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Julie Freyssenge[1,2,3], Florent Renard[3], Laurent Derex[1,4], Julien Fouques[5], Jean-Gabriel Damizet[5], Carlos El Khoury[1,2], Karim Tazarourte[1,6]

[1] Univ. Lyon, University Claude Bernard Lyon 1, HESPER EA 7425, F-69008 Lyon, France
[2] Emergency Department and RESCUe Network, Lucien Hussel Hospital
[3] University Jean Moulin Lyon 3 – UMR 5600 Environnement Ville Société CNRS - 18, rue Chevreul – 69007 Lyon
[4] Stroke Center, Department of Neurology, Hospices Civils de Lyon– 69500 Bron, France
[5] Service Départemental Métropolitain d'Incendie et de Secours – 69003 Lyon, France
[6] Hospices Civils de Lyon, Emergency Department – Lyon, F-69003, France

Corresponding author:
Julie Freyssenge
j.freyssenge@resuval.fr
Montée du Dr Chapuis – CH de Vienne
BP 127
38209 VIENNE

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Abstract

Introduction. Stroke is a leading cause of death and a major cause of irreversible sequelae. Stroke patients must be transported as fast as possible and their management should be as effective as possible. Firefighters transport a great proportion of these patients. Using a Geographical Information System can be a great tool to measure and predict travel times during stroke patient management.
Methods. This study modeled travel times from the nearest fire station to stroke patient using theorical data sets in order to compare them. The results were then compared with the on the job data measured by the Departmental Metropolitan Fire and Rescue Service (SDMIS) from 2015 to 2016 for suspected stroke. This comparison assessed the feasibility of using a theoretical model to predict travel times based on real-life data.
Results. A strong correlation was observed between the different theorical models for measuring accessibility to the nearest fire station, with a Root Mean Square Error (RMSE) about 1.5 minutes and Mean Absolute Percentage Error (MAPE) around 30%. However, when theorical data sets were compared to measured data, the correlation was lower, the RMSE was six minutes and MAPE from 60% (minimal times) to 25% (median times). This is satisfactory results. Although the coefficients of correlation remain low, due to the high heterogeneity of the measured times. These differences of few minutes represented a very small portion of the stroke patient's care pathway.
Conclusion. Theoretical models were highly correlated and the correlation with the measured data was mostly correct. The few minutes difference between theoretical models and measured data could be explained by traffic hazards and organizational vagaries that always tend to disrupt modeling results. Using measured data was found to be very useful to perform theorical model and to develop a robust model of stroke transportation.

Keywords : access time, stroke prehospital care, modeled, comparison, GIS

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1. Introduction

Stroke affects 150,000 new patients each year and can affect all major neurological functions: motor skills, sensitivity, language, vision, memory and executive functions (planning, anticipation, activity management (de Peretti et al., 2012). Stroke is a major public health issue in developed countries, particularly because of their ageing population. France is not immune to the burden of this disease : stroke was the leading cause of death among women (18,343 deaths) and the third leading cause of death among men (13,003 deaths) in 2013 (Lecoffre et al., 2017).

The care pathway of stroke patients consists of several sequences: the pre-hospital phase, with an urgent transfer to a neurovascular unit (PSC), then acute hospitalization, with emergency therapeutic management and, finally, return home directly or after a stay in a generalist or specialized follow-up care and rehabilitation (RRC) service. Time management is of the essence during the pre-hospital phase, as the patient needs to arrive as soon as possible to receive treatment, thrombolysis (within 4.5 hours after the onset of symptoms) or thrombectomy (within 6-24 hours) (Powers et al., 2018). In the acute phase of stroke, the patient loses two million neurons every minute and thus increases his chances of sustaining irreversible sequelae (Saver, 2006).

Good access to health care services for everyone, regardless of geography, remains a key objective of governments and societies worldwide (McGrail, 2012). Access is essential in the case of stroke: the patient must be treated as soon as possible and it is therefore important to know and optimize their trajectory during the pre-hospital phase. Timely access to health services is a major determinant of sequelae. As per Humphreys definition (Humphreys, 1998), health service planners need accurate, reliable and rigorous measures to determine the spatial variation of accessibility models. McGrail and Humphreys (McGrail and Humphreys, 2014) explain that distance and geographic isolation are the first barriers to accessing health care. Measuring accessibility can be a tool to identify areas to be monitored, especially when the density of care services is low and could lead to inequalities in access to treatment (Páez et al., 2013). Therefore, a geographical approach to accessibility in the case of stroke is essential.

The measurement of accessibility is one of the key concepts of health geography. A large number of studies investigated this concept, covering a wide range of topics, both from a geographical and contextual perspectives (Page et al., 2018). Since the 1980s, a large number of articles have been published on the subject in the field of access to health care, and this number has sharply increased since the 2000s (Apparicio et al., 2017).

