Strategic Visitor Flows and destination management

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Abstract

The relevance of the monitoring of visitor flows (VF), namely the general or aggregate patterns of travellers' movements in a given area is twofold. On the one hand, they are relevant for the spatial description of *travel networks*. On the other hand, VF patterns are challenging the traditional organization of destination management (DM) and becoming a *strategic tool*. VFs are useful for reshaping the DM organization's governance model from a static-central model to a dynamic network. The aim of this research is to estimate SVF using the data movement recorded by a test carried out with an anonymised and highly aggregated mobile phone data set, provided by Swisscom- a major Swiss mobile company. This research sheds some light on the relevance of VF in the understanding and improving of DM organization governance. Furthermore, it provides evidence of the existence of SVF at different levels of geographical scale obtained by network analysis techniques.

Keywords: spatial movement patterns of travellers, network models; mobile phone data, third Generation DMO.

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"From *flows of power* to the *power of flows*" (M.Castells)

1 Introduction

Spatial tourism behaviour has been in the research agenda since last century and some researchers have pointed out its importance in market segmentation (Dredge, 1999; Gunn, 1994; Lue, Crompton, & Fesenmaier, 1993). Research is interested in describing general or aggregate patterns of movements in a given area (Orellana, Bregt, Ligtenberg, & Wachowicz, 2012) of which the underlying structure has been characterised as a network (Leiper, 1990).

The lack of appropriate data describing these patterns was a barrier to showing empirical evidences of the network shape (Leiper, 1989) in XX century. The available methods were based on traditional research data gathering techniques called *small data approaches* (Baggio, 2016b) such as expert opinions collected from multiple participant interviews (workshop) (Beritelli, Bieger, & Laesser, 2014; Beritelli, Reinhold, Laesser, & Bieger, 2015).

Nowadays, other families of data have been available. 'Destination guest cards' having a chip embedded or not, also provide insights of the spatial travel behaviour at the intra-destination level. Digital traces obtained via geo-tagged photos on social media (Instagram, Flick, etc.) have also been useful for this empirical research (i.e. Kádár & Gede, 2013; Vu, Li, Law, & Ye, 2015). Global Positioning Systems (GPS) are also popular for these studies (Birenboim, Anton-Clavé, Russo, & Shoval, 2013). Finally, the capabilities of mobile phone positioning databases have also been tested and found pertinent as a tool for monitoring travellers' behaviour (Ahas, Aasa, Roose, Mark, & Silm, 2008; Steiner, Baggio, Scaglione, & Favre, 2016).

The research agenda of tourism behaviour has been considered as one of the most important aspects in the XXI century. The research object has been enlarged in order to take into account virtual dimensions besides spatial aspects which are referred to as *travel networks*. Evidence showing this virtual dimension consists of the following elements (Stienmetz & Fesenmaier, 2013): Firstly, travellers are creators and co-creators of the information contained by networks which support travel planning; secondly, travellers share their experiences in community-based space and finally, technologically supported networks are ubiquitous meaning that the information can be found before, during and after the trip (Pan & Fesenmaier, 2006; Y. Wang & Fesenmaier, 2004; Y. Wang & Xiang, 2007; Zach & Gretzel, 2011; Zheng Xiang, Wöber, & Fesenmaier, 2008). The concept of destination is also affected by this traveller network conception. Physical and virtual elements both contribute to the creation of value and make the analysis of the whole value system more difficult (Stienmetz & Fesenmaier, 2013).

The authors of this research have discussed that *tourism attraction* systems (Kim & Fesenmaier, 1990; Lue et al., 1993), as proposed in the '90s, have been enriched and updated by the *travel networks* concept (Stienmetz & Fesenmaier, 2013). Both are based on a network-natured structure, but in the former model, touch points or nodes were mostly identified by their special locations; whereas in *travel networks* touch points could be either physical or virtual - roughly speaking, experiences and informational elements are included. Therefore, describing general spatial patterns of travellers' movements or VF is only part of the story but not the least interesting one, and so it is the aim of this research (Baggio & Scaglione, 2017).

As a result, a shift of information and decision centrality into placeless and timeless networks has been observed, which also happens in other sectors. *Organisations* are changed to *flows* and the latter becomes the unit of work, decision and output (Castells, 1989, p. 142). “Thus, the dialectic between centralization and decentralization or the increasing tension between places and flows, in the final analysis could reflect the gradual transformation of the *flows of power* to the *power of flows*.” (op. cit., p. 171).

