BUILDING CONGESTION INDEXES FROM GPS DATA: DEMONSTRATION

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ABSTRACT

In the current context of increasing interests towards transportation due to both sustainability issues and growth in congestion in urban areas, efforts are deployed to better assess and monitor the travel conditions. Planners are seeking for the necessary information on road traffic conditions to measure their evolution, the impacts of interventions as well as to guide future projects. And this information needs to be precise enough, in space and time, to give evidence of the changes that can occur at various scales. The equipment and data required to develop such information (speed, travel time, flow, delay) are often expensive, resources consuming or difficult to obtain on a continuous basis (for temporal coverage) and on a wide scale (spatial coverage). This paper is an effort to add value to available sets of Global Positioning Systems (GPS) data providing spot speed data in order to assess the travel conditions on a highway network and feed the development of strategic indicators for planning purposes. Hence, this paper aims to define, select and estimate relevant congestion indexes and demonstrate their application using a large set of GPS points.
In Montreal, the carsharing company (Communauto inc.) has equipped 400 of its vehicles with GPS systems. Trips made with those equipped cars output files containing spot speed information at every 2-4 minutes. The paper confirms that sets of low resolution spot speed data derived from a GPS onboard system have the potential to feed the estimation of congestion indexes and provide continuous assessment of the congestion level on highways.

Keywords: congestion, traffic, indicator, GPS data

INTRODUCTION

Like many other metropolitan areas, the Montreal region experiences increasing congestion issues on its transportation network. The identification of the road segments more affected by congestion can feed decision-makers on deciding which measures should be implemented and where. Measures such as implementation of rapid transit lines, increasing road capacity, or congestion charging are recurrently discussed in hope to alleviate crowded road segments.

Also, a continuous assessment of congestion level helps to understand global trends and to highlight deterioration or improvements of road segments. It is often included in the set of indicators to assess the sustainability of transportation choices. For instance, the STPI Project (Gilbert, Irwin, Hollingworth, & Blais, 2002) wants to add, in the long-term, a congestion index into its initial set of indicators, in order to assess the efficiency of use of transportation infrastructures and services. In the I_SUM set of indicators, Rodrigues Da Silva , Costa, & Ramos (2010) include a congestion indicator to measure the freedom of movements and traffic. The Propolis set of indicator (Lautso, 2004) has an indicator of total time spent in traffic to evaluate the accessibility.

The general purpose of this paper is to develop highway congestion measures based on Global Positioning System (GPS) data. To meet planning expectations, the measures need to be spatially and temporarily flexible, aggregated for different spatial-temporal levels, and adequately sensitive to changes in traffic conditions. The main objective is to define a congestion indicator and propose an estimation methodology which reflects needs and questions of transportation planners and decision-makers. This paper also confirms the usability of readily-available sets of GPS database to develop congestion measures, test different formulations of these measures, and assess their sensitivity with respect to various traffic conditions. In the ELASTIC project, Castillo & Pitfield (2010) mention the ease of availability of an indicator as one of the five key criteria for an indicator, which includes an easy and reasonable cost collection of data.

It is worth mentioning that there is also a demand for real-time measures from operators and road users, which can only be fulfilled with a much larger amount of GPS or other types of data than the available GPS dataset used in this study. Our research does not aim to compete with those heavy systems and to provide real-time information; it focuses on the development of indicators for the monitoring of temporal and spatial trends in a large urban area, specifically for freeways and to feed transportation planning needs.

The paper is organized as follows: first, some background elements on the definition of congestion and the typical indicators used for its estimation are provided. Then, the general methodology is presented, namely the set of data used in the estimation as well as the database processing scheme. The following section describes some of the measures that were developed, demonstrates their estimation using Montreal data, and discusses the results, namely their sensitivity in space and time. The paper concludes with some limitations and further research work.

BACKGROUND

Congestion definition

Literature points out that there is no single definition for congestion (Downs, 2004). Definitions can be quite broad, such as the one from the Federal Highway Administration (Cambridge Systematics Inc. & Texas Transportation Institute, 2005) "*an excess of vehicles on a portion of roadway at a particular time resulting in speeds that are slower […] than normal or "free flow" speeds*", or specific, such as the one from the Metro District Office of

Operations and Maintenance & Regional Transportation Management Center of Minnesota (2013): "*traffic flowing at speeds less than or equal to 45 miles per hour*".
Researchers and practitioners emphasize that the identification of congestion is a matter of perception. To tag traffic conditions as being congested, the level of congestion may have to exceed some threshold value (Taylor, Woolley, & Zito, 2000). This acceptable level of traffic or expectation varies across user (Bertini, 2006), time of day geographic location, and type of transportation facility (Lomax, Turner, & Shunk, 1997).
Congestion variability in time and space is also important. Congestion level depends on variations of both demand and capacity (Bertini, 2006). The performance of the road system varies according to the type of transportation facility, the time of day and the spatial location (Lomax, et al., 1997). The intensity, the duration, the extent, and the reliability (Levinson & Lomax, 1996) are the four basic aspects of congestion.

The Need for Congestion Measures

The common perception is that congestion problems have worsens in Montreal in the recent years. Decision-makers and transportation agencies identify congestion as one major issue for the region (Ville de Montréal, 2005). Actually, there is agreement among the transportation organizations of the region that concerns with respect to congestion are increasing. Transportation organizations want to "*avoid, mitigate, [and] limit congestion*" (Agence métropolitaine de transport, 2002) and "*control congestion on highway network*" (Ville de Montréal, 2005).
Because of its many negative impacts on environment, economy, and society, concerns with respect to congestion are also increasing along with sustainability responsiveness. Transport Canada (2006) states that "*congestion is commonly cited as a major and growing urban economic and environmental issue*." Congestion translates into additional delays for travelers, increased fuel consumption and consequent greenhouse gas emissions.
Measuring extent, duration, and intensity of congestion is a major challenge for public policies and transport planning (Taylor, et al., 2000). Up-to-date congestion information helps evaluate road performance (Tong, Merry, & Coifman, 2006) and its evolution. Then, high resolution data provide the possibility to identify most and recurrently affected roads by congestion (Tong, et al., 2006). Moreover, political discussions on the implementation of rapid transit lines, new road infrastructures, increased capacity, or mitigation measures benefit from the availability of information on congestion levels in an urban area or over a specific road segment (Boarnet, Kim, & Parkany, 1998).
However, there is no standard method of measuring congestion (Medley & Demetsky, 2003), and decision-makers often tackle with the comparison of congestion levels between years (Boarnet, et al., 1998). Typical measures are often limited and aggregated, hence not particularly suited for comprehensive assessment of congestion (Bertini, 2006). These limitations are particularly important in a context where there is an increasing concern about the congestion problem which cannot completely be eradicated and a possibility of collecting more robust and numerous data.