Penchansky and Thomas (Penchansky and Thomas, 1981), defined the concept of health accessibility along five dimensions: availability, geographic accessibility, convenience (i.e. how the structure of care is organized), financial capacity and acceptability. Thus, spatial or geographical accessibility is an important component of the broader concept of access (Penchansky and Thomas, 1981). This approach takes into account the multidimensional aspect of access to care (Wang and Luo, 2005). Due to the complexity of the concept of access and its different components, there are a number of approaches to measure access. Talen (Talen, 2003) classified accessibility measures into five types of approaches: container, coverage, minimum distance, travel costs, and gravity-based measures. Similarly, Guagliardo (Guagliardo, 2004) summarized the measurement of spatial accessibility in four categories: provider-to-population ratios, distance to the nearest provider, average distance to a set of providers, gravitational models of provider influence.

Many of these approaches simultaneously take into account the notion of geographical accessibility and availability of the care service. This is the case, for example, for gravitational models, the Two Step Floating Catchment Area (2SFCA) method (McGrail, 2012) or Kernel density models (Guagliardo, 2004). These calculation methods are often used for their high level of satisfaction in measuring accessibility (Page et al., 2018). However, it remains essential to measure the geographical accessibility of the nearest health care service, not associated with availability. Since spatial accessibility is affected by factors such as the location of the patient, the location of health care services and the road network used to travel (Gharani et al., 2015), accessibility to the nearest service is an appropriate method. Thus, "key spatial variables include distance and travel time between the residential locations of potential patients in a region and the locations of health centers in their region" (Joseph and Bantock, 1982).

Despite its many uses, measuring travel time to the nearest service has some limitations because it only takes into account the proximity of a population to a resource, regardless of the availability of that resource (depending on the number of beds available for example and the size of the population pool concerned) (McGrail and Humphreys, 2009). Since the issue of availability in our analyses of emergency stroke treatment is only a secondary one, the measurement of access to each potential community where a patient is cared for from the nearest fire station has been selected.

As defined by Joseph and Phillips (Joseph and Phillips, 1984), measured accessibility "refers to prospective levels of accessibility based on the analysis of spatial patterns of physical access to services (rather than on patterns of service use; accessibility "achieved")", thus informing “policy makers of potential disparities [...] identifying areas where levels of accessibility are poor and targeted interventions needed".

This study modeled travel times from the nearest fire station to the stroke patient using data sets from different sources in order to compare them. The results of these models are then compared with the on the job data measured by the Departmental Metropolitan Fire and Rescue Service (*Service Départemental Métropolitain d'Incendie et de Secours* (SDMIS)) in 2015 and 2016. This comparison was used to assess the feasibility of using a theoretical model to predict travel times based on real-life data. Based on the results of this study, we hope in the long term to provide the best possible picture of the current state of care with reliable travel time data, in order to identify areas at risk of delayed care and access to treatment and provide recommendations for the organization of the prehospital care at all points of the network.

However, modeling travel time to the nearest fire station raises the question of the representativeness of the road network. Indeed, road networks are more or less accurately mapped and detailed according to the service providers. In stroke care, where every minute counts, it is essential to have the most efficient network analysis model possible. Two main road networks were available (IGN *BDCarto* and *Multinet TomTom*, described in the methods section), each with its own advantages and disadvantages. The second section presents the methods, describing the selected road networks, the procedures for modeling and creating isochrones, the SDMIS jobs database of measured travels and the procedures for comparing modeling and measurement results. The third section focuses on the results and their analysis, while making recommendations for a better organization of stroke management.

2. Material and methods

2.1. Study area

The analytical framework for this study was the Rhône department (one of the 96 administrative divisions of metropolitan France) (fig. 1), which corresponds to the SDMIS service area. However, accessibility from each fire station took into account the side effects linked to neighboring departments. The fire stations located in border departments were taken into account for the calculation of isochrones. According to the latest available census, the Rhône department had 1,798,511 inhabitants in 2014 (source: *Institut national de la statistique et des études*) for an area of 3,249 km². The Rhône county is mainly composed by metropolitan Lyon, with 1,300,000 inhabitants, organized into 59 municipalities (fig. 1), representing the most densely populated territory in the department. It is the second largest urban area in France and a major economic center in Southeastern France.