This research provides tools for finding generalised patterns of tourist movements in the canton of Fribourg, Switzerland. These results show the strategic nature of VF as they are the key in the reshaping process of Destination Management Organization (DMO) towards a better governance. The research also shows methodological approaches that seem to be appropriate in a Big Data environment to solve problems based on network metrics (see also: (Baggio, 2016a; Baggio & Klobas, 2017). In particular, modelling the system as a graph means that we can say much about the behaviour of the system even without studying the actual dynamics. It can be estimated *how much* one part of the network influences another and *how well* the network is optimized with respect to the dynamical system (Asgari, Gauthier, & Becker, 2013).

The paper is organised as follows. The following section is the literature review which gives an overview of the on the new conception of DM organization and the strategical nature of VF, followed by typical elements in relation with the mathematical theory of networks. The third section describes the data; the fourth section presents the results of the network analysis and following this is the conclusion, which presents limitations and also provides a future research agenda.

2 Literature review

2.1 The strategical nature of Visitor flows for a DMO

The conception of DMO articulated in the early 70’s as a comprehensive and static system has failed, at least in the last three decades (Beritelli et al., 2014). DMOs territories are more characterised by political borders such as municipalities or districts than by areas or regions where the main service providers are settled (Beritelli, Bieger, & Laesser, 2007). Roughly speaking, traditional DMOs are built around the geographical space such as political borders of the territory. The failure cycle is described by the impossibility of traditional DMOs to reconcile three different logical systems: territorial, business and travel experience (Beritelli et al., 2014). As a consequence, the supply side have limited information and few indications on which initiative and project may have an impact on the demand side. Innovation and cooperation fail not only because of limited time and resources but also because understanding what triggers visitors to choose one destination and what moves them along their trip never really was systematically and specifically exposed (Beritelli et al., 2014; Beritelli et al., 2015).

A destination has multiple visitor flows occurring at different paces and different places. Among these aforementioned flows there are those that are stable, recurring and well-catered to on the supply side also known as strategic visitor flows. They show a robust structure as they are repetitive and homogenous so they shed light on the clusters of attractions/activities difficult to be grasped otherwise. Therefore they are significant for business and can be considered strategic. These flows take into account the dynamic behaviour of the individual tourist as well as influences such as seasonality. It is also possible to identify weak connections and interdependencies and thus potential opportunities for innovation and capitalization in the future (i.e. the marketing and management process). SVFs as a unit of study represent the optimal concept to analyse, manage and market the destination. SVFs represent and link to one or more demand networks and a stable, implicitly or explicitly developed, best-practice supply network (Beritelli et al., 2015). These networks are either directly linked to one another or via virtual portals (various intermediaries and coordinating organizations as well as visitor-community related platforms providing brokering, coordinating and or supporting functions (Beritelli et al., 2015; Stienmetz & Fesenmaier, 2013).

Depicting flows in space enables decision-makers to understand and develop the variety of tourist demand as well as to break free of existing preconceptions. VFs allow the visualization of *space of flows* meaning the heterogeneous context on the supply side in space and generate meaningful discussion among the concerned actors about the destination space that goes beyond generic products and markets. Different product lines or themes are then considered for the whole destination (Beritelli et al., 2015).

This subsection tries to show that VFs challenge the DMOs traditionally territorial and top-down conception which is based on a local- regional perspective delineated by political borders to a kind of variable geometry conception that focuses on the space of flows. As a result, the marketing and management process should provide an overview of activities and responsibilities *for each SVF*, allowing the analysis of existing or unmet synergy potentials and subsequently allowing the drawing of conclusions for the future distribution of functions and responsibilities for a single SVF and across SVFs (Beritelli et al., 2015; Reinhold, Laesser, & Beritelli, 2015).

These findings are in line with the conception of a destination as a value system composed of a set of four different, but overlaying networks: the marketing and promotion level, experience design level, partnership configuration and sales & distribution (Stienmetz & Fesenmaier, 2013). Furthermore, they confirm Castells (2001) view in DMOs given that SVF shows that the decisions should shift from static and regional governance structure to one whose network structure is placeless and timeless.

