizations of the choice using MRIs are possible. Instead of arbitrarily deciding on one of them, we plan to investigate the possibility to combine several representations in a consistent way by means of a multi-layer approach.

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A Description of a work trip in Athens' road network

This appendix provides a qualitative example in support of the MRI assumption. The case study area is located in Athens, Greece. Athens is a big city and its transportation network is very dense and complicated. The characteristics of the driver are:

- Male;
- 54 years old;
- Familiar with the route as he has been doing this trip for more than 20 years;
- Experienced driver with very good knowledge of the network (living in Athens all his life and driving from the age of 18);
- He either uses a motorcycle or a car for his transportation.

Figure A1 depicts all the relevant components that we discuss hereafter. We asked the driver to describe his regular route from home to work. He said that there are two alternatives: either to go through the *city center* (red-shaded area) or to take the *peripheral* road (green polyline).

After asking the driver to give more details regarding the two itineraries, he described different options associated to each of these two alternatives. Given that he chooses to go through the peripheral he has several ways to reach it: (i) neighbourhood Y and then neighbourhood V, or (ii) neighbourhood I. Continuing describing his route, he stated that after exiting the peripheral and a while before reaching the destination he has another two options: (i) either through a main arterial (extension of the green line), or (ii) through cutting though neighbourhood P (blue line). The name of the peripheral road (Katechaki) came up several times during the description as it is associated with all of these itineraries.

When he chooses to go through the city centre, he regularly follows one specific itinerary along main arterials. He only pointed one minor deviation to a minor street in order to avoid a traffic light in cases of congestion. After being explicitly asked, the driver mentioned that he adjusts his itinerary in the level of minor streets, mainly due to bottlenecks that he may encounter. In this case though, he did not refer to the exact options.

Being asked what defines his choice, he said that it depends on his mood and on the current traffic conditions. He prefers to go through the city centre as it is more pleasant for him than the peripheral, that he called monotonous. The city centre alternative is also the shorter option with respect to kilometres, but it is usually more congested in the morning. For this reason he usually takes the peripheral road on his way to work. On the other hand, on his way back home in the evening he always chooses to go through the centre as it is not congested during this time of day. It worths noticing that apart from abstraction in the representation of the possible alternatives, there is abstraction in the association of attributes to them. It is highlighted by the use of adjectives, like fast, pleasant etc.

While talking, the respondent made use of major streets' names and neighbourhoods as described above, but he also referred to schools in one of the neighbourhoods, park in another, squares, an ancient stadium which is a landmark in Athens, a cemetery (the first and biggest of the city), several churches that are located along these routes, a cinema, the tower of Athens, and also home location of friends and relatives that signify reference points (anchor points and landmarks) along the way. When asked if locations such as the stadium play any role in his choice of route the answer was: *"No, I just meet them on my way"*. These elements facilitate the description of his route. They are used to improve communication and understanding, and they characterize the alternative routes. It should be underlined that there is a distinction between these reference points and landmarks along the way and the representations that consist alternatives. The former though can be used to construct explanatory variables. For instance, areas with increased number of landmarks and points of interest might be more attractive, or more familiar, to travelers. They may also serve as representative points for the definition of the MRIs that we discuss in this paper.

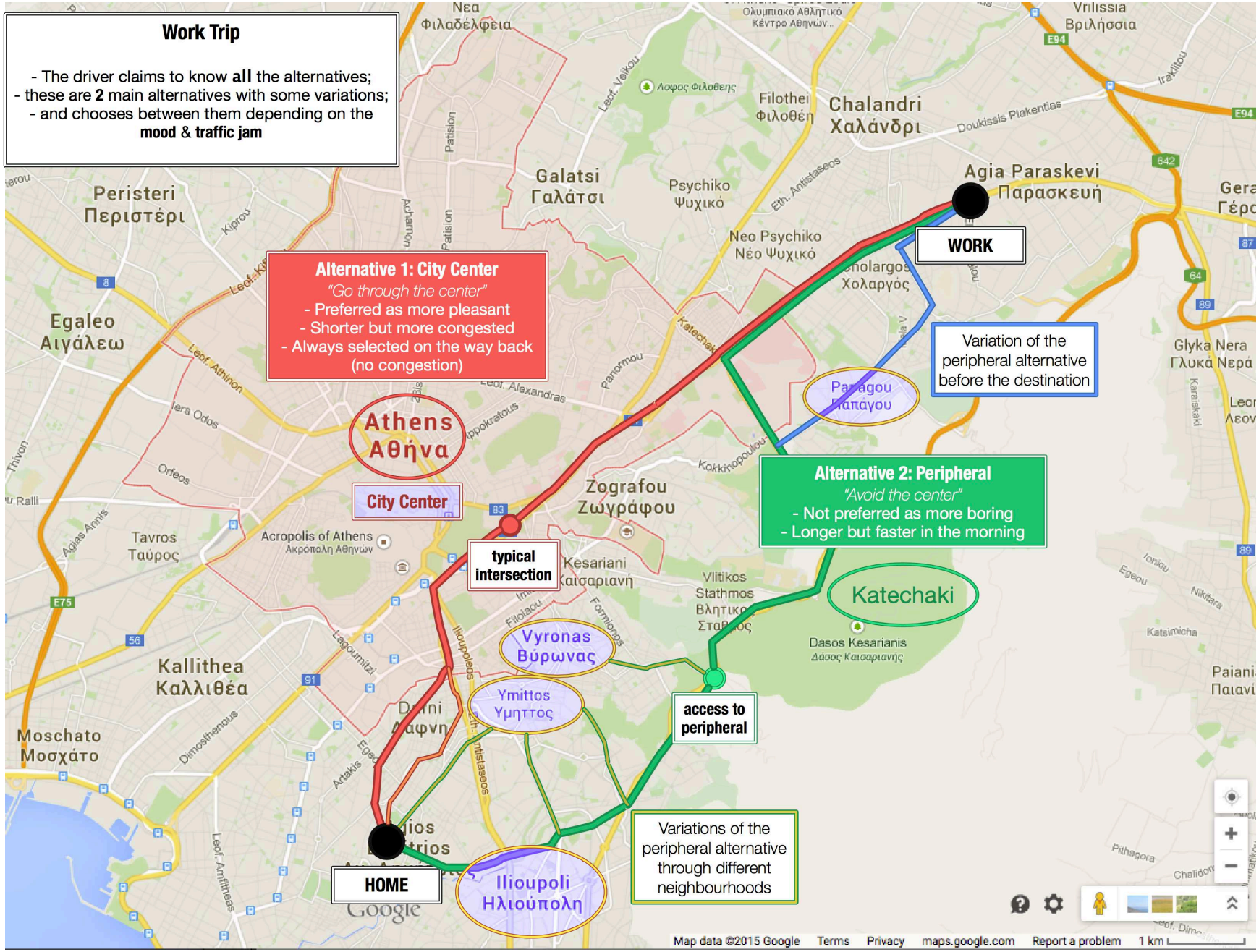

Figure A1: Sketch of the described route alternatives.

B Additional Figures

(a) Through CC.

(b) Avoid CC.

(c) Clockwise CC.

(d) Counter-clockwise CC.

(e) Avoid CC.

(f) Various.

Figure B1: Characteristic examples of observed trajectories.