Typical measures of congestion

Typical measures of road network performance rely on car or passenger volume, road capacity, speed, or travel time. Many traditional measures are based on volume and capacity, which require traffic volume and lane occupancy data. Lomax et al. (1997) and Boarnet et al. (1998) based their congestion indicator on a volume to capacity ratio.

Many other measures are rather based on average speed, travel time, and delay. The key congestion descriptive variables used in past studies are the speed, the travel rate (travel time divided by the segment length), and the delay rate (the difference between the actual travel rate and the free-flow travel rate). Simple ratios are derived from these, such as travel rate ratio and the delay ratio. All these basic measures can be estimated with spot speed data.

Some indicators are based on both travel time basic measures and volume measures. The next two indicators are some examples. The Congestion Burden Index (Surface Transportation Policy Project, 2001) is the travel rate ratio multiplied by the proportion of workers driving a car or riding a motorcycle to work. The total delay can also be calculated: it is the delay multiplied by the volume of vehicles. In this research, traffic volume data were not fully available, which limited the diversity of measures that could be estimated.

Other indicators are built only on travel time basic measures. For instance, Schrank, Eisele, & Lomax (2012) use the Travel Time Index, which is the ratio between travel time during peak period and the travel time under free-flow conditions, for highways. Levinson & Lomax (1996) developed the delay rate index. It is based on a relationship between speed, delay rate and the level of service, and has a 0 to 10 value. It was developed to better describe the severely congestion conditions. Some indicators are specifically developed to measure travel time reliability (Chang, 2010; Lomax, Schrank, Shawn, & Margiotta, 2003).

Other indicators are derived from the total travel delay to assess impacts of congestion, such as the excess fuel consumption and the congestion costs (Bertini, 2006). Finally, transportation organizations sometimes choose to estimate a percentage of the roadway system which is beyond a threshold. The specification of a threshold that indicates unacceptable traffic conditions is also required for many indicators presented above as well as other traditional measures such as the level of service (LOS) (Brilon & Estel, 2009). Used in the Highway Capacity Manual, LOS is a concept that ranges operating conditions from A to F. Qu & Lomax (2011) point out the important issue of setting the congestion threshold.

Desired features of a congestion measure

After reviewing the literature, Aftabuzzaman (2007) suggests six desirable attributes for a congestion measure. It should demonstrate clarity and simplicity, describe the magnitude of congestion, allow comparisons across metropolitan areas, provide a continuous range of values, include travel time, and relate to public transport congestion relief. Another important thing is that the indicator should be relatively inexpensive and easy to collect (Lomax, et al., 1997), and rely on widely available data (Boarnet, et al., 1998). This study uses a large GPS database which is available from a carsharing company and may not be so expensive in the future.

According to Lomax et al. (1997), the congestion indicator should also be able to reflect different geographic settings, time frames, and levels of detail, which is one of the objectives

of this paper. Boarnet et al. (1998) points out that we should pay more attention to the statistical reliability of congestion indicators. Mardsen, Kelly, & Snell (2006) mention two other important aspects for a good indicator: it should be noncorruptible (do not enable success to be achieved without a real situation improvement) and responsive (show change over a short time period).
We are aware that larger GPS datasets exist, usually coming from GPS companies. However, these datasets are either very expensive for public institutions, either sold to big enterprises that develop indicators with inaccessible methodologies for public institutions. In the present study, the raw database is freely made available to researchers to develop indicators for public institutions which can be well informed of the quality of the input and outputs (data and estimation methodologies).

GENERAL METHODOLOGY

Information system

A traditional way of collecting vehicle speed data is through loop detectors. However, these loop detectors are expensive, are only available in specific locations, and have a poor spatial coverage (Tong, et al., 2006). Their data quality is also dependant on the quality of the installation and calibration process. The Quebec ministry of transportation uses another common practice: probe vehicles. Typically, probe vehicles are dispatched among specific roads and timetables, and their driver collects speed and travel time using various types of equipments (electronic odometers, GPS). This data collection method requires a rigorous planning (Ishizaka, Fukuda, & Narupiti, 2005) and important financial support. With data from 1998 to 2004 gathered in the Montreal region, Loustau, Grasset, Morency, & Trépanier (2010) studied travel time distributions over segments of one-kilometer long. This same dataset was used as part of a comparative analysis examining travel times / speed estimates from various sources, for instance Bluetooth sensors and video detection (Saunier & Morency, 2011). Many researchers use data from video detectors to develop measures of severity, variability and duration of congestion (Ko & Guensler, 2005; Li, Chen, Huang, & Huang, 2008; Palubinskas, Kurz, & Reinartz, 2008).
In this research, a passive data collection method is used. Spot speed data is automatically gathered by GPS devices installed on shared vehicles that are travelling all over the road network, according to the carsharing member's travel needs. For operational purposes, the carsharing is using the GPS system to locate vehicles in real-time and to validate distances declared by users. Their needs do not require the storage of precise data. Hence, already available historical data have a typical time interval of two to four minutes. It provides a large set of GPS locations distributed throughout the whole metropolitan area. Until now, studies conducted using this dataset have focused on the comparison of the travel time estimates resulting from this database and the typical probe vehicle database of the ministry of transportation (Loustau, et al., 2010) as well as on the analysis of observed speeds in various locations and time (Verreault, Morency, & Saunier, 2011).
The database used in this paper includes all GPS data collected from some 400 shared cars, from January to November 2010. Using GPS implies low installation and data collection costs

and provides positioning with a high precision (Tong, et al., 2006). With a two to four minutes interval, the GPS releases signals when a vehicle is used by a carsharing member.
The spatial and temporal coverage of such GPS data (namely the itinerary, the type of day, and the hour of the trip) depends on the needs of carsharing members. It was observed that more than 90% of the carsharing users are occasional users; these members usually book a shared car for occasional trips, such as leisure and shopping trips. They mostly use transit, walk, or bike for their commuting trips (Sioui, Morency, & Trépanier, 2012). For instance, the current database contains more GPS points during weekends when most of the activities are for leisure and shopping. As carsharing members are more concentrated on the Montreal Island, a greater proportion of the GPS points are located in the central metropolitan area and fewer points are available towards downtown during the morning.