2.2 From traditional data to Big data in VF

In the recent past and still nowadays, the study of spatial patterns of movements has used surveys or opinion polls as primary data (Hwang, Gretzel, & Fesenmaier, 2006; Lew & McKercher, 2006) which were time-consuming and not very accurate (Vu et al., 2015). Most of the time they are based on information recalled by the interviewees. Another strategy was based on surveys built on diary reports of the trip (Stewart & Vogt, 1997). Exploratory methods were also used, such as expert opinions collected from multiple participant interviews (workshop) in order to individualise attractions and categorise them (i.e. getaway, egress) (Beritelli et al., 2014; Beritelli et al., 2015) . All of those methods are rooted in a long academic research tradition and we can call them *small data approaches* (Baggio, 2016a, 2016b).

Different technologies and strategies allow the collection of geo-localisation information, they could be on voluntary basis or not. Volunteered geographical information yielded by destination guest cards or GPS tracking records belongs to the former type whereas passive mobile positioning data belongs to the latter one. In what follows we briefly describe them.

Digital traces obtained via geo-tagged photos on social media (Instagram, Flickr, etc.) or mobile apps belong to the family called *volunteered geographical information* (VGI) which an increasing number of scholars take advantage of for analysing either resident or visitor flows (i.e. Kádár & Gede, 2013; Vu et al., 2015) The family of VGI is useful for quantifying elements of the structure of the travel network (Zach & Gretzel, 2011). A recent research shows through empirical elements that VGI approaches seem not to contain biased information and thus data gathered using those approaches are a reliable source to SVF (Stienmetz & Fesenmaier, 2013).

Destination guest cards having a chip embedded also give insights into intra-destination VF. These cards which tourists obtain from destination management offices allow free or highly discounted access to partner attraction and transportation (Zoltan & McKercher, 2015). Another destination card has been offered to tourists in the canton of Fribourg since 2016, without having a chip but having a mobile app which can constantly be updated by service suppliers (i.e. flash offers) (Union fribourgeoise du tourisme, 2015). Analysis made on the first season of data collection gives coherent results when crossed with the results of the present research (Scaglione, Baggio, Favre, & Trabichet, 2016).

Global positioning system (GPS) track data are very popular in VF studies although so far with a small sample of participants (Birenboim et al., 2013). Empirical research carried out on a volunteer basis proved that the three techniques could be effective tools for tracking tourism behaviour even though they show different levels of accuracy (Shoval & Isaacson, 2007).

The use of smartphones has increased in the everyday life of consumers such as when using social networks on mobiles phones (Scaglione, Giovannetti, & Hamoudia, 2015). The increasing importance of mobile devices is also evident during vacation periods (D. Wang, Xiang, & Fesenmaier, 2016). The capabilities of mobile phone positioning data have therefore become an interesting and pertinent tool for monitoring VF which can enlarge traditional and VGI data sources. Advantages are the following: “data can be collected for larger spatial units and in less visited areas; spatial and temporal preciseness is higher than for regular tourism statistics” (Ahas et al., 2008, p. 469).

The term *passive mobile positioning data* refers to automatically stored information which are kept in log files by mobile operators. The mobile geo-localisation information relies on the position of the cell network. A cellular network is physically placed at base stations which are usually towers supporting one or more directional antennae. The localisation of the cell network is determined by the base station (in the case of only one antenna) or several antennae. The size of the cell network is not fixed, therefore, and depends on the average load or number of phones connected. When the network is crowded, phones cannot switch to the nearest base station but connect to another one in the neighbourhood. The optimal distance from handset to antenna is less than 60 km (Ahas et al., 2008). Two projects were run contemporaneously in the last years in Europe focusing on passive mobile data use and tourism. The first one was a Eurostat project named Feasibility Study on the use of mobile positioning data for Tourism Statistics (Eurostat, 2013). The second was a feasibility project named Monitour (Scaglione, Favre, & Trabichet, 2016), which was financed by Swiss research funds. Both projects used the coordinate of the base station as proxy of the location of the mobile, thus geo-localising anonymised visitor (cf. Eurostat, 2013, p. 18). The studies showed that the method is quite beneficial and able to provide many useful insights.

Reliability evaluation of passive mobile positioning data was one of the aims of the European project. In the estimation of tourism frequentation, the results show that the quality and exhaustivity of those data is not inferior to other alternative methods such as a survey, moreover, their estimations are in coherence and well fitted with the official data gathered by Eurostat (2013, p18). One of the main difficulties that passive mobile positioning data faces is the identification of “natural environment” or “residence place” for the anonymised visitor and this concept is central in tourist identification. The European project solved this issues by the analysis of extended anonymous user’s data in order to follow the anonymous subscribers over “a longer period than the one under study in order to established their residency and/or usual environment” (cf. Eurostat, 2013, p. 18). In the same manner, anonymised visitors can be categorized as day-trippers or overnight tourists, the first category is difficult to grasp with traditional frequentation techniques (Scaglione & Perruchoud-Massy, 2013), even though bias in the classification between these two categories cannot be excluded.