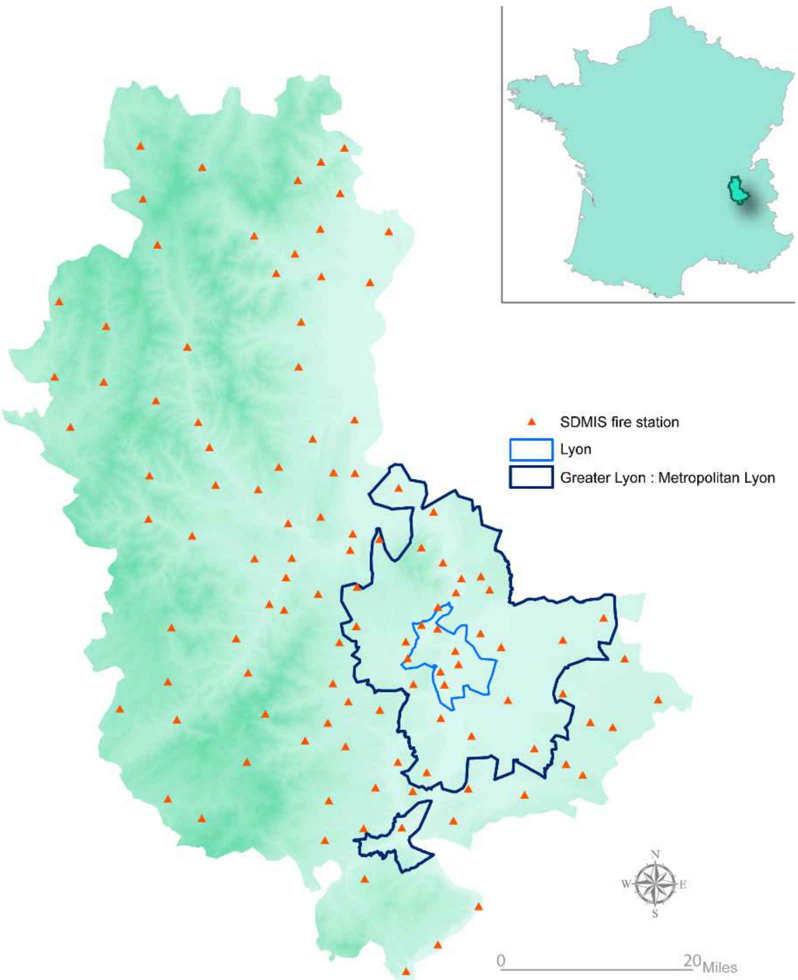

Figure 1: The Rhône department and its location in France – source: IGN

2.2. Stroke care by the SDMIS

In France, fire brigades are organized into SDIS (*Service Départemental d'Incendie et de Secours*) at the department level. According to Article L1424-2 of the General Code of Local Authorities, the SDIS provides emergency assistance to victims of accidents and, natural disasters, as well as their evacuation. In addition, according to article L1424-42, the SDIS can intervene at the request of the dispatch centre of the Emergency Medical Service (EMS) (*Service d'Aide Médicale Urgente* SAMU) when private health transporters are not available. In the Rhône department, SDIS is called SDMIS because it covers the Rhône department and metropolitan Lyon. The SDIS are classified into three categories, according to population size: category A for a population ≥ 900,000 inhabitants; category B for a population ≥ 400,000 inhabitants and < 900,000 inhabitants; category C for a population < 400,000 inhabitants. The SDMIS belongs to category A. The SDMIS has 110 fire stations (fig. 1), divided into seven territorial groupings. Each territorial grouping is in charge of one operational speciality, such as wildfire or rescue-clearing.

In the specific case of stroke management, 27% of patients were transported to hospital by the fire brigade, compared to 36% by private ambulance or taxi, 20% by their own means, 2% by EMS, and 15% undetermined (DREES, 2015). Dispatch is typically decided by the EMS. Patients were transported by the closest provider available. Firefighters transport many though not most patients. Patient transport is a challenge for firefighters because of the increasing numbers of patients they manage, as fire is no longer their main activity. We did not investigate private ambulances and taxis because the relevant databases are not searchable.

2.3. Databases: modeling and jobs measures

The aim of our study was to compare different theoretical accessibility models with measured jobs data to determine their validity, and, if applicable, which one is the most relevant to measure access for a stroke patient.

2.3.1. Theoretical databases for spatial accessibility modeling: *BDCarto* (IGN) and *Multinet TomTom* (ESRI)

The measurement of travel time over the network was complex and required "the use of geometric network files containing traffic directions, speed limits, turnaround restrictions and delays for each road segment" (Apparicio et al., 2008). Two different types of road network databases were used in this framework. The databases differed in their financial accessibility and exploitation.