Methodological framework

Figure 2 illustrates the methodological framework of the project. It is organised in five main parts: the data sources, the preparation of the database, the determination of parameters for the indicator estimations, the calculation of the indicators and the analysis of the results.

1. Data comes from two main **data sources**: the road network from the ministry of transportation, enhanced with speed limits, and the GPS observations from Communauto inc. Each GPS observation contains the latitude and the longitude, the time, the date, the instantaneous speed, and the heading of the vehicle.
2. The next step of the process is the **preparation of the database** for estimation purposes, which include validation of data and the allocation of GPS points to road sections. Validation operations are required to tackle with events, such as erroneous zero speeds. In this step, GPS points are linked to the network. A buffer characterised by the distance to road and the heading is used to link GPS points to road segments. More accurate map-matching methods cannot be used because of the low speed recording interval (2 to 4 minutes).
3. Then, some **parameters need to be fixed such as the part of the road network to consider as well as spatial and temporal units and limits**. Some choices are prescribed by sample size and purposes of the estimation.
    - This study only considers highways for the road network. Further work includes improved imputation methods and generalization to other types of segments.
    - For the spatial unit selection, the highway network that was split into segments of one-kilometer long is used. This segmentation strategy was applied in order to allow for the classification of road segments based on similarity of features (distribution of travel times for instance). Also, this strategy reduces the bias caused by the non-uniform spatial distribution of GPS points, which is implied by the random itineraries of carsharing users. The temporal unit selected are the typical peak and off-peak time periods.
    - The spatial limits are prescribed by the geographical scope of data. As shown in Figure 1, the number of GPS observations reduces as the distance from the carsharing service increases. Therefore, the sample size is too small for road segments in suburban areas (that are also less congested). The spatial limits of this study are then defined by the Montreal Island. For the temporal limits, only weekdays are included in the analysis in order to use typical peak and off-peak time periods. Estimations are aggregated to the whole database, which is almost a

year (from January to November, 2010).

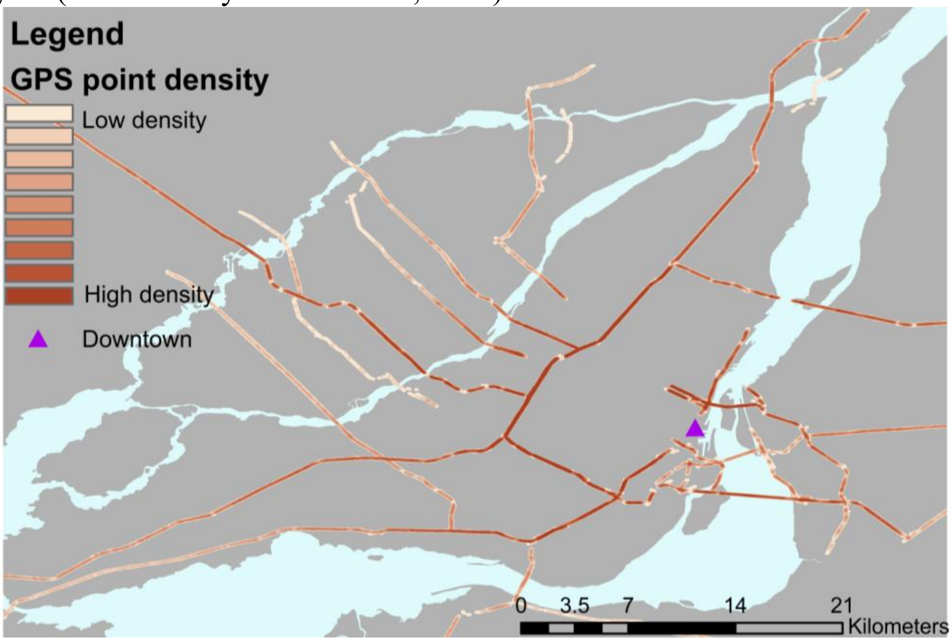


Figure 1 – Density of GPS points

4. The next part is the **estimation of indicators**, including the choice of the traffic parameter, the selection of spatial units that are to be included in the estimations, and the choice of a formulation for the aggregation
   - The traffic parameter chosen is a speed ratio. The speed associated to each highway segment corresponds to the speed limit. Since speed limits vary between 70 km/h and 100 km/h on the selected segments, raw speed cannot be the reference unit for traffic analyses. Instead, we define the reference unit as the speed ratio, which is the average of the observed speeds divided by the speed limit (1). In this case, we assume that the speed limit corresponds to the free-flow speed. This speed ratio allows the comparison of road segments. In fact, a speed ratio for peak period corresponds to the inverse of the Travel Time Index (Schrank, et al., 2012).

$$\text{Speed ratio} = \frac{\text{Average of observed speeds}}{\text{Speed limit}} \quad (1)$$

   - The spatial units included into the estimations vary from all road sections to some specific pre-selected road sections, such as ones with critical traffic conditions.
   - The formulation used to aggregate speed ratios into a single indicator also varies. For instance, it can be a simple average or the percentage beyond a threshold. Using weights for each road section is also a possibility which requires traffic volume data. Traffic volume data is not currently available, so this experimentation focuses on using available datasets.
5. Finally, the **results are analysed** in different ways. The variability and the sensibility of the indicator can be tested by looking at differences between various temporal units or simulations of infrastructure events. Maps and other data visualizations also help analysing the indicator results. For an indicator, it is interesting to discuss about the potential uses for planners.