In terms of frequentation statistics, passive mobile positioning data have a higher coverage when compared to traditional statistics such as overnights in non-paid or non-registered accommodation and better inbound and outbound statistics (Eurostat, 2013).

Gonzalez, Hidalgo, and Barabasi (2008) proposed a method exploiting the observed high degree of temporal and spatial regularity of human trajectories. This research shows that individual travel patterns collapse, in spite of their difference, into a single probability distribution. This research is a very promising path to point out the residence of tourists’ subscribers.

Some other limitations are more difficult to overcome. No or little information is available about qualitative aspects such as socio-demographic characteristics (excluding country of the company mobile provider), expenditure, purpose of the trip, etc. Some other related issues are coverage issues, or refer to the telecommunication market itself, such as the cost of calls or texting or roaming fees that could affect the use of mobiles especially in the case of international tourists (Eurostat, 2013).

The next section describes the mobile data used in this research more accurately.

3 Data

Swisscom, which is the major Swiss mobile provider having 60% of the market is a partner of this research and provided a set of test data. The data consists of 18,138 anonymised mobile users (AMUs) belonging to one of the top European incoming countries in Fribourg canton's tourism. The period under study is 11 days, from 17 to 28 August 2014. For confidentiality purposes, Swisscom anonymised the users using hashing-algorithm techniques and shifting of the date; no characteristics of the users are given. It is worth noting that this anonymization process does not affect the results of this research, whose aim is to show the inference of SVF using mobile data.

The data is comprised of 2G A Interface data, 2G IuPS Interface data, 3G IuCS data and 3G IuPS data, technology which does not allow accurate geo-localization of the mobile position (i.e. it was not possible to associate the data to specific tourist attractions). Thus, the authors used the position of the cells (namely antennas) as proxy for the geo-localization of an AMU, acknowledging that this is a limitation of this research. There are approximately 1,500 cells.

In order to identify SVF, the authors programmed a customised routine in Java which was run by the computer centre of Swisscom in order to yield a file consisting of trajectories. The structure of that file has the following fields: AMU, trajectory identification, time stamp, duration and cell identification. The time stamp field indicates the moment when AMU was captured by the cell identified in the observation. The duration indicates the period of time that the AMU remained captured by the cell, but this data was not used in this first analysis.

Cellphone positioning data suffer from some risk of spatial bias, which might lead to distortions of the final estimation, especially for what concerns over- or under-representation of certain locations at certain times. The quantitative assessment of these errors in real-world data remains an open issue (Ricciato, Widhalm, Craglia, & Pantisano, 2015). However, for the objectives of this work, a coarse identification of the locations is more than sufficient.

The data includes 18,138 trajectories, having a mean duration of 3 days and 15 hours and a standard deviation of 2 days 14 hours. The median number of steps per AMU is 13.

4 Network analysis

The network has been built in the following way. Records were given a unique identifier, then the different tracks were extracted (one trajectory per AMU). The length of a track is the number of segments connecting the different points (antennas) on the track. The tracks were then combined into a network whose nodes are the antennas and links are all the trajectories (cumulated) followed by people going from one antenna location to another; the network was analysed by using standard network analytic technique.

A full description of the methods of network science is beyond the aims of this work. Interested readers can find many details in the books of Newman and Barabási (Barabási, 2016; Newman, 2011) and in the review by Baggio, Scott, and Cooper (2010). In what follows we provide only a brief description for the metrics and the methods actually used in this work.

The network is directed and weighted (the weight is the number of trajectory segments that connect two locations). Self-loops, that correspond to individuals that spend the whole period in a single location were removed. They are less than 5%, and not influential for the analyses conducted here. The removal simply cleans the data and avoids introducing noise that can reduce the efficiency of the algorithms. All scripts were written in Python and analyses used the Python *Networkx* library (Hagberg, Schult, & Swart, 2008), Pajek was used for visualisation (Batagelj & Mrvar, 1998).

