DOI: 10.48011/asba.v2i1.1360

# A Visual Analytics Approach for Inferring Passenger Demand in Public Transport System based on Bus Trajectory

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Abstract: The control and monitoring of public transport buses considering the Global Positioning System (GPS) produce a data tsunami for the creation of indicators related to public transportation. The conventional techniques of data analysis for this type of information require programming effort, execution of algorithms with high processing in extensive databases to get at the end the production of the idealized statistical and visualization reports. In this process, the search for new analyzes or visualizations may require a restart of the process, a control of the versioning of the developed programs and repetitive high processing algorithm. This form of acting hinder the cognitive process, the analysis capability and the inference of relevant information. In this context, this paper proposes a methodology based on Visual Analytics to infer passenger demand based on the trajectory of conventional buses for planning new routes served by electric buses at the State University of Campinas - UNICAMP. The methodology includes a space-time stage and another for human interactivity, with easily configurable graphics for evaluation of indicators. Results show the locations and times with the highest use of the transportation service and can be used to identifying new routes to be served by electric buses on campus.

*Keywords*: Visual analytics; Big traffic data, Public transport; Passenger demand; Urban mobility.

## 1. INTRODUCTION

Public transport is one of the main means of moving people in urban areas due to its comprehensive passenger service and a great influence on urban traffic systems. The quality of the public transport system service is a fundamental condition for making the decision of the passengers on whether or not to use this means of transport. In order to improve passenger satisfaction, it is essential to know the demands of the public transport service being necessary to extract the route features with respect to the space-time (Liang, Q. et al. 2018).

Many researchers have analyzed the travel features of public transport exploring methods of extracting valuable information to understand the relationship of various variables that make up this problem. Overall, these earlier studies focused on conventional techniques, machine learning, and visual analysis. The science of visual analysis is in constant development based on methods that make synergistic work between man and machine feasible through interactive interfaces for a good understanding of the problem from large and complex databases (Andrienko, G. et al. 2017).

Understanding traffic is critical to understanding passenger behavior patterns within the transportation system. The data considered in this type of problem allow us to explore various aspects and features in space-time. In Zeng, W. et al. (2014), the authors propose methods that allow the analysis of passenger routes in public transport. This method estimates the efficiency of each trip on a given route considering the driving, waiting and transfer times. This visual analysis is carried out by a map-based isochrone view. A 3D visual analysis is proposed in Itoh, M., et. al. (2016) to show the passenger demands along the lines of a metro network, using graphs with ribbon widths proportional to the passenger numbers, and the colors representing the crowdedness level. The authors of Laharotte, P. A. et al. (2014), Bhaskar, A. et al. (2014), Hamad, K. et al. (2015) and Chen, W. et al. (2017) analyze traffic data more intuitively and conveniently by introducing visualization technology when analyzing traffic data. These works consider the trajectory of the trip, the critical points in the cities, the trip of specific passengers, the congestion situation in the road network, and the impact of other events in the road network. Despite considerable research on the characteristics of travel on the public transport system, research on passenger correlation is even more limited.

The advent of vehicle electrification technologies is gradually incorporated into different mobility modes, among which, the use of electric buses as public transport is very promising. This modality has been the subject of several studies that evaluate the technical feasibility (Kontou, A. et al. 2015) and (Mahmoud, M. et al. 2016), economic (Göhlich, D. et al. 2014) and (Laizāns, A. et al. 2016), reduction of polluting emissions and effects on health (Columbia U. 2016), and noise reduction in the urban environment (Laib, F. et al. 2019). This is possible with the Living Lab Project in

UNICAMP, which will introduce an electric bus to support the existing diesel conventional ones (Ugarte, L. F. et al. 2019). To plan the route of the new electric bus, it is necessary to know the passenger behavior so that alternatives to the existing routes can be explored. However, on current buses, there are no access control systems, so there are no metrics on passenger demand.

As an alternative to the use of turnstiles and/or access control systems in public transport to estimate the passenger demand, several studies in the literature address this problem. These studies involve the proposal of automatic passenger counting systems (I. Pinna et al. 2010) and (Geetha, S., & Cicilia, D. 2017), applications on using cell phones (Farkas, K. et al. 2015) and (Brakewood, C. E. 2014), as well as the use of Wi-Fi signal transmission systems installed in buses for detection of mobile equipment at the entrance and exit to estimate the capacity and the routes traveled by passengers (Handte, M. et al. 2016), (Junior, M. R. et el.) and (Paradeda, D. B. et al. 2018).

