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Research Article

Intersection movements delay modelling based on crowd-sensed global positioning system trajectory data

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Abstract

Developing accurate large-scale transportation models, used to guide policy adoption and evaluate infrastructure alternatives or changes in sociodemographic conditions, is data and resource intensive. This research proposes a novel method for modeling intersection movement delay using crowd-sensed Global Positioning System (GPS) data. This is achieved by providing a general definition of turning movements and extracting travel times thought GPS trajectory data analysis. Additionally, a straightforward method is proposed to integrate the observed delays per movement type into volume-delay functions. The spatial definition provided for turning movements captured distinct speed profiles per turn type. The significant differences in mean speeds for different turn types highlights the importance of integrating turn penalty functions based on real observations and underscore the importance of crowd-sensed GPS data. A simple technique is also proposed to integrate the proposed method into the volume-delay functions used in large scale transport models.

Key words: intersection delay model, macroscopic model, turn performance function, Global Positioning System, transport planning

Introduction

Transport models are decision-making tools used to evaluate current system conditions and propose modifications to it to optimize its performance (Jacyna et al. 2014). They assist in evaluating the impact of policies, sociodemographic changes, and infrastructure projects on the transport system (Wegener et al. 1991). Large-scale transport models, known as macroscopic transport models, consists of three components: (i) the supply, a digital representation of the transport network for all modeled transport modes, (ii) the transport demand, representing all the trips that need to be made, and (iii) the performance, depicting network conditions when the demand is assigned to the transport network reflecting the influence of demand on route choice and traffic conditions (Ortúzar and Willumsen 2011). Road network performance is usually evaluated by examining travel time delays on road segments and at intersections (Sun et al. 2014; Ledezma-Navarro et al. 2018). Delays at intersections originate from two main sources, traffic signals and turning movements. Turning movement delay at intersections depends on multiple factors, such as the number of approaches, intersection control type, intersection size, number of conflicting movements, traffic intensity, presence of dedicated turning lanes, and traffic signal phasing and timing (in presence of traffic lights) (HCM 2022). Acquiring data for all these variables at a regional level is challenging and even more complex to maintain up to date. Due to the complexity of developing such models, some modelers rely on major assumptions regarding turn penalty functions (TPF) that represent turn movement delays in macroscopic models or use generic penalties that represent turning movement delays with sufficient accuracy. The impact of these inaccuracies is directly reflected in the route choice results since the generalized cost is mostly based on delays or travel times, which can lead to misleading results. This weakness has also been identified by Abedini (2022) who proposed a data-driven method to calibrate more accurate link performance functions.

Recently, Global Positioning System's (GPS) trajectory data has been collected by GPS enabled smartphones, creating large databases of GPS trajectories. This emerging data source has the potential to provide high-resolution and high-coverage information about the observed motorist's speed or travel time throughout the road network, offering an opportunity to improve the current macroscopic modelling practice. The objective of this work is to demonstrate the potential of crowd-sensed GPS data to accurately model road intersection turning movement delay, using as a case study dataset from Quebec City, Canada. It also aims to show how such information can be integrated into large-scale simulation models to provide more accurate intersection delay functions. This is achieved through the adoption of a replicable and standardized procedure to calculate the average speed per turning movement. Average speed is selected since large-scale transport models are deterministic and represent an average day. This method is not adapted for use with dynamic traffic assignment models since it does not model turning movement delay as a random variable. The case study examined in this paper examines the turning movement delays at traffic signal-controlled intersections of arterial-arterial or arterial-collector type roads.

Literature review

Intersection delay estimation and modelling, using GPS trajectory data, has been addressed in multiple studies (Jiang and Zhu 2005; Ko et al. 2008; Strauss and Miranda-Moreno 2017). These studies can be categorized based on the examined transport mode (car, bus, or bicycle).

Strauss and Miranda-Moreno (2017) conducted a study using crowd-sensed GPS trajectory data in Montreal, Canada to estimate performance measures at signalized intersections. They developed models to relate bicycle intersection delays to predictors such as intersection geometry and built environment. While this work provides detailed steps in GPS data processing, it confines the analysis to the approach and intersection levels without exploring detailed intersection movements. Another study by Gillis et al. (2020) used crowd-sensed cyclist GPS trajectory data to determine road intersection delays. This research focuses on the main cyclist movements across the intersection and emphasizes the importance of having an adequate sampling rate to capture details before and after the intersection. The main limitations of the two studies examining cyclist GPS data are the fact that they do not consider the impact of traffic flow on delay and that they do not propose a standardized method to extract delays at the intersection movement level.

Using real-time bus GPS trajectories, Wang et al. (2016*b*) proposed a method to predict intersection delays and bus arrival time. This method, designed for real time use, does not explicitly consider intersection movements, making it inapplicable for macroscopic transport models. Another study by Wang et al. (2016*a*) uses low-resolution transit bus GPS data to estimate control delays; however, it does not consider turning movements. In addition, using bus GPS data to estimate control delays cannot be used to represent the dynamics of the general population of motorists, as it may be biased due to differences in vehicle characteristics and the presence of bus stops, which can create additional delays.

One of the most commonly used methods to estimate intersection movement delays is proposed by the Highway Capacity Manual (HCM). It combines three models: uniform, random, and overflow delay models. This method can be seen in the work by Leong (2017) and requires the collection of signal phasing and timing information, in addition to intersection configuration. Although this method can yield good results, it requires significant data collection efforts for large-scale models, limiting its suitability to small-scale models.