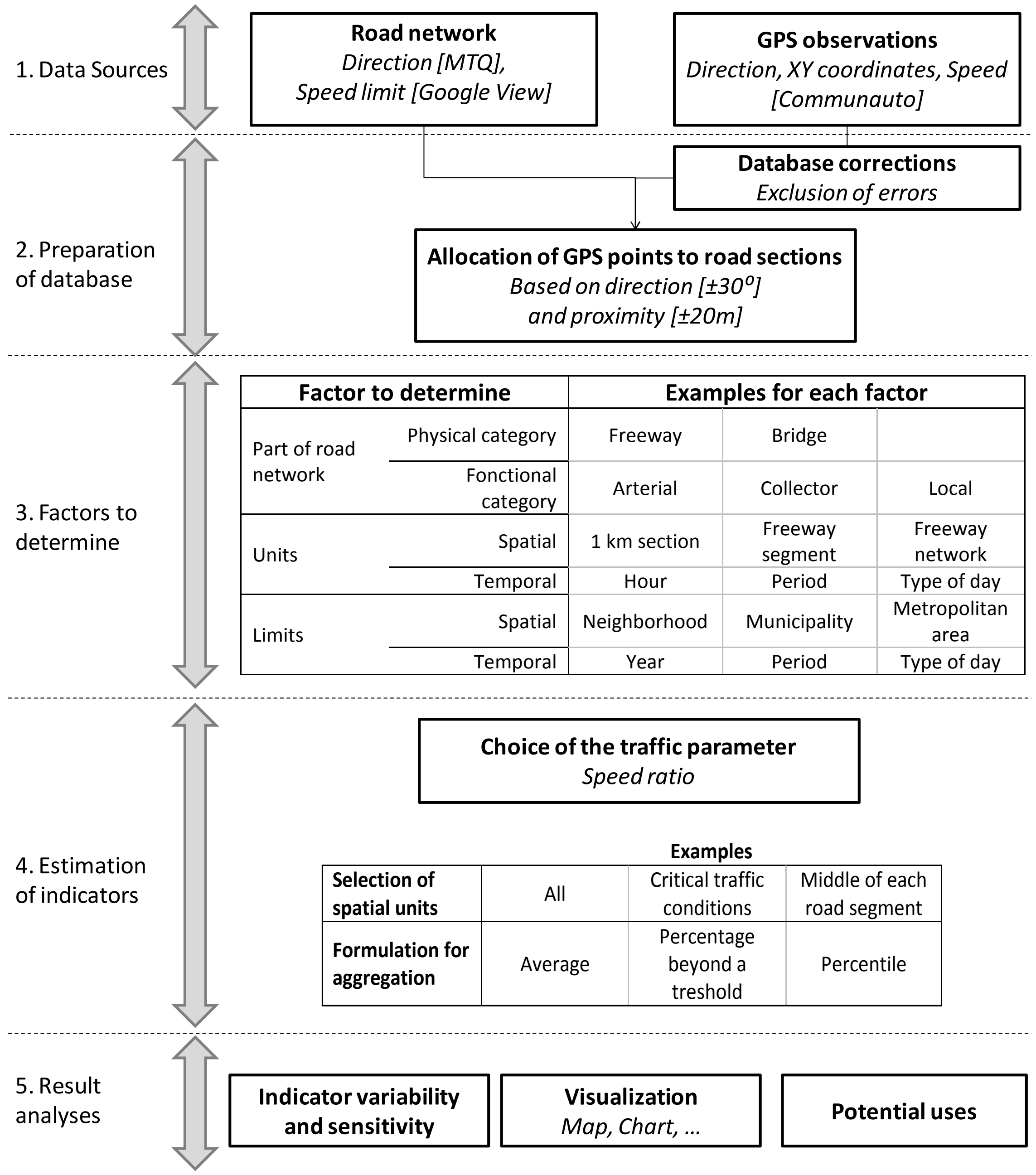


Figure 2 – Methodological framework

In summary, this study relies on 185,000 GPS points collected during weekdays and linked to one of 231 highway road segments of 1 km and located on the Montreal Island. We arbitrarily set the minimal number of observations for a road segment to ten. Therefore, a road segment with less than 10 GPS observations during the temporal unit under examination will be removed from the estimation.

Indicators tested

Various applications (called cases) were tested; they are summarised in Table 1 and illustrated in Figure 3. They share some similarities that were mentioned previously: the indicators are estimated for the highway network within the Montreal Island. The GPS observations are aggregated into 1 km road segment as well as according to four main temporal periods of typical weekdays: night off-peak (18h-6h), AM peak (6h-9h), day off-peak (9h-15h), and PM peak (15h-18h).

Cases differ mainly with respect to the selection of spatial units for the indicator estimation.

1. The case #1 includes all road segments with at least 10 GPS observations in the four time periods: 188 segments. The three other cases are also developed from these 188 segments.
2. The case #2 includes the fifteen road segments with the most critical traffic conditions, critical conditions being described by a low observed speed ratio. The fifteen segments with the lowest speed ratios are selected to estimate the indicator. This selection aims to create an indicator that monitors the worst traffic conditions and indicates deterioration or progress for the segments with high congestion.
3. The case #3 is built with road segments at the entry or the exit of one of eight highway bridges of the Montreal Island. These bridge segments are selected because they are critical road segments in the area for those having to cross the rivers and that they are typically congested during peak hours. Over the 16 bridge segments for both directions, only 13 have the minimum required of 10 observations.
4. For the case #4, highway network is cut into 13 highway corridors. Note that a highway corridor gathers many one-kilometer road segments in both directions and that ends at an intersection of another highway or a bridge. For each corridor, two segments located in the middle of the corridor are selected, one for each direction. It makes a total of 28 road segments for this case.