The network has 1430 nodes and 21,122 links (13,933 have weight=1). The average (unweighted) degree is 29.54. The average weighted degree is: 44.92. The network is practically connected (only 14 nodes are isolated). Its density (number of links/max possible no. of links) is 0.01 and its reciprocity (% of nodes connected bidirectionally) is 0.47. Considering the network unweighted (so considering only how antennas are connected by user trajectories) the average path length (no. of antennas traversed) is 3.2 and the diameter (longest distance between 2 antennas) is 10. The weighted degree distributions (in-degree and out-degree, see Fig. 1) are consistent with a power-law (for the main tail) distribution with parameters (quite similar): InDegree exponent = 2.91±0.17; OutDegree exponent = 2.97±0.19 (calculations were made according to Clauset et al., 2009).

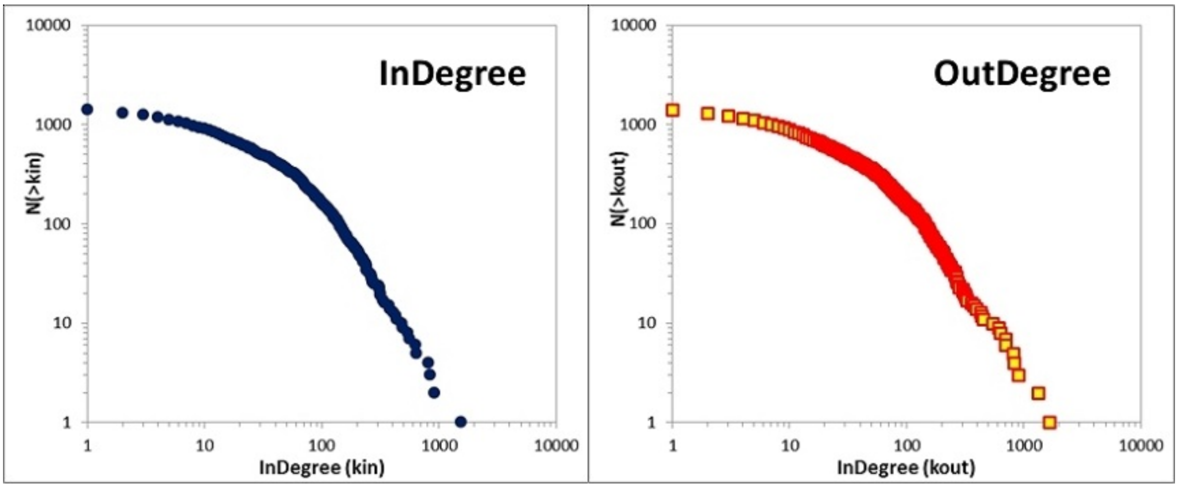

Fig. 1. Cumulative degree distributions (in- and out-degree)

Using the idea of a bow-tie structure (Broder et al., 2000), i.e. a large connected component (SCC), an IN and OUT component with a unidirectional connection, and a disconnected (DISC) component (Broder et al., 2000), we have the following split: connected component (SCC): 97.0%; IN: 1.1%; OUT: 0.9%; other (disconnected nodes): 1.0%.

A second possibility to explore the inner (mesoscopic) structure of a network is that of running a modularity analysis. A software algorithm finds the best set of subnetworks (clusters, modules) so that the nodes belonging to a group are more densely connected within the group than to other groups. A modularity index Q measures the level of separation. Q is normalised so that Q=0 means no separation (no modules found), and Q=1 complete separation into well-defined modules. Among the many possible algorithms proposed we used the *Louvain* method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008), which gives a good resolution power while providing a small number of well-balanced clusters.

The algorithm relies upon a heuristic for maximizing the modularity. The method consists of a repeated application of two steps. Nodes are first assigned randomly to a number of communities and moved from one community to another in so that modularity increases. In a second step a coarse-grained network is formed with the communities found in the first step and optimized for modularity. The two steps are repeated until the reassignments of communities produces no further increase in modularity. The method is computationally very efficient so it allows the study of very large networks and accepts directed as well as weighted links. This makes it one of the most popular methods and especially suitable for our purposes. The algorithm also uses a resolution parameter with which it is possible to set the capability to recognize communities at different scales. Here we use the standard value that gives a relatively good result without increasing the number of communities too much. As many other methods it can have limitations and pitfalls in the interpretation of the community structure, but these are essentially shared by all modularity optimization algorithms. A thorough discussion of these can be found in the reviews by Fortunato (2010) and Fortunato and Hric (2016).