2.3.1.1. BDCarto

BDCarto is an open access dataset for non-commercial use, which was developed by the National Institute for Geographical and Forestry Information (*Institut National de l'information Géographique et forestière* (IGN)). *BDCarto* maps all French roads, with more than one million kilometers of network represented: highways, national and departmental roads, residential and urban sections. However, this dataset does not specify the speed limit allowed on each section. As speed limit could not be estimated from road type (Mao and Nekorchuk, 2013), a two-step process was carried out. Firstly, the *OpenStreetMap* collaborative database was used to extract the speed limit of 87% of roads in the Rhône department as listed in the *BDCarto* database. An estimation based on land use was made to complete missing data (13% of roads). We used the European land use database *CORINE Land Cover*: we attributed a speed limit of 50 kph (31 mph) to urban roads and 90 kph (56 mph) to rural roads (Author et al., 2018).

In addition, it is physically impossible to maintain constant speed on the road, even with an SDMIS vehicle which is allowed to disregard the highway code. Thus, we modeled four scenarios corresponding to different traffic conditions, management mode and weather conditions (Table 1). Scenario 1, corresponds to compliance to national speed limits. This was the basic scenario. For scenario 2, average ambulance speed was based on measured travel times compiled from the Rhône department's EMS registry, i.e. an average speed of 20 km/h above speed limit (Table 1).

Scenario	**Modeling**	**Speed**	**Justification of speed adaptations**
Scenario 1	Initial database	Compliance to national speed limits	Private car complying to French Highway Code
Scenario 2	Emergency transport	20 kph (12 mph) above speed limit throughout the road network	Analysis based on the Rhône department's SAMU stroke jobs between 2012 and 2016, and Petzäll et al (2011) (Petzäll et al., 2011) study
Scenario 3	Difficult weather conditions (rain, fog, snow)	20 kph (12 mph) below speed limit throughout the	Compliance to Article R413-2 of the French Highway Code in the

		road network	case of severe weather conditions
Scenario 4	Emergency transport with traffic congestion in metropolitan Lyon	20 kph (12 mph) below speed limit in metropolitan Lyon network (59 municipalities), 20 kph (12 mph) higher than speed limit elsewhere	Petzäll et al (2011) (Petzäll et al., 2011) study and SAMU jobs analysis for 20 kph above speed limit and SAMU jobs analysis during traffic congestion for 20 kph below speed limit

Table 1: Scenarios built from the open access database for non-commercial use *BDCarto*

2.3.1.2. Multinet Tomtom

The second source for theoretical road network data used was the *Multinet Tomtom* database (MultiNet® EUR 2015.06, Version - V1.0) (Esri - GIS Mapping), a commercial data set developed by ESRI. This dataset covers the entire road network in France. In addition, it contains a traffic history (weekday, weekend, precise schedules) as well as speed limits depending on different modes of transport (private car, taxi, bus, bicycle, walking). As with the *BDCarto* database, scenarios were calculated based on traffic conditions (Table 2).

Scenario	**Modeling**	**Speed**
Scenario A	Weekday (Monday to Friday) with heavy traffic (06:00 – 09:00 et 16:30 – 18:30)	Lower than the usual limit due to traffic congestion. Speed varies depending on the

		traffic history reported in Multinet. E. g. a section of road with a speed limit of 90 kph (56 mph) can have a reported speed of 50 kph (31 mph), especially in urban areas.
Scenario B	Weekday (Monday to Friday) with normal traffic (09:00 – 16:30)	Speed varies depending on the traffic history reported in Multinet for Monday to Friday outside of rush hours.
Scenario C	Weekend	Speed varies depending on the traffic history reported in Multinet for Saturday to Sunday.

Table 2: Scenarios built from *Multinet Tomtom* commercial database

The models from the two databases were then compared with the data measured in the field during SDMIS in the field.

2.3.2. Measured data of travel times in SDMIS jobs

The models of travel times were compared with the SDMIS in the field measures. These measurements were performed as part of SDMIS jobs for suspected stroke between January 1, 2015 and December 31, 2016 inclusive. A total of 2,886 measures were identified. For each job compiled in the register, the departure fire stations and the municipality of arrival were known as well as the travel time. Each trip was made with a Victim Assistance and Rescue Vehicle (*Véhicule de Secours et d'Assistance aux Victimes* (VSAV)). This type of vehicle can transport a patient with medical equipment and is not subject to traffic regulations (speed limits, traffic lights, right of way, etc.).

2.4. Comparing modeled data with measured data: spatial and statistical analysis

2.4.1. Spatial analysis with GIS

This part aimed to model access times at any point in the territory from the 110 fire stations of the Rhône department's SDMIS. Initially, the fire stations were geolocated according to their exact postal address using a Geographical Information System (GIS). The GIS software used for this project was Environmental Systems Research Institute (ESRI) ArcMap, version 10.5.1 ("Esri - GIS Mapping Software, Solutions, Services, Map Apps, and Data," n.d.). All accessibility measures were calculated using the network analyst extension available in ArcGIS™. Then, the modeling was carried out using isochrones, i.e. lines representing areas of equal travel time from the fire stations of the study area (fig. 2), using the existing road network. For each model, we drew a 1-minute travel time isochrone for each fire station in the department (§ 2.3.1.1.1 and 2.3.1.2).