Other studies have explored the use of passenger vehicle GPS trajectory data to estimate delays while reducing data collection efforts and having a satisfying accuracy level. In fact, a study by Liu et al. (2006) investigated the effect of different GPS trajectory sampling rates on delay estimation quality and the ability to capture the delay. This study focused on reducing the cost of real-time data transmission and does not propose a method to estimate or model intersection movement delays.

In another study, Alkaissi et al. (2021) conducted an experiment by instrumenting a vehicle with a GPS device to record 50 trips through an arterial corridor. Based on speed and acceleration, they were able to determine delays at intersection; however, the study only considered a limited number of trips and did not examine delays from movements at the intersection.

Intersection delay estimation techniques were examined based on a theoretical framework of vehicle dynamics. In a study by Jiang and Zhu (2005), a GPS-equipped vehicle was used to collect trajectory data, proposing a method to calculate the approach delay. The approach delay is defined as the difference between the actual time for the vehicle to pass the intersection and the time it would take to pass the intersection at the driver's desired speed. This delay can be estimated by measuring various components such as stopped delay, control delay, approach delay, midblock delay, or segment delay. A variation of this technique was explored by Hoeschen et al. (2005). However, these measures remain limited to traffic signal operation applications and only consider delays at the intersection approach level.

Intersection delay is crucial information for assessing intersection control performance and determine the level of service (LOS). Tišljarić et al. (2018) estimated intersection control delays based on GPS trajectory points by locating the first deceleration and stopping points upstream on the intersection. The information was also used to create a queuing profile for the examined intersections. However, this technique was limited to the approach level and the queuing profiles were not compared to ground truth for validation.

Most recently, Saldivar-Carranza et al. (2021*a*) have been using connected vehicle trajectory data to optimize traffic signal operation. This type of data, also referred to as internet connected vehicle (ICV) data, can include additional information in comparison to traditional GPS trajectory data, such as hard braking or hard acceleration events and was also used by Khadka et al. (2022). The purpose of their study was to evaluate queue length and propagation, and delay estimation on arterials in addition to the generation of time-speed diagrams by combining the data with available traffic signal timing information. The increasing availability of ICV data enables the collection of statistically significant amounts of data in a very short time which helps evaluate the safety conditions of a specific intersection movement using surrogate measures as demonstrated by Saldivar-Carranza et al. (2021*b*). Although studies using ICV data are focusing on traffic operation optimization and traffic safety evaluation through surrogate measures, they demonstrate that large scale trajectory data has a great a potential to evaluate traffic delay related variables at a disaggregate level (ex.: intersection movement).

When studying delay modelling, understanding the level of detail required depends on the model type and the capabilities available in transport planning and modelling software to be able to produce results that can be integrated to the modelling tool. Macroscopic models integrate intersection movement delays differently depending on the modelling tool used. For example, the Aimsun simulation software divides delay into three different components: link delay functions, TPF, and junction delay functions (JDF). TPF and JDF are used for traffic signal-controlled intersections and stop or yield controlled intersections, respectively. The TPF is also capable of using the programmed signal timing plan to estimate macroscopic level delays based on green time, cycle duration, and equations provided in the HCM. Although this possibility is interesting, integrating and maintaining all signal timing plans for different time periods and for a whole metropolitan region requires important resources and is generally not feasible.

Other tools used for macroscopic modelling, such as EMME or Visum also offer the possibility to add turn penalties for each possible movement at an intersection. However, the challenge remains in finding the correct values or functions that represent the observed conditions adequately. Due to limited resources, in practice, this usually results in the oversimplification of turn delay modelling by assuming fixed generic values or even by limiting turn modelling to simple turning permissions indicating whether each movement is permitted or prohibited.

In summary, intersection delay was studied by multiple researchers using GPS trajectory collected by different transport modes, such as, bicycle, buses, and passenger cars. Depending on the study objective, delay was defined differently in terms of spatial or temporal resolutions (intersection level or approach level) to obtain indicators used for traffic signal control operation and optimization. However, additional work is required to explore crowd sensed GPS data and develop methods that consider delays at the intersection movement level without the knowledge of signal phasing and timing or signal groups. This is essential to model turning movement delays for large-scale models. Therefore, this work proposes a framework and method to extract intersection movement delays for use in large-scale transport models from GPS data, avoiding the use of data that is difficult to obtain or collect.

Methodology

Definitions

Before describing the theoretical framework and the proposed method, it is important to define a few terms. An intersection turning movement refers to a possible vehicular movement at an intersection, usually described by the direction and the turn type (Board et al. 2022). Intersection turn type refers to the maneuver performed at the intersection, which can be left turn, through movement, or right turn. Although delay and speed are two different concepts, this work interchangeably uses the two words. Since the proposed method needs to be applicable to intersections of different dimensions, speed was calculated instead of delay to eliminate the distance dimension and reduce the bias. This is important for the proposed method, as it includes the upstream segment travel time in the delay (speed) calculation. Calculating a typical delay value for all types of intersections would incorrectly assume that all intersections have the same geometric configurations and upstream road segment length.

To capture the average delay incurred by a vehicle associated with a given turning movement and keeping in mind the macroscopic aspect of the transport model, it was important to have an adequate definition of intersection movements. For each intersection, an intersection zone is defined as the area containing the road intersection in addition to all the upstream and downstream road segments that connect the given intersection to the neighboring intersections (see Fig. 1).