As a different approach to the other authors mentioned, this paper uses statistical techniques combined with visual analytics, applied to the historical records of location shown in (Barbosa, R. A. et al. 2018). In this article, we propose an interactive visual analysis system that can intuitively explore associations between passengers in a public transport system, evaluating physical greatness such as acceleration, duration and number of stops at the bus stops, to infer the demand for transport services by users in the University.

The rest of this paper is organized as follows. Section 2 describes the methodology for inferring passenger demand. Sections 3 and 4 describe the model features, and the discussion and results, respectively. Section 5 gives the conclusion of this paper and future works.

## 2. METODOLOGY

Visual analytics technology is a multidisciplinary area, which integrates visualization, analysis, data mining and management techniques, statistics, cognitive science, among others (Keim, D. A. et al. 2010). The mining techniques allow extracting the relevant information from the available data and the visualization techniques provide their representing in easily interpretable images.

In this section, it is presented the used architecture for visual analytics and the source database employed for the analyses.

### *2.1 Architecture for Visual Analytics*

When a system is used in integrating large databases with appropriate visualization techniques, using a graphical interface and allowing interactive resources, it favors the logical reasoning of the user so that he has a greater understanding of relevant information and can make more effective decisions.

The visual analytics architecture proposed in this study includes a first stage of processing with space-time models, which extract physical quantities from the trajectory records of the buses and make them available for visualization at a second stage, as shown in Fig. 1.

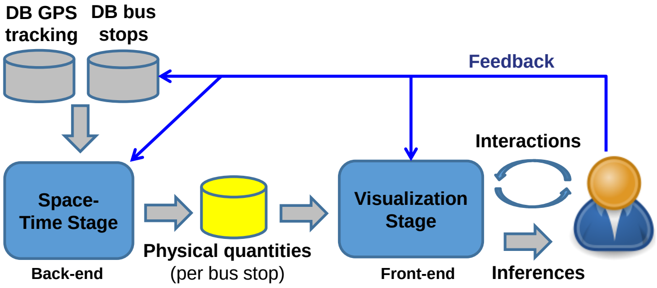


Fig. 1 Demand inference methodology using visual analytics.

In the process involving visual analytics used, the feedback received from the user analysis is also contemplated to improve the models and the quality of the data involved. At the end of the process, the user can get inferences about the passenger demand.

### *2.2 Source Data Bases*

The methodology uses two databases as source of information:

• Database of bus stops and;

• Database of GPS historical tracking.

The first one corresponds to the specification of bus stops, referenced by a text identification and a bus stop number. Each bus stop is associated to a bus line number (route) and the sequence number in the route. Additionally, in order to carry out localized analyzes, in which more than one bus stop is present in a restricted area for several bus lines, the concept of location was created. The database of bus stop points is formed by the following fields:

- Text identification;
- Bus stop number;
- GPS coordinates;
- Location number;
- Bus line number and;
- Line sequence number.

The database of historical GPS tracking consists of information records of the internal buses operation in the University and gotten from the Circulino system (Barbosa, R. A. et al. 2018). The data comprises the following information fields:

- GPS coordinates;
- Date and time;
- Line number;
- Bus number and;
- Altitude.

In the transport system studied, the data base contains records of seven circulating buses that operate on four different lines, with average measurements every 3 seconds, covering working days from 01/01/2018 to 01/30/2019.

## 3. MODEL DEVELOPMENT

Performing tasks with raw tracking data while running the visualization tool, such as selecting and filtering bus lines, could lead to a long waiting process and would greatly impair the inference process. For this reason, a preprocessing of information is necessary and the implementation of the model of visual analytics, illustrated in Fig. 1, results in the development of the stages explained in this section:

- Space-time stage and;
- Visualization stage.

The space-time stage performs the calculations to obtain the physical quantities of the buses near bus stops. As physical quantities are values of acceleration, number and duration time on the bus stops, which are subsequently explored in the visualization stage. In this way, the preprocessing and transformation of source data allow them to be ready for the subsequent visualization process.

### *3.1 Space-time stage*

The space-time stage is part of the back-end and is responsible for the preprocessing of the input data, which consists of the GPS trajectory measurement and bus stop databases. An important aspect is that the model does not require detailed route specification, using as the configuration information only the specification of bus stops ordered sequentially. Internally, the algorithm of the stage is executed separately for each line and bus number and is structured as a finite state machine to follow the trajectory of the buses, as shown in Fig. 2.