Figure 2: The Rhone department's accessibility measure from fire stations to patients with acute stroke (*BD Carto* maps: **1.** Compliance to speed limit, **2.** emergency transport, **3.** difficult weather conditions, **4.** emergency transport with traffic congestion; and *Multinet Tomtom* maps: **A.** weekday heavy traffic, **B.** weekday free-flowing traffic, **C.** weekend regular traffic)

Then, the modeled isochrones were compared with the measured travel times. From 1 January 2015 to 31 December 2016, several jobs were compiled for the same municipality. As a result, there were several measured travel times for each municipality. We used the minimum travel time and the median travel time. Finally, we compared the modeled travel times for each of the municipalities where measured time information was available (i.e. 238 out of the 295 municipalities in the department; fig. 3). For the comparison, we used the isochron located on the centroid of the municipality.

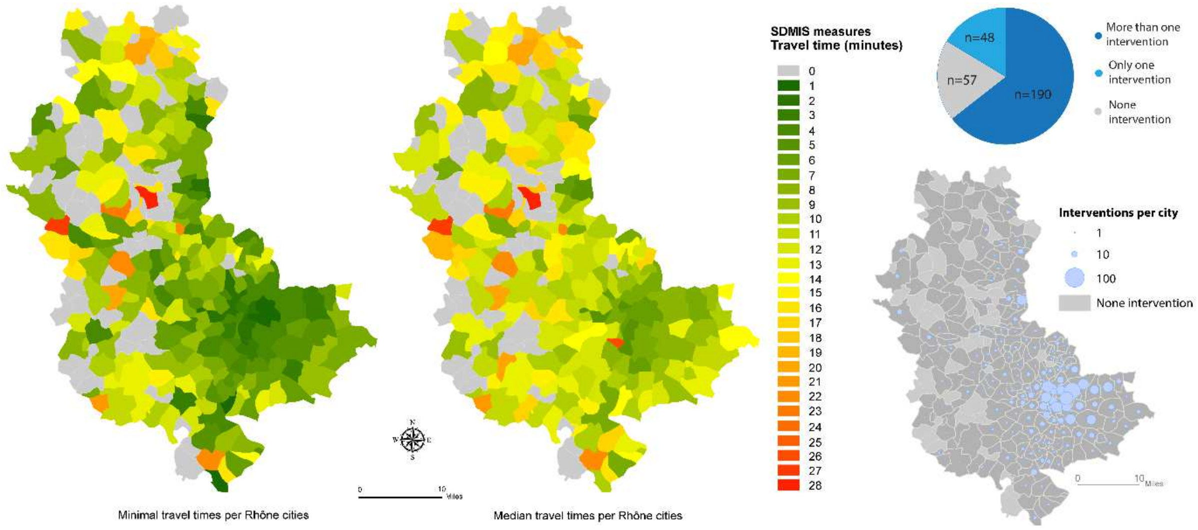

Figure 3: Minimum and median travel time measured by municipality on the basis of 2886 SDMIS jobs.

2.4.2. Statistical comparison of models to measures

To compare accessibility models to measured, we used a correlation coefficient (Apparicio et al., 2008). Normality was checked using the Shapiro-Wilk test (Shapiro and Wilk, 1965). "The correlation coefficient gives an indication of the level of good fit" between the different measurement models (Apparicio et al., 2003). As our sample was not normally distributed, we used the Spearman coefficient, a non-parametric test. The Spearman coefficient uses the observations' rows and thus makes it possible to measure the level of linear relationship between rows. The correlation coefficient varied from -1 to 1, a positive value indicating a positive correlation, while a negative value indicates a negative correlation. A value close to zero indicates an absence of linear correlation. A p-value < 0.05 was considered statistically significant.

In addition to the correlation coefficient, performance of the different models was assessed using the following three measures (Willmott, 1981) :

Mean squared error (MSE) = $\frac{1}{W-p*}\sum_{i=1}^{n} w_i(y-\hat{y}_i)^2$

Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{W-p*}\sum_{i=1}^{n} w_i(y-\hat{y}_i)^2}$

Mean Absolute Percentage Error (MAPE) = $\frac{100}{W}\sum_{i=1}^{n} w_i\left|\frac{y_i-\hat{y}_i}{y_i}\right|$

Where y = model predicted value (real time), y_i = observed value (measured theoretical time), n = number of observations.
Models performance was evaluated against the measured data. In a complementary way, the modeled results from the two databases were compared with each other (fig. 4). Statistical analyses were carried out using XLSTAT software, version 2019.1.2 (Addinsoft (2019). XLSTAT statistical and data analysis solution. Long Island, NY, USA. https://www.xlstat.com).