Moreover, the start and end points for each movement type (left turn, through movement, and right turn) are defined as seen in Fig. 2. The start point of every movement is the entrance point of the upstream road segment (LT_{Start}, T_{Start}, RT_{Start}). The movement end point is the point where the vehicle exits the analyzed intersection (LT_{End}, T_{End}, RT_{End}). Defining the start and end point of every movement enables the calculation of length of each of the left, through, and right movements, which are LLT, LT, and LRT, respectively. This definition makes it possible to differentiate between delays of vehicles performing different movement types. In a similar logic, the traffic flows for each of the movement types are referred to as F_{LT}, F_T, and F_{RT}, representing flows for left turn, through, and right turn movements, respectively. Connecting back to macroscopic models, it becomes possible to adjust turn penalties based on real observations while considering mid-block traffic delays due to traffic propagation associated with the downstream control type and turning movement type.

Proposed procedure

The method proposed by this work uses GPS trajectory points, traffic counts, and a road network geographic representation to create an integrated database containing, for each intersection movement, the mean 15 min speed and the corresponding 15 min traffic count. Figure 3 presents a summarized diagram of the procedure used to create the traffic count-speed database.

The yellow boxes represent input data while the grey rectangles represent data processing steps, and the green cylinder represents the final output database.

The first step consists of spatially filtering the map-matched GPS trajectory data to allow only relevant data points to be kept and reduce the size of the data base. This step is required to only keep the required GPS points and avoid working with a large data file. The second step is to manually select, for each trip segment within the intersection, the first point (LT_{Start}, T_{Start}, RT_{Start}) and the last point (LT_{End}, T_{End}, RT_{End}). Each trip within an intersection zone is visually inspected to verify if its start point and end point are located at an acceptable distance of the theoretical start and end points defined above. This step is carried out manually and is labor intensive given the large number of trips per intersection. At the third step, the trip ends' timestamps and the geographic coordinates are extracted to create a polyline representing the turn movement of each trip segment within

Fig. 1. Intersection zone example. Figure was created using QGIS version 3 and assembled from the following data sources: road network (OpenStreetMap 2023), satellite imagery (Google Maps, 2023).

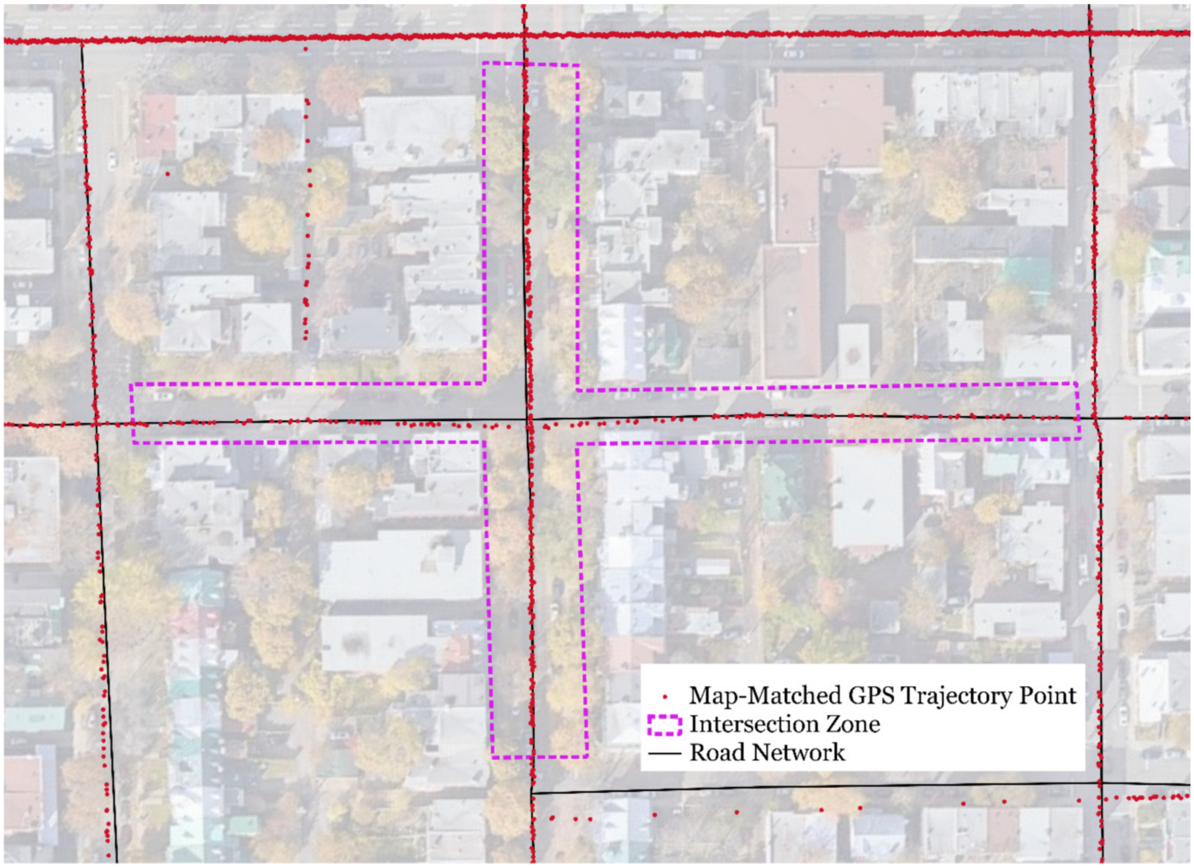


Fig. 2. Intersection movement definitions.