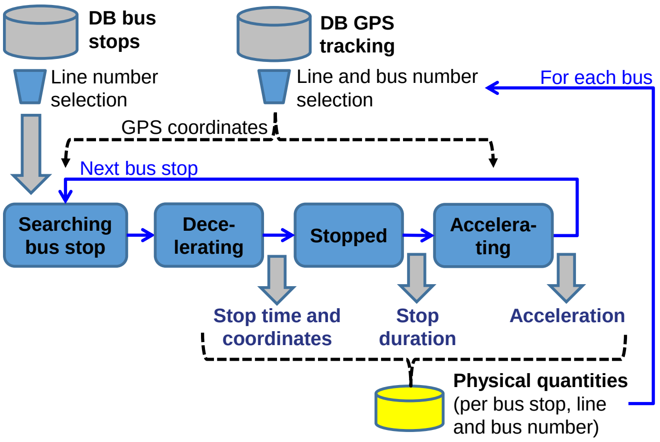


Fig. 2 Finite-state diagram in the space-time stage.

According to Fig. 2, there is a selector to choose information of each line and bus number from the source row data. From the data of each line and bus number selected, the finite state machine analyzes sequentially the GPS coordinates tracking information to identify when the bus pass through a bus stop. The states used in this state machine are:

- Searching bus stop;
- Decelerating;
- Stopped and;
- Accelerating.

In the first state, searching bus stop, the algorithm search for a bus stop according to the sequence list of the line that is selected. The algorithm makes this detection by scanning the trajectory traveled and observing if the distance of the bus in relation to one of the stops is below an approach threshold.

Regarding this threshold, values that are too low can lead to loss in detection and too high can result in false uptake. The threshold value that generates good results in the resolution of the used tracking data is 25 meters.

In this process, it is used a window observation of three bus stops as a way to reduce the occurrence of false detections of other near bus stops. This was a necessary resource due to the proximity between non-adjacent bus stops on the same line. As they are circular lines, incorrect detection of some points outside the normal sequence could occur, as shown in Fig. 3.

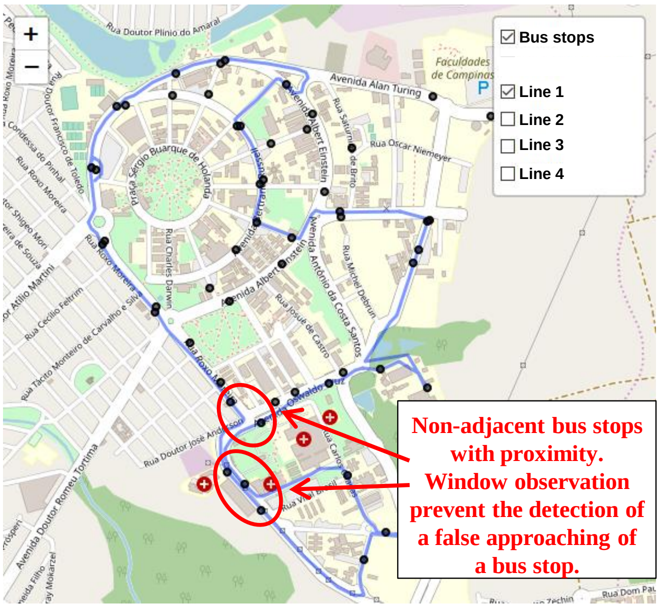


Fig. 3 Circular line with proximity to non-adjacent points.

In the Decelerating state, the trajectory of the bus is followed until the bus reduce to a minimum speed. At this position, the georeferenced coordinates, the time and the distance relative to the bus stop are recorded. It was also observed that, due to the sampling rate of 3 seconds, it is not always possible to capture the moment of zero speed. For this reason, the displayed residual speed is also recorded.

Subsequently, the algorithm goes to stop state, which is awaiting to reestablish the movement. At the end of this state, the time in which the bus remained stationary is obtained and recorded. Finally, in the Accelerating state, the trajectory is followed in order to record the maximum bus acceleration observed at the exit from the bus stop.

Another relevant aspect was the need to implement checks for consistency of the route due to failures in the recording of the trajectory measurements that could cause gaps in time and displacements. In such circumstances, the analysis in the finite state model must be restored to the initial state and the bus stop search window is extended to all stops. In addition, repetitive measurements could be present and have to be discarded.

Finally, as a result of the space-time stage applied to all buses, the following physical quantities associated with the bus stops, date, time, line and bus number are recorded:

- Acceleration;
- Residual speed when stopping;
- Distance from the bus stop with the minimum speed;
- Time during the stopping and;
- GPS coordinates.