The analysis found 14 communities (plus one with the disconnected nodes) and a modularity index Q=0.665, showing thus a set of relatively well-defined groups. They share the same set of attractions, thus identifying the aggregation points that are most popular among the visitors. Fig. 2 shows the network, its bow-tie components and the clusters uncovered.

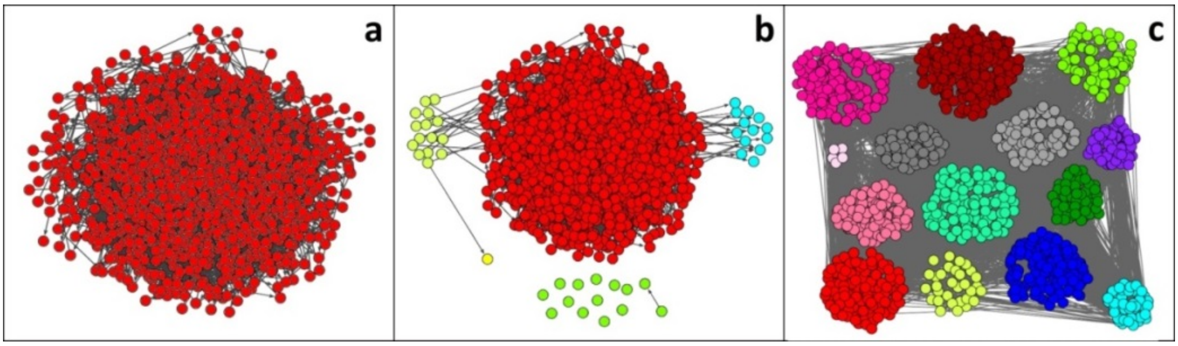

Fig. 2. The network (a), its bow-tie components (b), and the clusters from the modularity analysis (c)

The high fraction of the bow-tie SCC structure signals a high concentration of the movements in the area and indicates strong preferences for a limited set of locations. In fact the degree distribution of the SCC is quite steeper than the degree distribution of the whole network confirming this higher concentration (see Fig. 3).

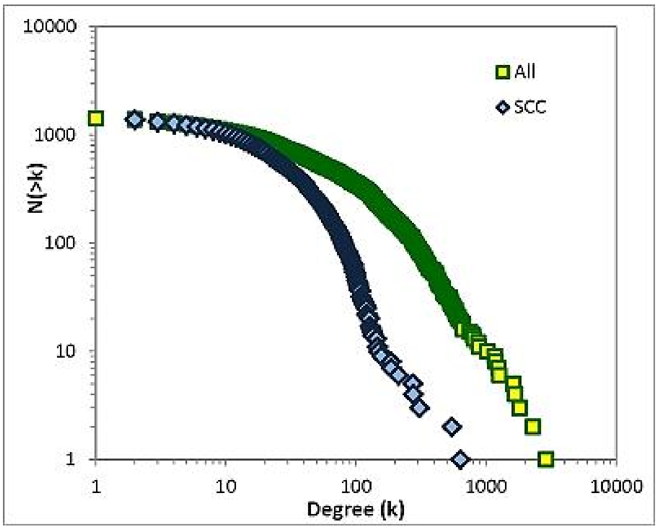

Fig. 3. The cumulative degree distributions of the whole network (All) and of the SCC

This effect can also be well detected with a geographic rendering of the modules uncovered, providing a more intuitive visualisation of this fact and better highlighting the mostly *local* nature of the movements recorded (Fig. 4).

Finally we identified the most *popular* paths by selecting the links with a weight > 25 and calculating those with the highest total weight. The results are shown in Fig. 5 which shows the distribution of the number of different points visited (hops). There is a clear distinction between a large majority of short paths and those with a higher number of locations. The main peak is at 8 (short path) and a secondary peak at 25 (long paths).