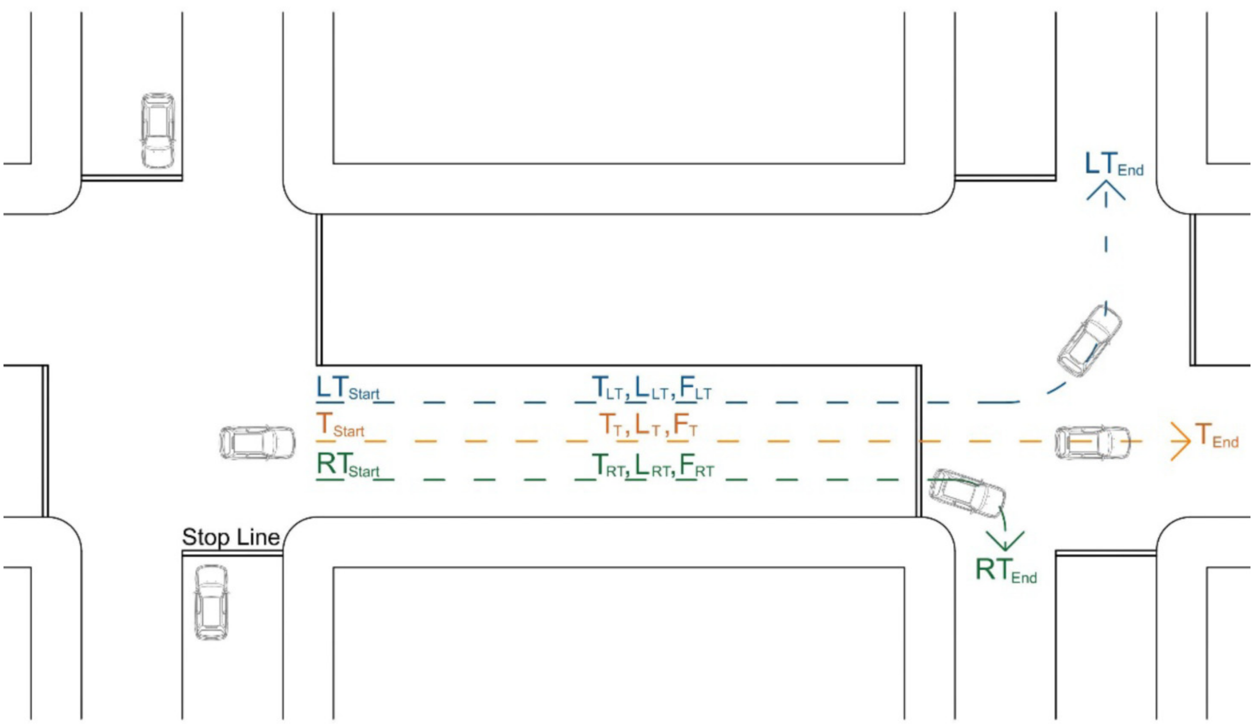
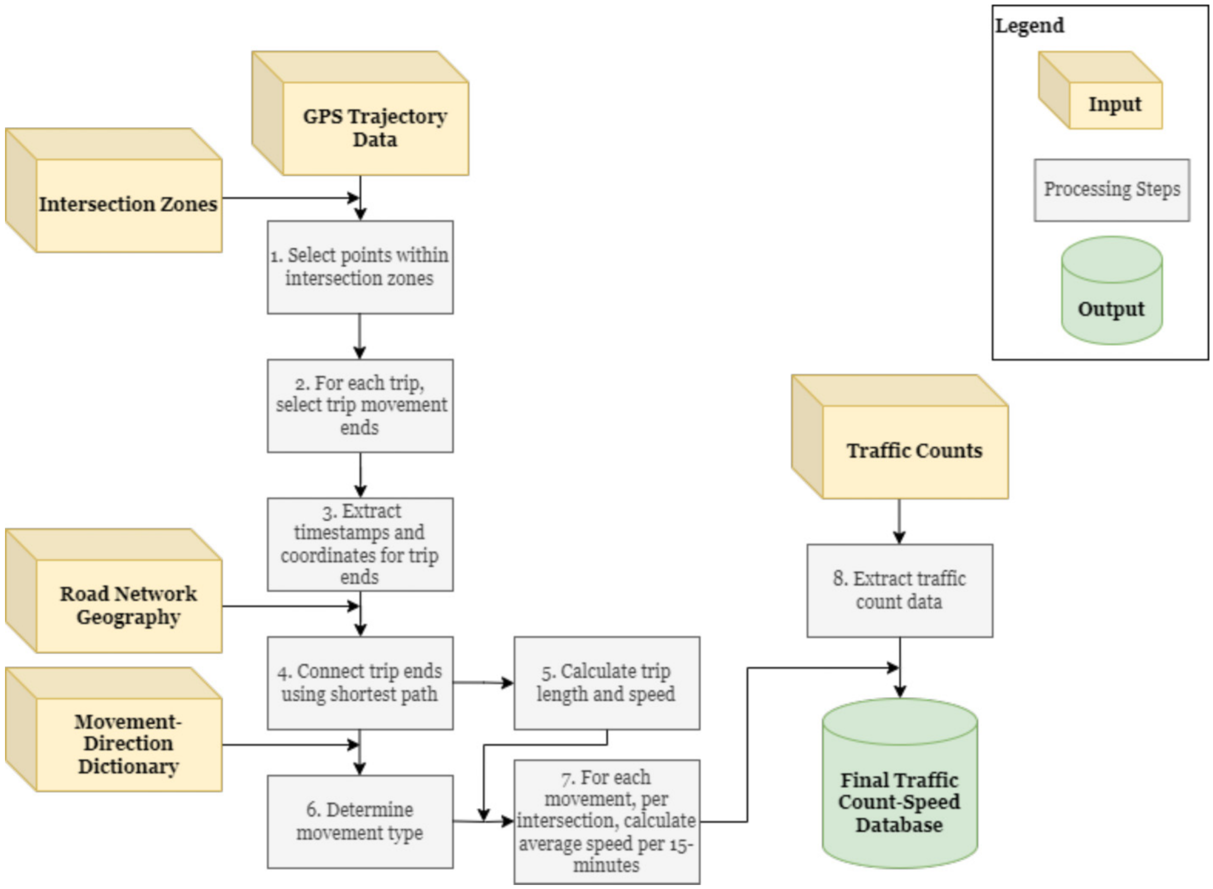