The stage was implemented in R script. In the processing of approximately 13.5 million records of historical GPS tracking of bus routes, the algorithm required approximately one and a half hour on a computer with an i7 processor, a 3 GHz clock and 4 physical cores.

### *3.2 Visualization stage*

The visualization stage corresponds to the front-end. In it, the results of the physical quantities calculated in the space-time stage are mapped in an interactive graphical interface with the objective of providing the user with a greater understanding of the relevant information and, thus, been assisted in his decisions.

The implementation is also done in R script and with the following packages to assist in the user experience and allow availability on a web interface:

- Shiny - Development of interactive interfaces and;
- Leaflet - Interactive map view, which uses information from © OpenStreetMap contributors, CC-BY-SA (OpenStreetMap, 2020).

The developed interface was organized in thematic visualization panels to:

- Physical quantities selectable by bus stop, location and time of day;
- Thematic map;
- Histogram and dispersions of the physical quantities and;
- Interdependence among lines, buses and date.

There is also a control panel that provides options for selecting indicators, statistical operation and filters applicable to all visualization panels, which are shown in Fig. 4. The positioning of the controls considers the relevance during the exploration carried out by the user, being those most frequently used at the top of the panel, but also preserving functional proximity between them.

As a result of visual interactivity, the user can select the desired indicator (physical quantity) in order to seek a better inference for the demand of the transportation services at the university, guided by bus stops, locations and times of day. In addition, it is possible filter part of the information to determine seasonal differences monthly and / or over days of the week. Given the number of objects evaluated in the graphs of the indicators, the results were classified according to the position in the quartiles, being presented in blue for the first quartile, black for the second and third quartiles and red for the fourth quartile. The captions accompany the colors for easy observation.

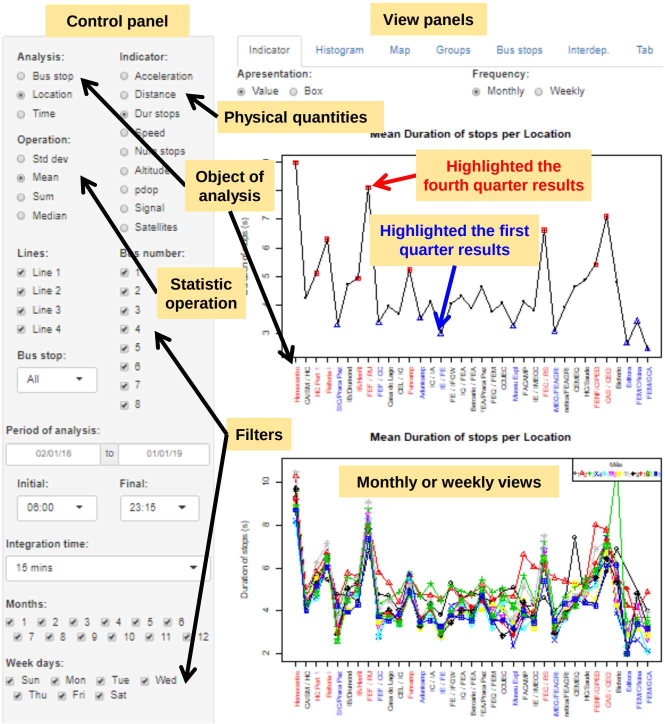


Fig. 4 Organization of display panels.

On the computer used, the developed solution obtained response times to user commands below one second. Except for the first access to the thematic display panels, taking up to three seconds to load. This achievement ensures an interactive process suitable for the exploration activities by the user with high performance, as required for visual analytics (Keim, D. A. et al. 2010).

## 4. DISCUSSIONS AND RESULTS

The first results for the models presented were not so accurate in detecting stops during the execution of the space-time module. This led to the need to review the registration data of bus stops, as a feedback from the results, improving the analysis process, as shown in Fig. 1. The space-time stage was then reprocessed and the indicators obtained were again evaluated.

The following items present the procedure to review the geolocation coordinates of bus stops, the process of analysis, and the inference of the indicators obtained.

### *4.1 Analysis of the positions of bus stops*

The bus stop detection failures had presented several causes, including incorrectly defined detection thresholds and detection of some points out of the correct sequence, problems already mentioned above. Furthermore, there was an inaccuracy in specifying the position of the points, as shown in Fig. 5, which could lead to non-detection of bus stops and/or false detection.