Table 1 – Cases tested

Factor to determine		**Case #1**	**Case #2**	**Case #3**	**Case #4**
Part of road network	Physical category	Freeway			
	Fonctional category	Primary			
Smallest units	Spatial	1 km road segment			
	Temporal	Time period (AM, day, PM, night)			
Limits	Spatial	Montreal Island			
	Temporal	Year (January to November of the year 2010), week days			
Indicator calculation method	Selected spatial units	All	15 segments with critical traffic conditions	Bridge entries & exits	Middle of highway corridors
	Formulation	(a) Over-all average (b) 85th percentile (c) Average to highway corridor, then to whole network (d) % below a fixed threshold of 0.6 (e) % below a variable threshold (average for each time period)			
	Sensitivity analysis	1) Differences between time periods 2) Differences with a simulation : a 50% reduction of the speed ratio on a specific highway corridor			

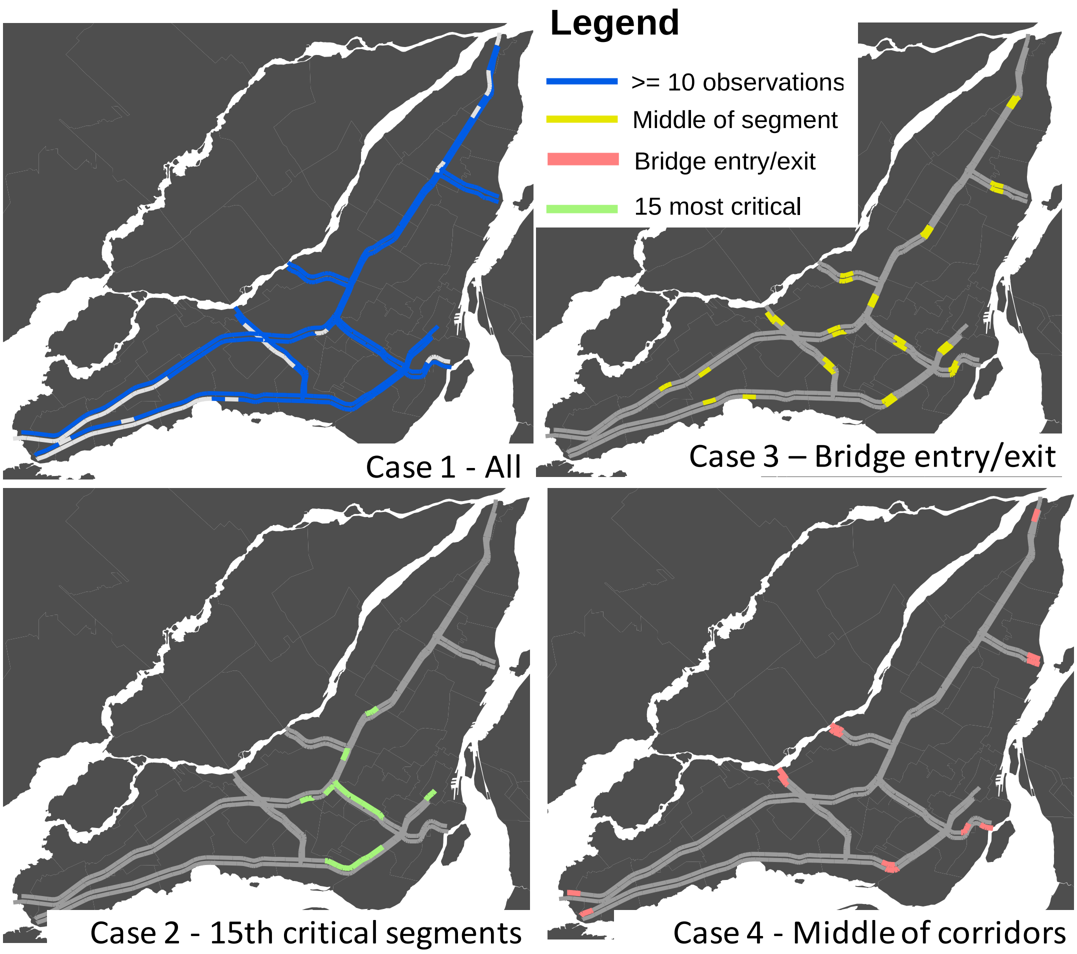


Figure 3 – Cartography of selected road segments for the four different cases

Five formulations are tested for each case:

- Formulation (a) is a typical average.
- Formulation (b) reflects the 85th percentile of the distribution of the road segments selected for the estimation.
- Formulation (c) is a multi-level aggregation measure: the first aggregation is an average of all selected road segments upon each highway corridor; the second aggregation is an average of these highway corridors.
- Formulations (d) and (e) are the percentage of the selected road segments which have a speed ratio under a threshold.
    - The threshold for (d) is fixed to 0.6, which corresponds to an observed average speed of 60 km/h on a 100 km/h posted speed road segment. Lomax et al. (1997) state that "*motorists usually are aware of congestion when travel speeds reduce to about 60 % to 70 % of the free-flow speeds.*" This threshold of 0.6 has also been suggested by the Quebec ministry of transportation (Gourvil & Joubert, 2004). However, the traveler expectations may change throughout the day: trip duration during peak period is expected to be longer than during off-peak period.
    - To reflect that idea, formulation (e) uses a variable threshold that equals to the annual average for the considered time period.

Regarding the analyses, statistical comparison tests of the speed ratio distributions of all four time period are made. These tests play a referential role. If two distributions are statistically different, it means the congestion indicator should vary between these two time periods. If two distributions are not statistically different, it means the congestion indicator should not vary between these two time periods. Therefore, the variability between time periods can be assessed for all the four cases described before. Also, the variability of the indicators is tested by a simple simulation of a construction area on one highway segment. The indicators are then re-estimated with a 50% reduction of speed ratio on all the road segments of the Highway 20 between highways 13 and 15.

RESULTS

Statistic comparison tests

In Figure 4, maps illustrate the spatial and temporal distribution of speed ratios and congestion levels. As expected, segments with too few observations (gray) are further from the center of the island and mostly heading downtown, which confirms that sampling is lower in the morning. Congestion (red segments in the maps) seems to be concentrated in the center of the island and during the day (from 6h to 18h), which corroborate expectations.

In Figure 5, the speed ratio distributions and the statistic comparison test are presented. As not all the four distributions are parametric, the two-sample Wilcoxon-Mann-Whitney rank-sum test is applied. The results also indicate which distribution has the greater values. The two off-peak periods are similar with a large proportion of segments between 0.8 and 1.0 speed ratio, though night has slightly higher values. The comparison test confirms that night and day off-peak periods are not significantly different.

PM peak speed ratios are spread between 0.2 and 1.0. Almost no road segment has a value greater than 1.0. At a lower extent, AM peak also has small speed ratios. The comparison test shows that both peak period distributions are statistically different from the night distribution. Having higher speed ratios, AM is also statistically different from PM.