Fig. 3. Diagram of database creation procedure. GPS, Global Positioning System.



the intersection. The fourth step connects the trip ends using the shortest path algorithm over the digital road network. The process allows the elimination of noise caused by the GPS signal when a vehicle is stationary at trajectory points situated between the trip ends. This step is carried out using the Network Analyst Extension of the ArcGIS software which implements Dijkstra's algorithm to find the shortest path. This algorithm was deemed suitable since it was able to correctly connect the first and last points of intersection trajectories. Figure 4 presents the raw GPS data in addition to two sample trip segments that were manually selected to be processed into a line using the shortest path algorithm and considered in the delay analysis.

The fifth step consists of using the turning movement trip segment polyline to calculate the intersection movement length and speed.

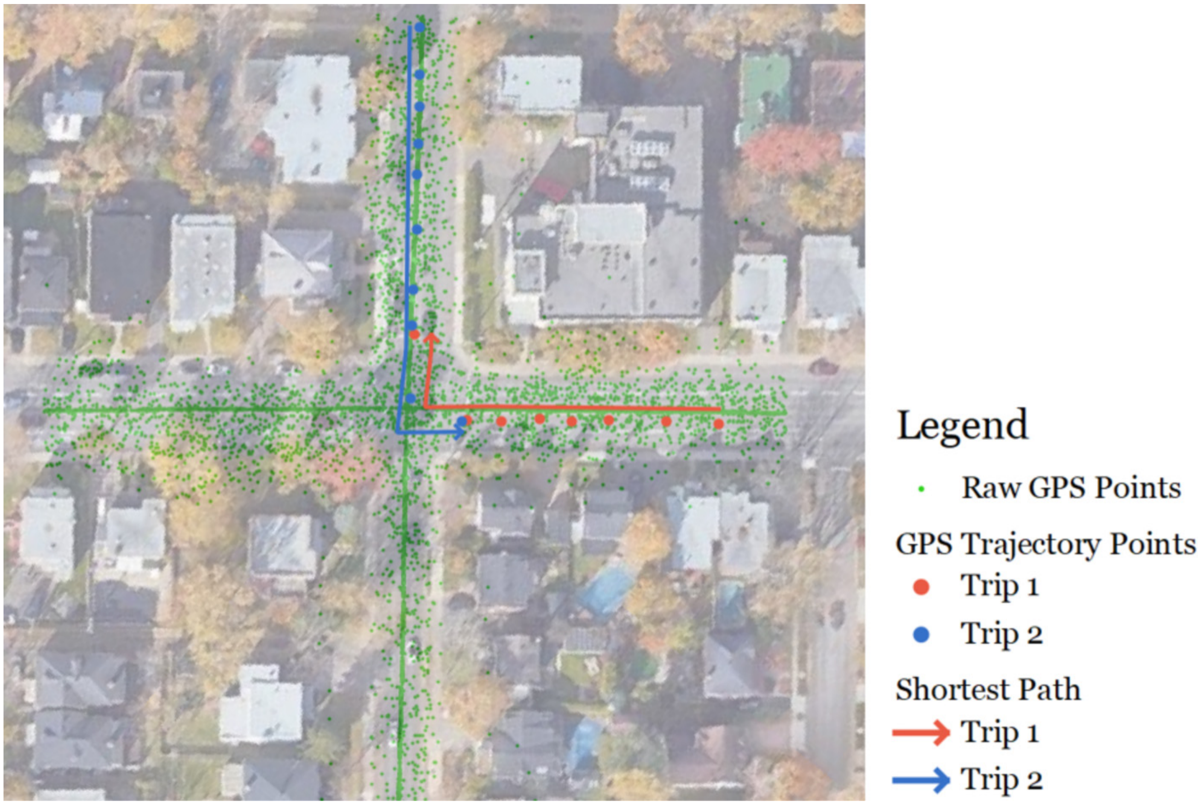
The following step, each turning movement trip segment is analyzed to determine the movement type (left turn, through movement, or right turn) based on the movement's in and out directions. A movement type-direction correspondence dictionary is used at that step to determine the entering and exiting direction for each trip and associate it to the correct movement type. For example, a vehicle entering an intersection from the south and exiting from the east is considered a right turn. At the seventh step, mean 15 min speeds are calculated per intersection movement.

The last (eighth) step is an independent treatment of traffic counts carried out to extract and prepare traffic count data to be integrated to the mean 15 min speed table. Therefore, a traffic count database is created containing detailed 15 min traffic counts for all intersections per turning movement. This database is integrated to the mean 15 min speed table based on the intersection ID and the turning movement to create the final 15 min traffic count-speed database. The final database is used to perform exploratory analysis to gain insight into the different movement types.