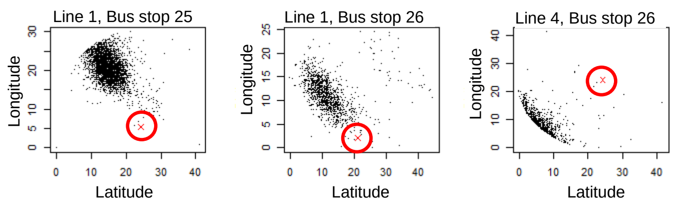


Fig. 5 Inaccuracy of the positioning register of bus stops. (Black points are the detected stops of the buses and red points are the locations previously specified for the bus stops).

Based on this observation, the feedback was made in the bus stop database with adjustments to the georeferenced coordinates of their locations, assigning them to the median coordinates of the effective stops of the buses. This process was repeated until the results stabilized.

Similarly, the space-time stage for bus tracking has also been improved and has now incorporated bus stops search windows.

*4.2 Inference of demand in the transport system*

For the inference of passenger demand in the public transport system, indicators such as acceleration of the bus, mean of stop time, sum of stop time and number of stops at the bus stops were evaluated.

**Mean acceleration of the buses.**

In the assessment of acceleration, from a theoretical viewpoint, urban buses with a capacity of approximately 70 passengers, considering the variation in gross weight (ViaCircular, 2019), can accelerate up to 45% more when empty than with maximum capacity.

Considering this premise, the possibility of relating the difference in bus acceleration with the level of capacity at the exit of bus stops is analyzed. However, according to Fig. 6, no significant difference was observed. The results showed uniformity of the measured values as a time function for the consolidation of the bus stops, except between 6:00 and 6:30. In the assessment at some specific bus stops, the acceleration shows only a slight decrease in the lunch hour and at night.

As shown in Fig. 7, only moderate differences are observed between the bus stops and still with a large dispersion of values. The major values are from bus stops in a downhill, as in Economic Institute (IE), Faculty of Mechanical Engineering (FEM) and Computing Center (CCCUEC).

Thus, the acceleration indicator suggests the existence of dependence on mobility restrictions in some bus stops, the influence of the traffic condition and for the street characteristics. For the passenger demand, the study indicated a poor association. Despite of the great variability of the results, this can be in part resulted from noise estimation due the high sampling time, which is approximately 3 seconds.

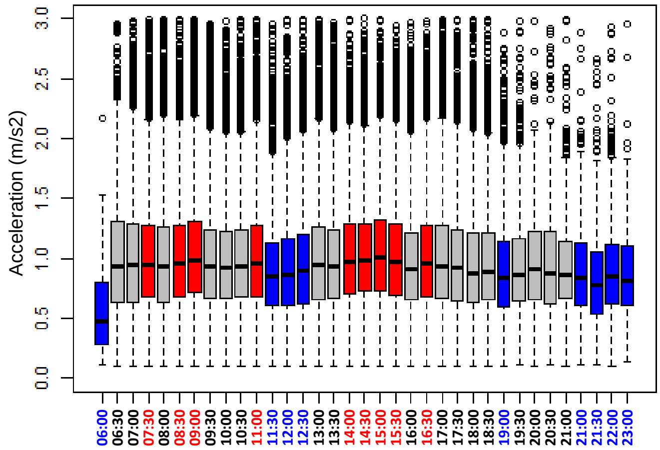


Fig. 6 Variation of bus acceleration by time range.

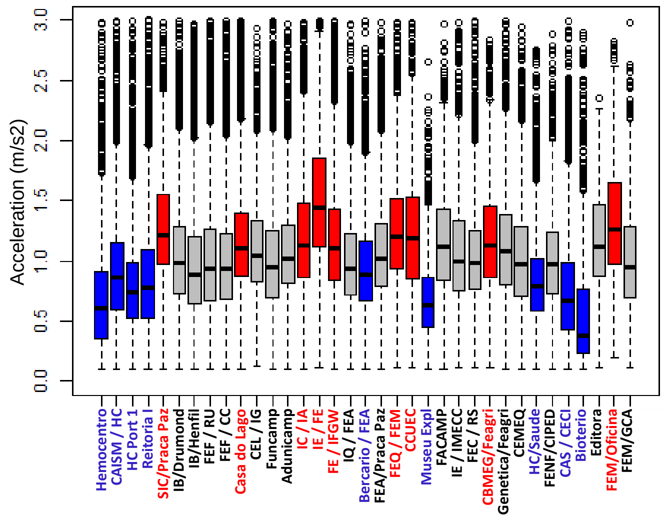


Fig. 7 Variation of bus acceleration by location.

**Number of stops at the bus stops.**

In the evaluation of the number of stops identified for the buses, the results showed significant differences between bus stops and timetables, as shown in Fig. 8 e Fig. 9. There are a large number of stops from 6:30 am until 6:00 pm and a low at night, also due to a lower offer of transport services.