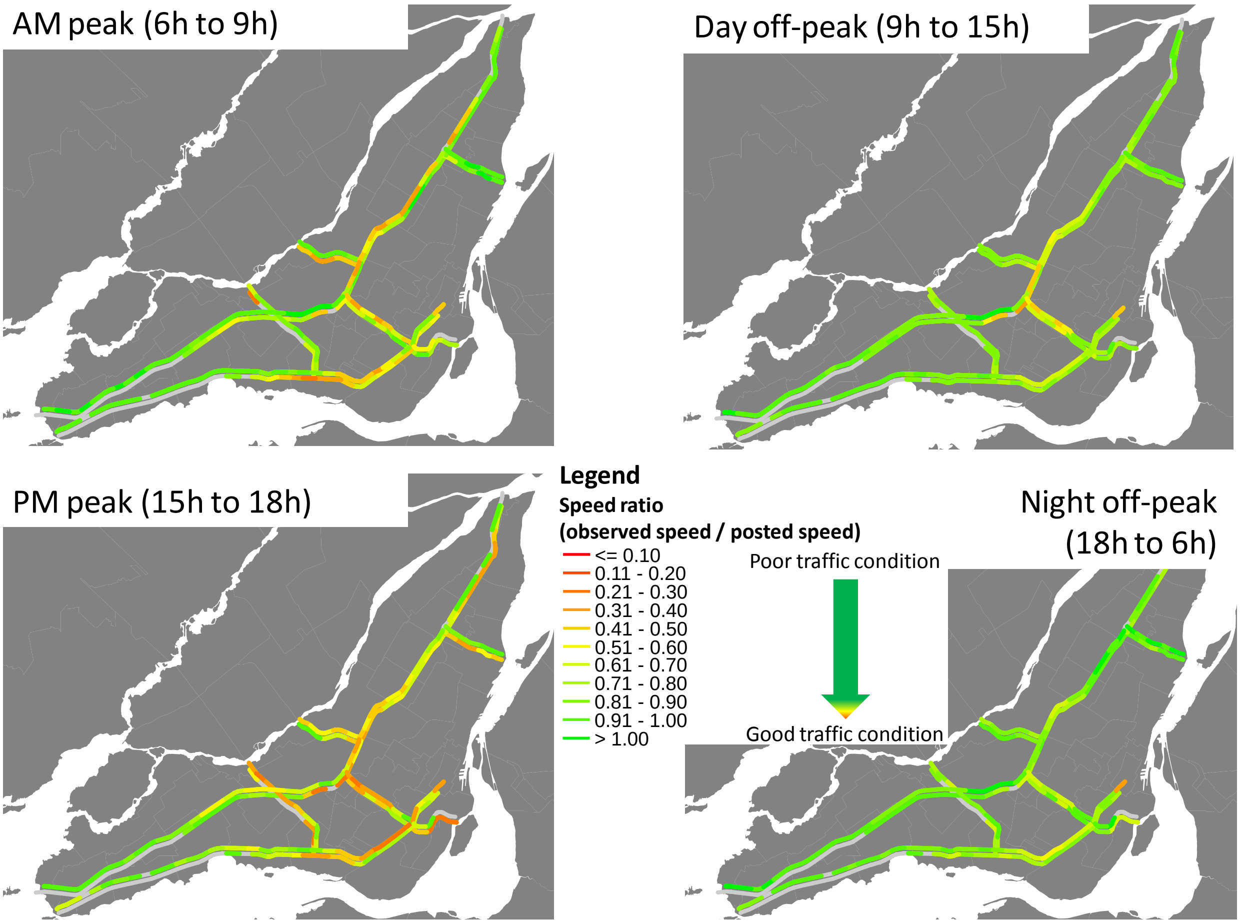
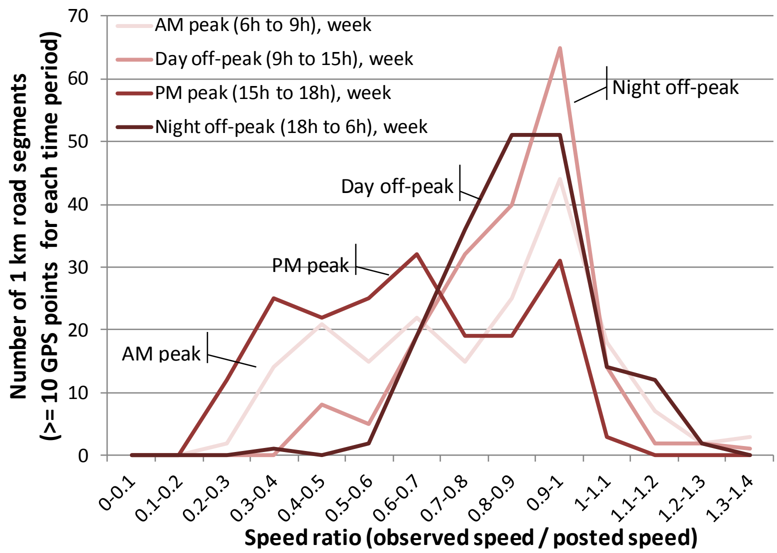


Figure 4 – Cartography of speed ratios for all 189 road segments



Wilcoxon-Mann-Whitney H_0 : Equality of samples H_0 is rejected if $p < 0.05$			**Conclusion**
AM	Night	0.0007	Different AM<<Night
PM	Night	0	Different PM<<Night
Day	Night	0.2477	Not different Day < Night
AM	PM	0	Different AM >> PM

Figure 5 – Speed ratios distributions for each time period

Indicator estimations

The five formulations are tested for the four cases presented in the methodology. Results are shown in Figure 6. The first three formulations (a to c) can be interpreted as speed ratios. For instance, a speed ratio of 1.0 corresponds to an average observed speed equal to the speed limit. A low speed ratio implies difficult traffic conditions (congestion). The last two formulations (d and e) indicate the proportion of road segments under a specific threshold. Therefore, a high percentage of segments under the threshold means that the traffic conditions are difficult.