Integration to macroscopic models

To connect with large scale transport models, a method is then proposed to integrate the findings to the volume delay functions used in macroscopic simulation models. Assuming that through movement delays are already included in the link, or road segment, volume delay function, it is possible to express the turn penalty, seen as an additional delay, as a function of through movement travel time TT. This assumption is applicable since large scale transport models are calibrated based on floating vehicles that drive straight through main road corridors without turning at intersections. This results in link volume delay functions that integrate road segment and intersection delay for through movement only (T_T in Fig. 2). The following are the proposed left turn and right

Fig. 4. Sample Global Positioning System (GPS) trip points converted to lines. Figure was created using QGIS version 3 and assembled from the following data source: satellite imagery (Google Maps, 2023).



turn penalty functions based on the observed GPS trajectory data:

(1) $T_{LT} = T_T + a * T_T = T_T(1 + a)$

(2) $T_{RT} = T_T + b * T_T = T_T(1 + b)$

where T_{LT} and T_{RT} are the travel times for the left and right turns, respectively, and parameters a and b are the speed adjustment ratios for left and right turns, respectively. These parameters are calculated using the trajectory length and travel time extracted from the GPS trajectory points. The parameters a and b are calculated as follows:

(3) $a = 1 - \frac{L_{LT}/T_{LT}}{L_T/T_T}$

(4) $b = 1 - \frac{L_{RT}/T_{RT}}{L_T/T_T}$

For macroscopic models, the adjusted travel time for turning movements at intersections, or turn penalty functions can be considered as follows:

(5) $TP_{LT} = a * T_T$

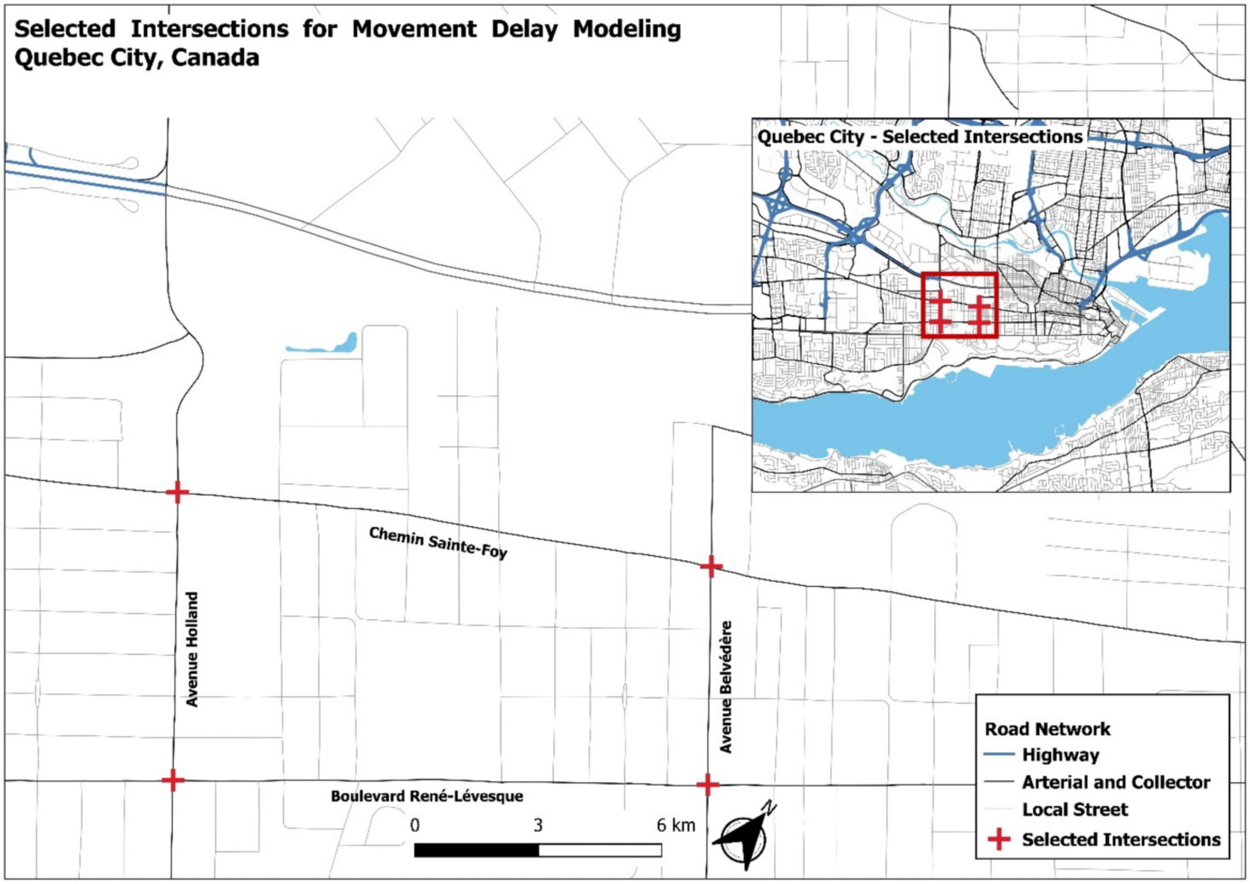
(6) $TP_{RT} = b * T_T$

where TP_{LT} and TP_{RT} are the additional delay incurred for left turning vehicles and right turning vehicles, respectively, with respect to the through movement travel time. The use of these penalties results in the inclusion of all delays incurred at the intersection for all turn types.