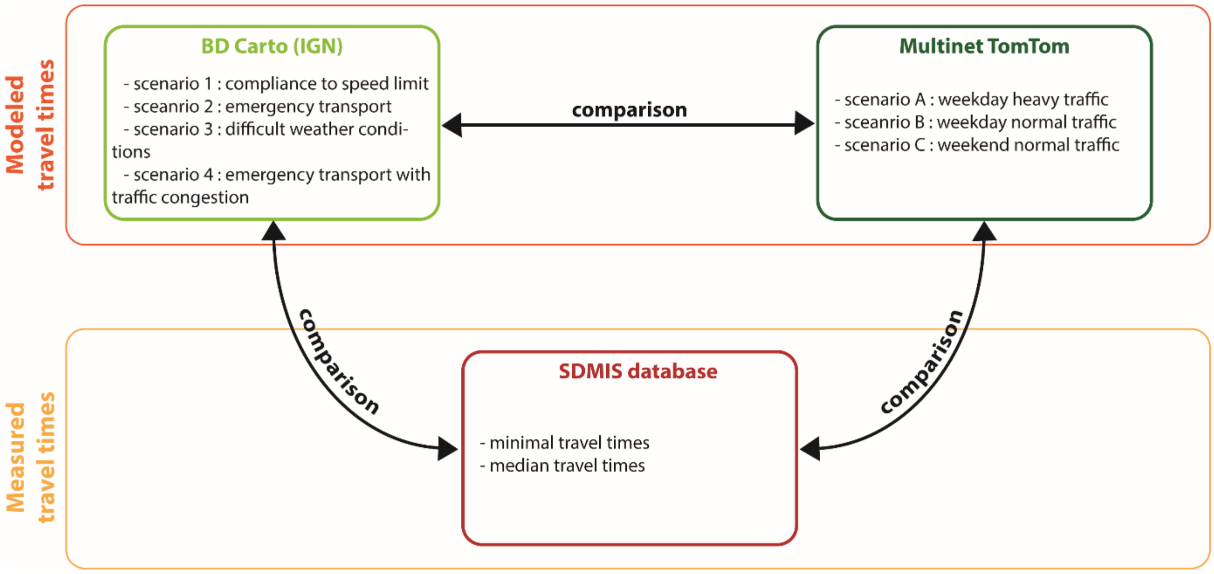

Figure 4: Diagram of database analysis

As traffic conditions outside Lyon are not similar to those in dense urban areas, statistical analyses were carried out on a global scale throughout the Rhône department, as well as on a more local scale (metropolitan Lyon).

3. Results

3.1. Comparison of the results from the two theoretical models

Our study aimed to compare different theoretical accessibility models with measured SDMIS jobs data. Before meeting this objective, a first comparison was made between the models in order to evaluate the performance of the model founded on the open access dataset for non-commercial use *BDCarto* compared to the *Multinet TomTom* commercial model. For this purpose, the performance indicators described above were used (Table 3). *Multinet TomTom*'s three scenarios were compared to the four scenarios from *BDCarto*, on the scale of the Rhône department and Greater Lyon.
A strong correlation was observed between the models measuring theoretical accessibility at the scale of the department (Table 3). The maximum RMSE between the scenarios of the two models was 2.2 minutes for scenario 4 of the IGN when compared to scenarios A to C of Multinet. Similarly, the lowest Spearman coefficient was found for the latter, with values between 0.62 and 0.63. The other scenarios were very strongly correlated with RMSEs about 1.5 minutes (e.g. scenarios 1, 2 and

3 and scenario A) and Spearman's rho of about 0.85 (Table 3). On the scale of Greater Lyon, the observation was similar with very small differences between the models (RMSE of about 1.5 minutes) and high Spearman’s rho around 0.7 (table 3). From 25 to 30 %, MAPE confirmed the results of RMSEs and Spearman’s rho.
For Greater Lyon models and for scenario four (both scales), correlations were lower. This was due to the heterogeneity of dense traffic. MAPEs were also worse for scenario 4, explained by the traffic.