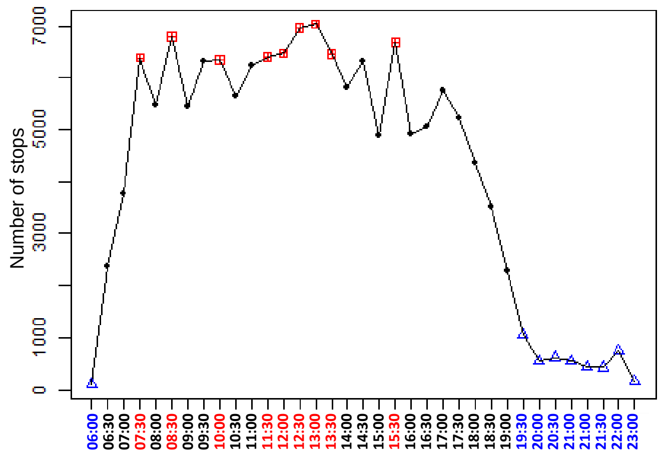


Fig. 8 Number of bus stops by timetable.

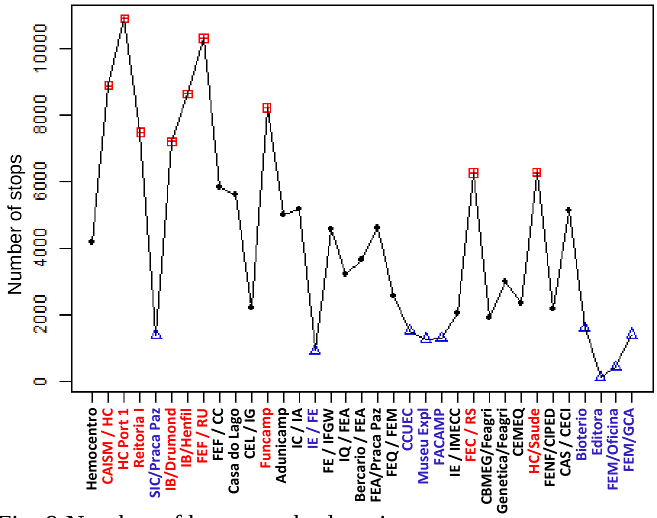


Fig. 9 Number of bus stops by location.

Through this indicator cannot be associated with the numbers of passengers entering or leaving the bus. However, the results suggest a strong association of the number of stops with the locations and times with interest in transportation by passengers.

Hence, other indicators should be investigated for a better inference related to the passengers demand.

**Mean of stop times.**

Regarding the indicator of the mean of stop times in the bus stops, the results showed moderate differences between timetables. The highest times occur during the lunch period, as shown in Fig. 10.

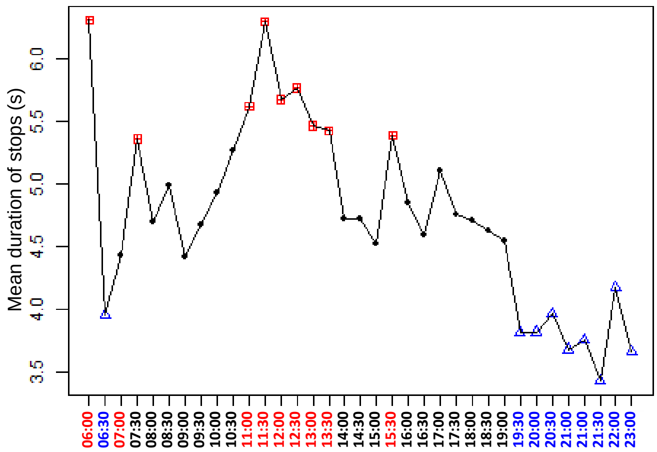


Fig. 10 Mean of stop times by timetables.

However, when comparing the different bus stops there is a higher difference, with the mean stop time in some locations twice the value of the majority of the locations, as shown in Fig. 11. The mean of stop times can be associated with the number of passengers entering or leaving individual buses. Nevertheless, as the whole system is served by several buses and lines, this association does not correspond with the total demand. Therefore, the indicator mean of the stop times suggests only the association with the flow of passengers by bus.