Case study

This study is based on data collected in Quebec City, Canada. Three sources of data were necessary. First, GPS trajectories data was recorded by motorists during the spring of 2014 in Quebec City, Canada. It was collected during 21 days by 2000 voluntary users through the Mon Trajet smartphone app, made available by the municipality. Each point is described by the following attributes: X and Y coordinates, trip ID, speed, and timestamp (year-month-day-hour-minute-second). The GPS data had gone through a preliminary round of preparation and map matching. The second data source, used at step number 8 of the methodology, is traffic counts collected and provided by the Municipality of Quebec City. Traffic counts were available for a one-day period per intersection for 15 min time intervals from 7:00 to 10:00 and from 15:00 to 18:00. These periods were selected by the municipality to cover peak traffic periods. Finally, the last data source was a geographic representation of the road network in the form of a shapefile, which was obtained from OpenStreetMap (OpenStreetMap 2023). Figure 5 presents the location of the four intersections selected to perform this study. These intersections were selected based on the road type and the control type. These variables are expected to have an influence on intersection movement delay and can be obtained with a rea-

Fig. 5. Study location—selected intersections. Figure was created using QGIS version 3 and assembled from the following data sources: road network (OpenStreetMap 2023), hydrology (Government of Quebec Open Data "https://www.donneesquebec.ca/recherche/dataset/hydrographie-cours-d-eau-surfaciques,'' 2023).



sonable amount of effort for large scale transport models. In this study, traffic light-controlled intersections were selected, and the road type was limited to arterial-arterial or arterial-collector intersections.

A total of 1400 intersection movements were individually examined and 1136 were found to be adequate and selected for further analysis.

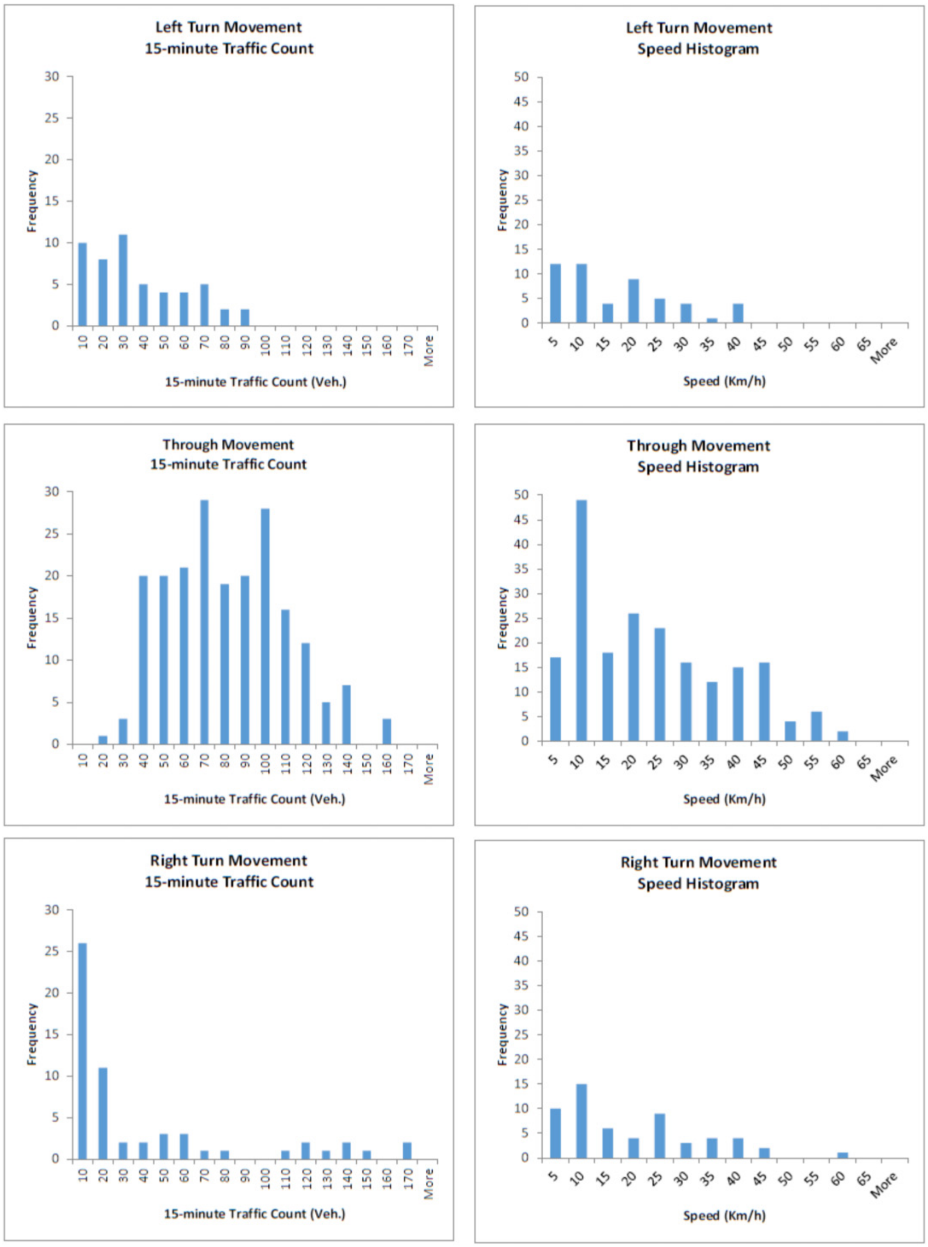
Results

Considering the four intersections that were analyzed in the case study, a total of 1136 trip segments (126 left turns, 153 right turns, 857 through movements) were extracted for the analysis period. The 15 min mean speed was the lowest for left turns at 14 km/h, followed by the right turns at 17 km/h, and through movement at 21 km/hr. Left turns are typically face conflicts with the opposite through traffic, requiring sharing of the green phase (with priority given to the opposite direction). In addition, left turns often conflict with pedestrian and cyclist users who also have priority over motorists. To mitigate these conflicts, left turn movements are sometimes given a dedicated protected phase depending on traffic control design standards. Both situations contribute to the expectation that left turning movements have often slower travel times with respect to right. Regarding right turns, generally this movement conflicts with cyclists and pedestrians (who have priority), and occasionally conflicts with left turns from the opposite direction, but this is less frequent and less critical. Therefore, right turn delays are expected to fall between left turn delays and through movement delays. Through movement generally do not conflict with other movements (except for right turn on red); however, its delay depends on the signal timing design based on traffic flows for all movements. Thus, observed speeds for through movements are reasonable since they are expected to be the fastest.