			Rhône department				Greater Lyon			
			BD Carto modeling							
			scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)	scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)
Multinet TomTom modeling	Scenario A (weekday heavy traffic)	MSE	2.1	2	2.4	4.8	2.3	2.4	2.2	2.8
		RMSE	1.4	1.4	1.5	2.2	1.5	1.5	1.5	1.7
		MAPE	24.4	27.1	26.5	46.1	28.2	31.6	25.2	35
		Spearman coefficient	0.86	0.85	0.84	0.63	0.73	0.74	0.73	0.67
	Scenario B (weekday normal traffic)	MSE	2	1.9	2.3	4.7	2.1	2.2	2,0	2.5
		RMSE	1.4	1.4	1.5	2.2	1.4	1.5	1.4	1.6
		MAPE	24	26.1	26.2	46.2	27.6	30.8	25.3	33
		Spearman coefficient	0.87	0.86	0.85	0.63	0.73	0.73	0.71	0.67
	Scenario C (weekend)	MSE	2	2	2.3	4.8	2.4	2.6	2.1	2.8
		RMSE	1.4	1.4	1.5	2.2	1.5	1.6	1.5	1.7
		MAPE	24.3	26	26.5	47.3	27.4	30.8	24.9	32.5
		Spearman coefficient	0.87	0.86	0.85	0.62	0.75	0.74	0.74	0.68

Table 3: Spearman correlation and performance metrics of open access database model v. commercial database model

3.2. Comparison of the results from the two theoretical models to measured data

From the outset, Spearman's coefficients were low between the models and the measured times, both at the scale of Rhône department or that of Greater Lyon. However, the RMSE study for the Rhône department indicated that all the differences between the modeled and measured minimum and median times ranged between 5.6 and 5.8 minutes (Table 4). The MAPEs at the scale of Rhône department were around 57% for the measured minimum times, but for the median measured times they were around 26%. While the RMSEs were similar between minimum and median measures, the MAPE suggested that the percentage error between theoretical models and median travel times was lower. The RMSEs for Greater Lyon were even lower, with Spearman's rho slightly higher. The RMSEs for modeled vs. minimum measured travel time were 2.9 or three minutes. The RMSEs for median times ranged between three and 3.1 minutes. For MAPEs, the observation is identical that at the scale of Rhône department. Regardless of scale, the differences in estimates between the models were minimal.

		Rhône department							Greater Lyon						
		BD Carto modeling				Multinet TomTom modeling			BD Carto modeling				Multinet TomTom modeling		
		scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)	scenario A (weekday heavy traffic)	scenario B (weekday normal traffic)	scenario C (weekend)	scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)	scenario A (weekday heavy traffic)	scenario B (weekday normal traffic)	scenario C (weekend)
SDMIS (minimal traveltime)	MSE	31.4	31.4	31.5	31.5	31.5	31.5	31.5	8.7	8.7	9	8.9	9	8.9	9
	RMSE	5.6	5.6	5.6	5.6	5.6	5.6	5.6	3	2.9	3	3	3	3	3
	MAPE	56.6	56.3	57.4	57.8	57.5	57.4	57.4	63	62.6	62.8	62	63.2	63.4	62.9
	Spearman coefficient	0	0.04	-0.04	-0.07	0.02	0.02	0.02	0.1	0.2	-0.01	-0.1	-0.01	0.01	0
SDMIS (median traveltime)	MSE	34	34	34	34	33.9	33.9	33.9	9.2	9.1	9.7	9.9	9.9	9.8	9.9
	RMSE	5.8	5.8	5.8	5.8	5.8	5.8	5.8	3	3	3,1	3,1	3,1	3,1	3,1
	MAPE	26.9	26.9	26.8	26.7	26.6	26.6	26.6	27	26	26.5	25.7	26.3	26.4	26
	Spearman coefficient	0.04	0,07	0	-0.02	0.03	0,03	0.03	0.2	0.23	0.07	-0.03	0.02	0.04	0.02

Table 4: Spearman correlation and performance metrics of database models compare to SDMIS travel times (minimal and median)

4. Discussion

Measuring accessibility is a complex concept. The study compared travel time for stroke management in models using two databases vs as measured on the job, with the aim of generalizing a theoretical model to a territory that does not have reliable field surveys. We investigated travel times from the nearest fire station to stroke patient, complementing our previous study (Author and al, 2018) on time of care, time to dispatch and time spent on scene. The present study compared theoretical models with actual data to determine the feasibility of using theoretical databases to estimate travel time. So, only one travel time out of the total duration of the care was sufficient, since the purpose of this study was to estimate the travel time of a vehicle. The first step of this study was to measure theoretical accessibility. We compared theoretical models to assess the performance and validity of using a model based on open access data for non-commercial use. In the second step, we measured the performance of the theoretical accessibility models against the SDMIS data.

The theoretical model built from *BDCarto* was strongly correlated to the commercial model. The most correlated scenario was that of a 12 mph increase in speed compared to the commercial scenario of normal traffic on a weekday, with a RMSE of 1.4 minutes in the Rhône department. However, all the scenarios were very similar. This may seem surprising but the small size of the study area combined with relatively small differences in scenarios explains this homogeneity. The theoretical model developed from *BDCarto* was found to be a reliable tool for modelling theoretical spatial accessibility and a good alternative to a paid model.