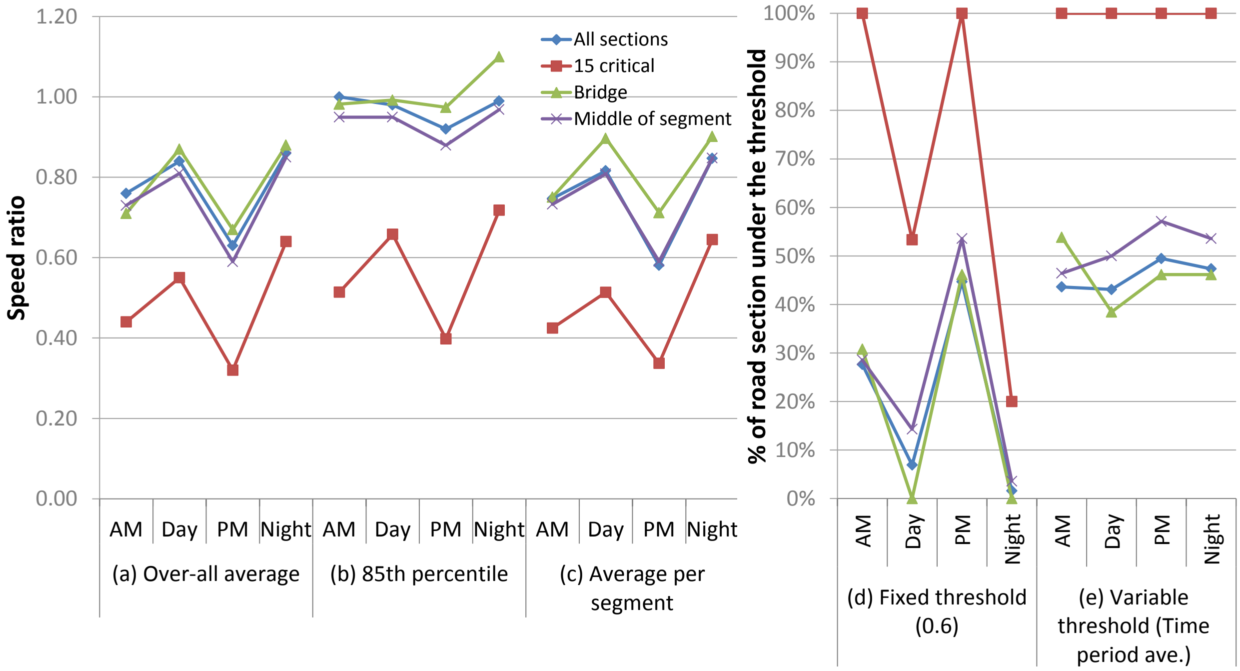


Figure 6 – Time period indicators: five different formulations and four selections of spatial units

Selecting all the road segments, only the entry and exit of a bridge, or the middle of each corridor seems to be equivalent. Still, the bridges segments and the middle segments of corridors give respectively slightly higher and smaller speed ratios. The indicator based on the 15 most critical segments gives the lowest speed ratios and varies more between time periods. It suggests a more alarming condition and is more sensitive to changes in traffic conditions.

Almost all the indicators fit the statistical trends illustrated in the previous segment. However, the 85th percentile formulation does not vary exactly as the statistical trends. As the ideal free -flow situation tends to concentrate speed ratios near 1.0, this formulation would not be sensitive enough to changes, in particular in an acceptable transportation system.

The fixed threshold indicators are very concentrated in lower and upper limits (0% and 100%). The 0.6 value of the threshold seems too high for the peak periods and too low for the off-peak periods: the resulting indicator is probably not sensitive enough to changes in traffic conditions. Different thresholds for different time periods may help estimating a more sensitive indicator. This option is tested by formulation (e), for which statistical trends are still not always consistent. For instance in cases #1 and #4, night off-peak period has worse traffic conditions than AM peak and day off-peak. Also, with the 15 most critical segments (case #2), this indicator sticks to 100%, which means all the critical segments are beyond the annual average threshold for each time period.

According to the statistic comparison tests presented in the previous section of this paper, day off-peak is not statistically different from night. The 15 most critical segments indicator (case #3) does not fit these statistical trends since they reveal a high difference of values between day and night. Therefore, this indicator appears to be too responsive.

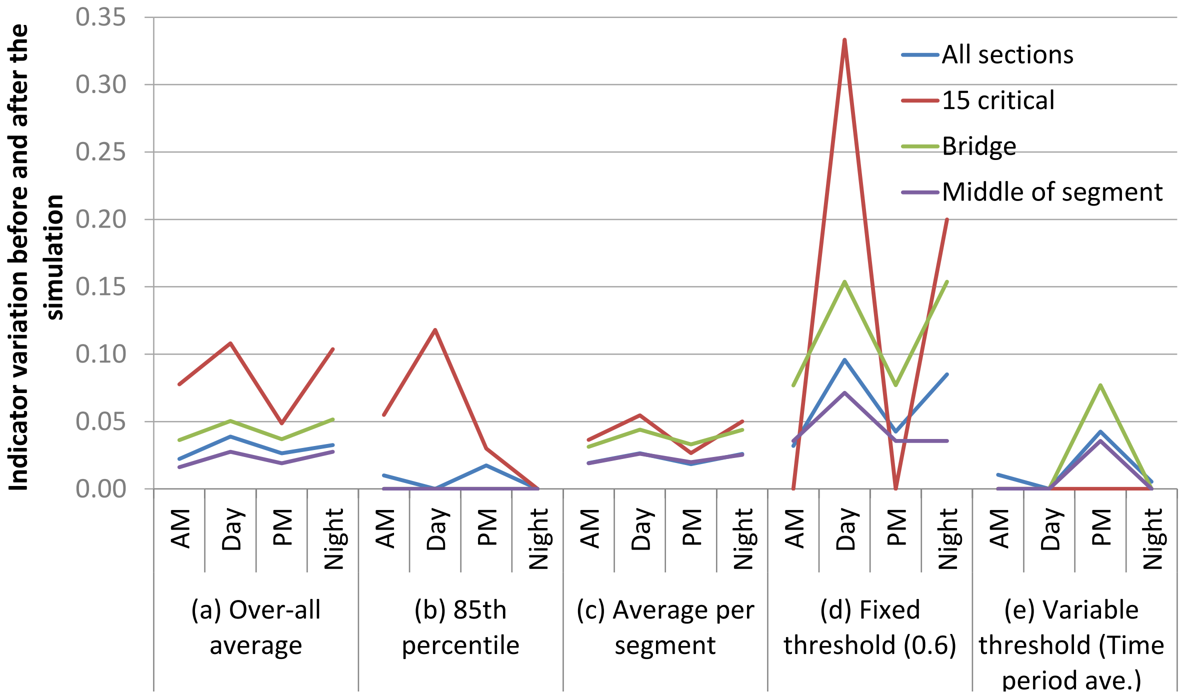


Figure 7 – Indicator variations before and after the simulation of a major road event on a specific highway corridor (a positive variation indicates worse traffic conditions)