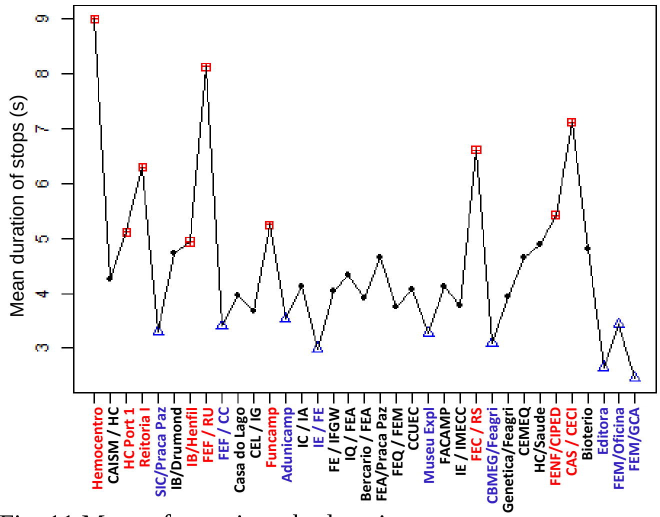


Fig. 11 Mean of stop times by location.

**Sum of stop times.**

Regarding the indicator of the sum of stop times, results showed great differences among timetables and bus stops, according to Fig. 12 e Fig. 13. The sum is higher over the lunch period and with isolated peaks in the morning and afternoon.

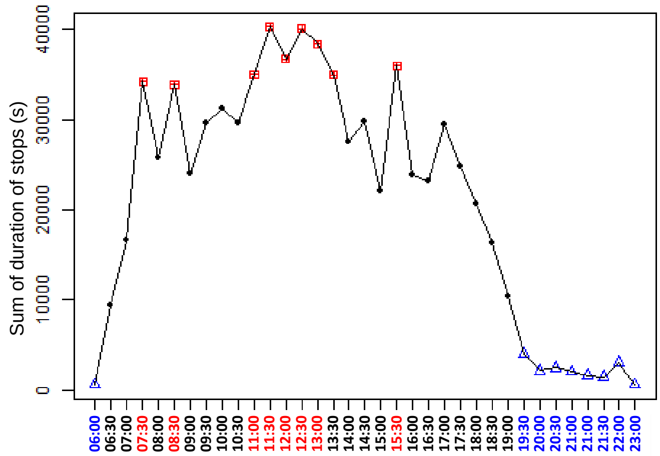


Fig. 12 Sum of stop times by timetables.

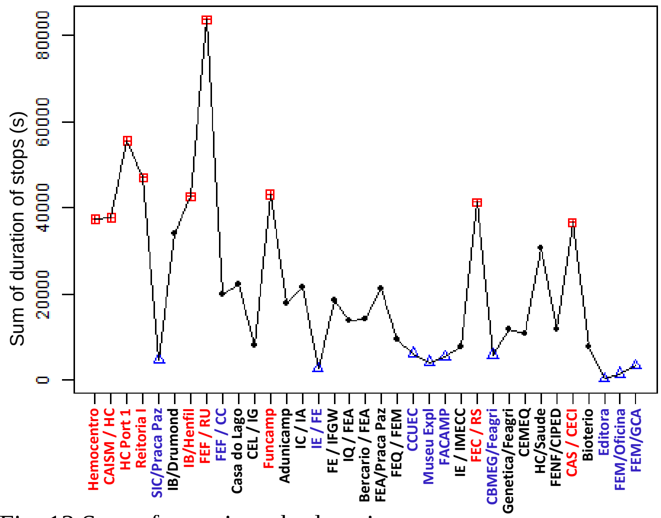


Fig. 13 Sum of stop times by location.

The sum of stop times combine the results of the number of stops and the mean of stop times indicators, which in turn is dependent on the passenger flow by bus, locations and times. Therefore, the results suggest an association of this indicator at the locations and periods with the highest passenger demand.

### *4.3 Locations with the highest passenger demand*

For better visualization of the locations with the highest demand of passengers, a thematic map of the Campus is best suited. In Fig. 14, the thematic map shows the locations highlighted with circles, which radius are proportional to the sum of stop times.