The comparison of the theoretical models' performance with real SDMIS job data led to several interesting conclusions. First, the RMSEs between the models and the minimum measured times were low: about 5.6 minutes at the scale of the Rhône department and three minutes at the scale of Greater Lyon. The same was true for median times, with very slightly higher RMSEs. This can be explained by the higher variability of median travel times compared to minimum times. Indeed, to get to a given place, travel time can vary by up to a factor of two, which explains the better performance of the models with regard to minimum times, which are the optimal times for jobs. MAPEs confirmed that minimum times are optimal times for jobs, because the percentage error is higher (60%) for minimal times than median times (26%). However, the differences between modeled and measured travel times remain acceptable from the point of view of patient management. Indeed, a maximum approximation of six minutes when managing a patient as part of his care pathway (transport, imaging and treatment) remains minimal.

The coefficients of correlation were low because, for many municipalities, the modeling was different from the measured value. In some municipalities, there was a wide dispersion of time in relation to a given interval of access time. However, compared to the RMSEs and MAPE, this low correlation should be put into perspective, as dispersion of travel times was found in RMSEs of around six minutes. The correlations might have been better if we had sampled the measured data in weekdays (48 %, n= 2035), weekend (20 %, n= 827) and days of difficult weather (32

%, n= 1350) and compared the corresponding theoretical models. However, modeling reality remains challenging.

Secondly, it appears that the differences between the different scenarios of the theoretical models compared to the measured data were low. This can be explained similarly with the small size of the study area and small differences between traffic speeds.

In order to optimize modeling results, a number of additional factors should be taken into account. These are mainly related to traffic conditions and vehicle type. The random aspect of traffic conditions is part of the measured data of travel time on the field of the SDMIS, which is an inherent limitation of the theoretical models. Considering the difficulty of predicting traffic incidents, one possible improvement of the theoretical model from *BDCarto* could be to develop a scenario based on an estimate of the average traveling speed of an SDMIS vehicle.

However, there are limitations regarding representativeness and exhaustiveness of the travel times measured by SDMIS. Indeed, there is a wide dispersion of travel times to access the same municipality (see above). This variation can be explained by the large fluctuation in traffic conditions over time, and it cannot be easily anticipated.

Furthermore, the quality of the measures also raises concerns. Some of the data in the SDMIS jobs register seems to be improper. Delays seem unusually high. For example, the municipality of Oullins was reached in 23 minutes, while the median time was nine minutes and the minimum time was four minutes. For Rillieux-la-Pape, the minimum time was three minutes, the median seven minutes and the maximum time 25 minutes. However, these differences could be explained by very difficult traffic conditions at certain times, such as traffic incidents.

In addition, the method used to measure travel time is debatable. Travel time was measured from the moment the vehicle was started. A delay between the start of the measurement, i.e. when the vehicle is started, and the movement of the vehicle could exist. This time is thus added to the real travel time on network between fire station and patient location. So, in some case, the time analyzed in our study was not exact.

Another explanation for this variability may lie in the very organization of the SDMIS in the Rhône department. Outside of urban areas, firefighters are volunteers and most of them are not on call at the fire station. The high extreme values of the sample could be explained by the time it may take for some firefighters to reach the response vehicle at the fire station.

Finally, the size of the sample and its representativeness must be taken into consideration. Indeed, the SDMIS jobs data analyzed are those of two calendar years. While 2886 measures may seem a relatively representative sample, 57 communes did not have associated measured data and 48 communes had only one measure. All these communes are located outside Greater Lyon, with lower residential densities, which reduces the probability of an SDMIS jobs and thus decreases the representativeness of the measures.

5. Conclusion

The primary objective of this study was to model travel times from the nearest fire station to a stroke patient using different data sets. The results of the models were compared with the data measured in the field during jobs by SDMIS. The purpose of this comparison was to evaluate the performance of the models in relation to the reality of the field when managing stroke patients.

The results of the two theoretical models were very strongly correlated with each other, with modeling based on open access data playing equal parts with the commercial model, with travel time differences of around one minute. Comparing of modeled isochrones to measured times provided satisfactory results with differences of only a few minutes, which represents a very small portion of time during the stroke patient's care pathway. However, Spearman's correlations were low because the modeled travels were different from the measured values in some municipalities. This is explained by the dispersion of these times. But this dispersion is not very important since the RMSEs are about six minutes. A discretization of the real data according to the different scenarios (weekend, weekday, weather conditions) modeled could improve the correlation. Modeling reality remains a very complex exercise as traffic hazards and organizational imponderables disrupt modeling results. Collecting and relying on real travel time data such as that of the SDMIS is essential to developing and validating a relevant predictive model of stroke management travel times.

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