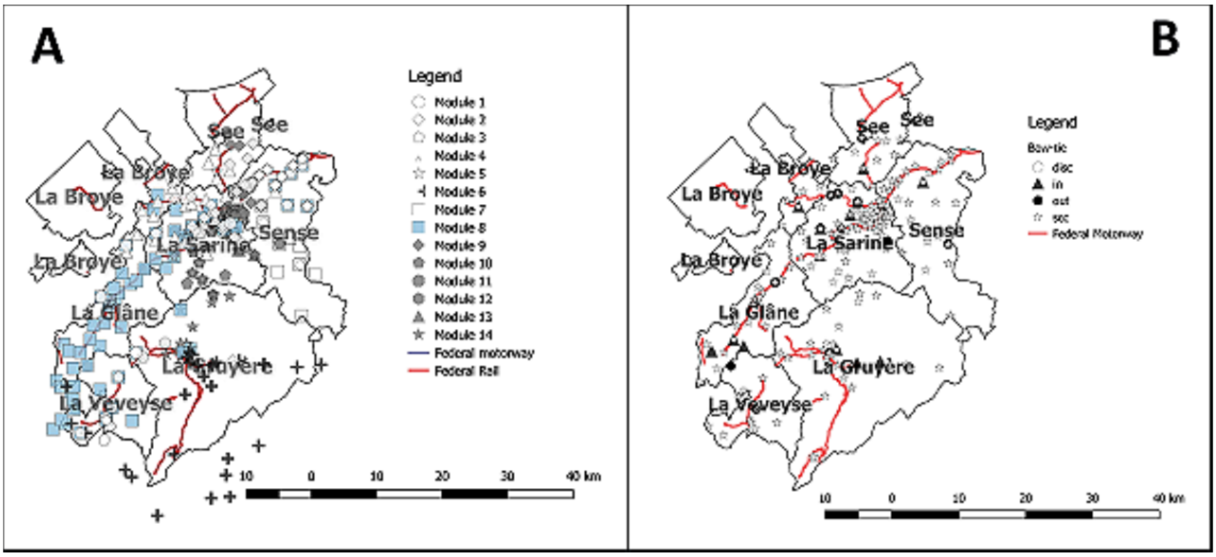

Fig. 4. The geographic rendering of the different modules found (panel A: different shapes represent the different modules) and of the bow-tie components (panel B: SCC=connected component, IN, OUT components and DISC=disconnected elements)

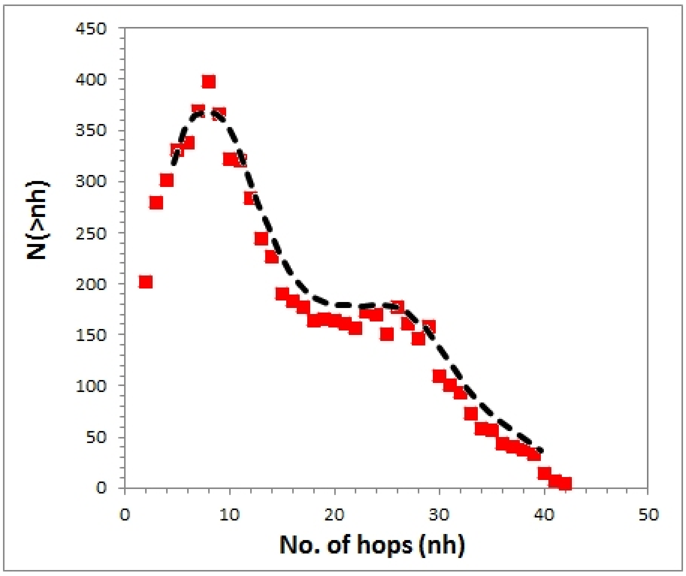

Fig. 5. The most popular paths in terms of number of visited locations (dotted line has the sole purpose of guiding the eye for a better visualization of the pattern)