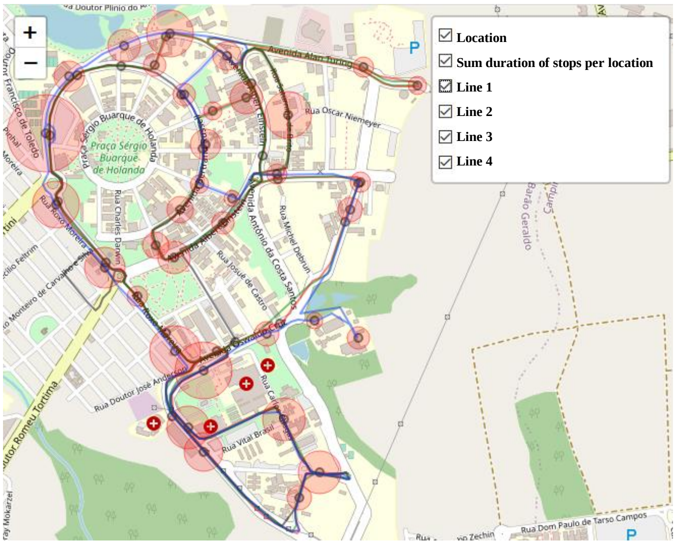


Fig. 14 Map with the sum of stop times by location.

According to a thematic map in Fig. 14, it can better inferred the passenger demand in the transport system of UNICAMP. The places with the highest passenger demand is in the health sector (Hospital of Clinics, CAISM, Hemocentro, CAS/CECI), university restaurants (RU and RS), bus stops near Funcamp and CEPETRO, as well as those located on Érico Veríssimo Avenue.

The map view of Fig. 14 also allows the resource of brushing and linking. A selection of one or more bus stops or locations in the map acts as a filter in the data, allowing the assessment of the selected elements, changing the graph views of the indicators and facilitating the visual analysis.

### *4.4 Seasonality of passenger demand.*

Also considering the sum of stop times to infer the passenger demand in the transport system of UNICAMP, as shown in Fig. 15, the greatest passenger demand is in April, May, and June, highlighting the months of January and February as the least demand. On the other hand, in an analysis of demand according to the working days of the week, the results did not show significant differences.

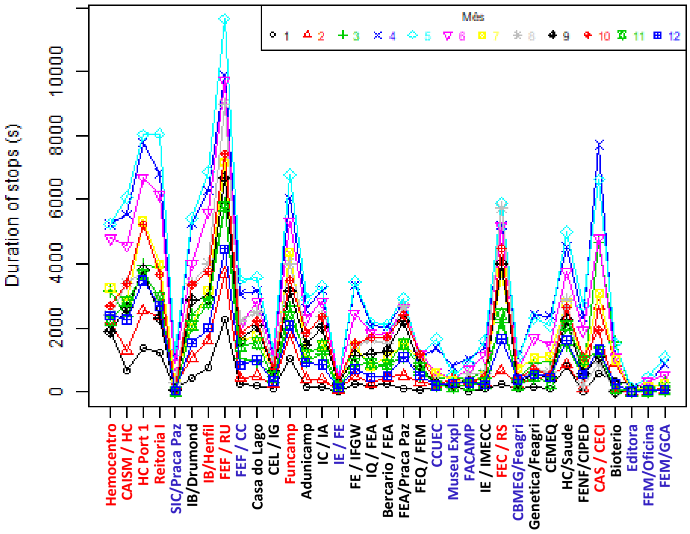


Fig. 15 Sum of stop times by locations over the month.

## 5. CONCLUSIONS

With the support of visual analytics techniques, results obtained proved very intuitive. In the aspect of demand inference, the proposal initially exercised with the use of acceleration to estimate the bus capacity was not shown to be suitable due to the great dispersion and variability of results. In this case, the long sampling time in the bus tracking measurements, the low average speed, the traffic influence on the routes, and the low distance between bus stops as well as street characteristics influence the results.

On the other hand, when evaluating other indicator, the sum of stop times, suggests an association with passenger demand. Through this metric, it is possible to establish indications of locations, times, and periods of the year with greater use of the transport system.

The proposed methodology is easy to apply, since it requires the configuration of the bus stop sequence and its georeferenced coordinates.

From this experiment, new lines of circulars served by electric bus may be proposed in UNICAMP, taking into account the locations and times with the greatest user interest. The application of this methodology can be adapted and applied by the public authorities/concessionaires, being able to improve the notion of the demand of the bus lines in their respective itineraries and, from that, develop strategies aimed at improving the services provided.

As further studies, the methodology can be refined by more detailed tracking information, using local measurements of speed and acceleration and higher rate of the samples, in periods of 1 or 2 seconds. Additionally, compensation in the acceleration based on the height inclination of the street could be applied. Finally, the comparison of these results with real passenger demands values to investigate the veracity of the inferences and a development of a more generalized model to estimation of passenger demand.

## ACKNOWLEDGMENTS

The authors would like to thank CAPES, CNPq, FAPESP and CPFL, through ANEEL R&D Program on the project PD-00063-3043/2018, for funding this research.

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