The indicators are estimated another time after the simulation of a major road event on a whole highway corridor; results are presented in Figure 7. This corridor contains a bridge entry and exit and five critical segments. The simulation affects all the segments of the road corridor, by dividing speed ratios by two. As shown in Figure 7, worse traffic conditions reduce speed ratios (a to c) and increase proportions of segments under a threshold (d and e). The 85th percentile indicator (b) is the less sensitive and the overall average (a) and the multi-level aggregation formulation (c) vary lightly. The sensitivity of the indicators is greater when the indicator is based on fewer segments. Concerning the indicators based on a threshold, the variability is high for the fixed 0.6 threshold (d), and low for the variable threshold based on the time period annual average (e). In formulation (d), the variations among time periods are high even though similar variations were expected due to an identical simulation performed for all time periods. For instance in the 15 most critical segments indicator (case #2) and the fixed threshold formulation (d), day and night indicators vary of 0.33 and 0.20, but do not vary at all for AM and PM.

DISCUSSION

Proposed indicators

The indicators based on a threshold are very sensitive, but variations are unpredictable. On one side, small changes in speed ratios far from the threshold value do not result in changes in the indicator value. On the other side, small changes in speed ratios near the threshold value result in a high variation of the indicator value. In fact, such an indicator has an unpredictable responsiveness in respect to changes of traffic conditions. Also, the threshold value is critical. Selecting a unique threshold for very different distributions, as for peak and off-peak time periods, results in an indicator concentrated in bounding values (0 % or 100 %). Therefore, the indicator becomes non-responsive to changes in traffic conditions. Moreover, various thresholds for very different distributions, as the annual average for each time period, create an indicator with no extreme values. However, these various thresholds have to be fixed to allow comparison between years. The solution may be to fix different thresholds for peak and off-peak periods. In order to reduce the unpredictability of such an indicator based on a threshold, two thresholds may be used to differentiate congestion (travel time in excess of that normally incurred) from unacceptable congestion (travel time in excess of an agreed-upon norm), as suggested by Levinson and Lomax (1996). The exact values of the thresholds are not so significant since Qu &Lomax (2011) showed that worst road segments are always the worst.

The 85th percentile indicator does not seem appropriate to reflect changes because of its low and sometimes incorrect responsiveness.

In the case of indicators based on an average, the indicators have low responsiveness. On the one hand, selecting all the road segments appears to give more weight to longer highway corridors, which have not necessarily the most important vehicle flows. Therefore, short highway corridors with more volume and congestion, for instance those in the center of the Montreal Island, have only a small influence on the over-all average. On the other hand, the average value per highway corridor assures an equal weight to each corridor, even if they do not have the same length. The two indicators have hence different roles to play in the assessment of congestion levels.

Finally, the selection of spatial units influences the meaning, the value, and the variability of the indicators. Selecting specific road segments as for the bridge case creates an indicator only sensitive to changes on these specific segments. It therefore cannot assume to represent global trends. Also, it seems that selecting a road segment in the middle of each highway corridor creates an indicator similar but less sensitive to the one with all road segments. Selecting the fifteen most critical road segments appears to build the most sensitive indicator. Nevertheless, it will never capture any changes in road segments with higher speed ratios.

Estimation methodology of indicators and contribution to the decision-making process

Traffic condition measures fulfill three main functions. The first objective is to understand the evolution of a phenomenon : to overview the situation (Mardsen, et al., 2006) and to identify trends (Rodrigues da Silva, et al., 2010). The indicators related to this objective are based on relatively simple formulations, such as average, sum, or percentile.

The second objective is to measure the impact of public action. Indicators are used to define policies, to monitor the impacts of policies, and to measure the degree of success in achieving goals (Bouni, 1998). This involves the definition of targets. Targets typically reflect political acceptance, traveler expectations, and service reliability. Indicators therefore have to integrate these targets in their formulation. The indicators developed for the previous objective are then used with specific spatial and temporal units. These units are chosen depending on what needs to be improved: improving global traffic conditions during peak periods, stopping the deterioration of the most critical road segments, reducing congestion at the entry of bridges and tunnels, etc.

Finally, decision-makers also need traffic condition measures in order to make decisions and take actions where and when it is the most likely to be successful. Targeted interventions will help to have good performance and to progress towards the identified goals. Therefore, indicators provide decision assistance and help to anticipates problems (Rodrigues da Silva, et al., 2010). Decision-making benefits from disaggregate data which makes it possible to spatially and temporarily localize critical conditions. Disaggregate data is also necessary to understand social trends and to target population groups which are likely to change their behaviors, especially when data is combined with socio-demographic characteristics or mobility behaviors.

Limits and perspectives

GPS data collection depends on the driver's behavior, which influences speed, itinerary, and time of departure. GPS data collected by carsharing fleet rely on a broad diversity of carsharing members which have their own driver behavior. Carsharing members share other characteristics and needs: the members' home locations and their trip purposes (mostly leisure and shopping) dictates the sample size both in space and time. In a near future, it is possible to increase the current sample size either by equipping more cars (up to about 1,500 shared cars) but also by increasing the frequency of spatial location recording.
The paper confirms that sets of low resolution spot speed data derived from a GPS onboard system have the potential to feed the estimation of congestion indicators and provide continuous assessment of the congestion level on highways. The findings of this study on traffic level indicators can be useful in the development of a monitoring tool for the assessment of various strategies impacts, as well as the evolution in space and time. The comparisons between various measures and spatial and temporal divisions show that multiple indicators may be needed to monitor adequately the traffic conditions. Along with a larger sample, various spatial and temporal aggregations can be tested. For instance, month and year variations of indicators can be studied as well as a larger territory that can include suburban areas. Also, additional indicators need to be tested, such as traditional congestion measures. Additional cases of segments selections for the estimations will further be conducted.

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