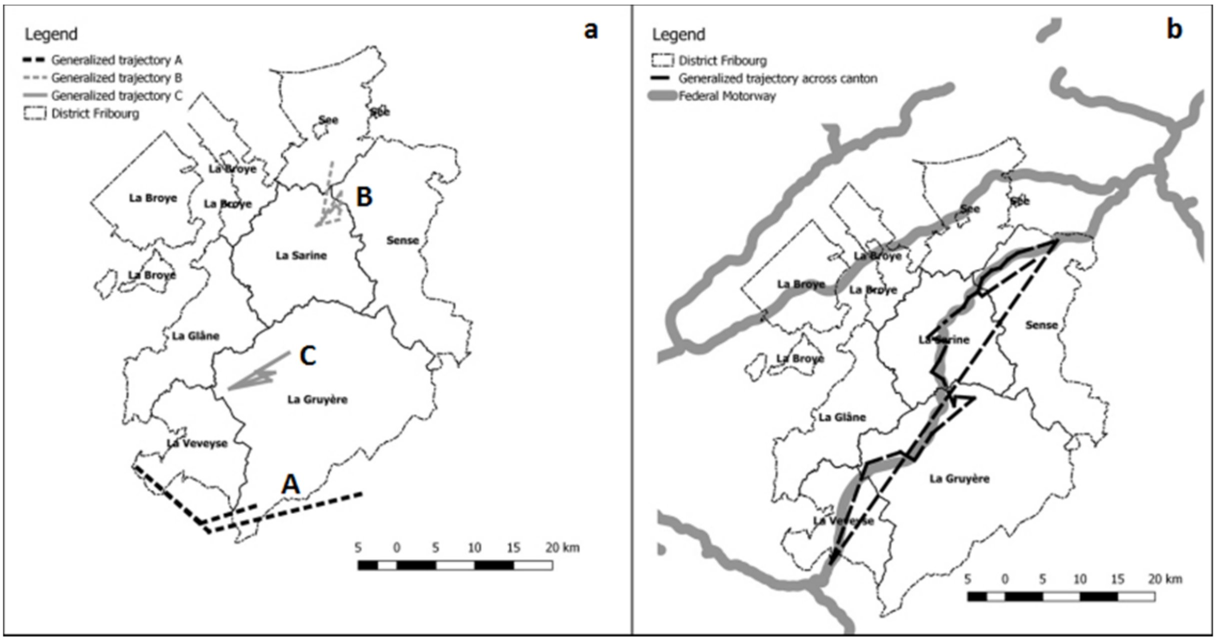

Fig. 6. Examples of VFs: three short local paths (panel **a**) and one (panel **b**) extending across the whole area.

5 Conclusions, limits and future research

The results using network analysis techniques on passive mobile positioning data yield the following results. The bow-tie structure identifies gateway and egress to the attraction system of the region. The network analysis clusters VF in paths weighted by popularity and at different spatial levels. Fig. 6 shows three examples; panel (a) is composed by local trajectories: trajectory C is totally inside the regional DMO of La Gruyere whereas trajectory B is shared by the district of Sense and La Sarine which are also two distinct regional DMOs. Panel (b) shows a trajectory across the canton mostly overlapping the Federal Motorway.

Network analysis applied to mobile phone data is a useful tool for depicting SVF in the two following ways. Not only could it be used for testing the information gathered using other techniques such as expert workshops (Beritelli et al., 2014; Beritelli et al., 2015) but it could also shed light on some VF patterns that have not yet been perceived by experts. This will be a very important trigger for innovating products and services.

From the point of view of the governance, the SVF evidences yielded by the mobile data network analysis would be perceived by stakeholders as more *objective* than experts' opinion panels. Thus, SFV could encourage the discussion among the concerned actors in order to go beyond a static-central model to one which is a dynamic network.

Last but not least, network analysis seems to be suitable for dealing with large amounts of data such as those on passive mobile positioning. The main reason is that the techniques used for this type of analysis are insensitive to the size of the data examined, differently from more traditional statistical procedures that may suffer from a large sample size fallacy (Lantz, 2013). From a practical point of view most software tools used in network analysis can smoothly process very large networks (for example, the 6-bit version of Pajek-3XL, available at http://mrvar.fdv.uni-lj.si/pajek/, can handle a maximum of 10 billion nodes).

Data used in this research belongs to one specific European country, replication of this methodology on other countries and cross comparisons will be useful in better coordinating the methods and gaining wider knowledge of the phenomenon. Finally, the results reported here will be compared with those obtained in expert workshops at the destination in order to increase the level of collaboration between the different providers and stakeholders.

Further research will need to address the analysis of trajectories classified by duration (length) in order to show possible differences or similarities in the interest expressed by visitors who spend less than one day, one full day, or more days at the destination.

This research takes into account the spatial SFV, a deeper research including virtual nodes such as experiences and informational elements thus belong this study. Nevertheless, the authors think that these findings are one important element to consider for the travel networks agenda (Stienmetz & Fesenmaier, 2013).

The classification between residents and tourism AMUs using performance algothims such as the ones proposed by Gonzalez et al. (2008) needs a wider set of data and this could raise some confidentialty issues, at least in some countries.

This research is limited to AMUs of only one European country and limited in time. Nevertheless, the relevance of the network analysis has been demostrated. Future research will analyse trajectories classified by their duration, namely day-trippers and tourists with overnigths stays, and will shed some light on the possible differences in SVFs across these two categories.

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