In parallel, the mean traffic count was the lowest for left turns at 33 vehicles per 15 min, followed by right turns at 36 vehicles per 15 min, and through movement at 77 vehicles per 15 min. The final database was used to visualize the frequency distribution of mean 15 min speeds and 15 min traffic counts for each intersection movement type, as shown in Fig. 6.

Further analysis was conducted to examine the relationship between speeds and observed traffic counts. No evident relationship was found between the two variables. Additionally, the mean 15 min speed is relatively volatile, explained by the fact that speed is affected the intersection's signal

Fig. 6. Frequency distributions of mean 15 min speeds and 15 min traffic counts.



timing, operation mode, and geometric configuration rather than traffic flow. Additionally, traffic counts and GPS trajectories were not collected at the same moment, which is not ideal when comparing relatively fine resolution data.

For this case study, "a" and "b" for traffic light controlled arterial-arterial or arterial-collector intersections are calculated using eqs. 3 and 4 to be 0.33 and 0.19, respectively. In other words, a left turn movement is 33% slower than a through movement, considering movement definitions in Fig. 2, and a right turn movement is 19% slower than a through movement. These parameters (a and b) represent an average behavior of the analysis period as estimated using all observations. However, with more data available, it is possible to recalculate these parameters per peak period or hour of the day to increase the accuracy.

Discussion

The large-scale aspect of macroscopic transport models, sometimes referred to as strategic level models, can benefit from the availability of new sources of data for calibration. The proposed framework and methodology can process crowd-sensed GPS data to estimate turning movement delays and integrate them to macroscopic models. The proposed solution is a balance between the delay estimation methods proposed by the HCM or by Hoeschen et al. (2005) and Jiang and Zhu (2005), which are data-intensive when the model is very large, and the simplifications imposed to macroscopic models due to the lack of data and resources. Using GPS trajectory data, it was possible to develop a standardized method to extract speed information at the intersection turning movement level. Traditionally, delays were only calculated for operational purposes to design and optimize traffic signal phasing and timing, therefore, research has mainly examined approach level delay, which is also used for LOS assessment, as can be seen in the work by Tišljarić et al. (2018).

Using the extracted results, it was possible to determine the frequency distribution of speeds and traffic counts for each of the turning movement types. These distributions can eventually serve to calibrate other stochastic transport models through distribution fitting and sampling variable delays based on the observed mean and variance values. However, for macroscopic transport models, aggregate speed results were used to propose a method to include GPS-based delays to turning movements. In fact, the main finding is that left turn movements for traffic signal-controlled arterial-arterial or arterial-collector intersections have the lowest average speed compared to through movements and right turns. In addition, right turns were also found to have a lower average speed than through movements. This justifies the importance of including turn penalty functions that reflect this difference in observed speeds, which was the motivation of this work.

The proposed method can be applied to a larger sample of intersections, a larger sample of GPS trajectories, and for a variety of road types for better coverage of the road network. The procedure is semi-automated for the moment and will require the automation of some the tasks to make it feasible to treat many trajectories rapidly. This will also allow for the inclusion of more GPS trajectories in the analysis allowing for better temporal coverage.

No clear relationship was found between mean 15 min speeds and 15 min traffic counts. Although this is explained mainly by the intersection control type, which in this study was traffic signal control, the fact that only one day of traffic counts was available per intersection from a different year might contribute to the randomness observed in the speed-flow chart.

This study accounts for the impact of intersection control type and road type on intersection movement delay. Intersection delay can be influenced by additional variables such as the number of available lanes, the presence of dedicated turning lanes, the permission to perform a right turn on red, the number of conflicts, the type of traffic signal (fixed vs. actuated). Obtaining and maintaining these variables up to date at a regional level is challenging. However, if any of them is available, it could be interesting to include it to improve the classification of turning movements and improve the delay prediction.

Limitations

This work explores a new method to use GPS trajectory data to model turn movement delay per road type, movement type, and intersection control type for large-scale transport models. Although it makes use of the emerging availability of GPS trajectory, it is not without limitations. First, the applicability of the proposed method is to deterministic static transport models that aim to represent an average situation to be used for strategic planning and alternative comparison. Therefore, it is not possible to apply this method to dynamic traffic assignments, further analysis would be required to do so. Moreover, the case study examined in this work was limited by the available data. The GPS trajectory data sample, traffic counts availability, and unavailability of ground truth data were all limiting factors. To cover all intersection turn types, road types, and control types, a larger road network should be used in addition to a larger GPS trajectory data sample. Moreover, a larger GPS trajectory data temporal coverage will enable the modelling of turning movement delay per time of day to better reflect the variation of travel time during peak and off-peak periods.

Conclusion

This work emphasizes the need to consider intersection movement delays in macroscopic transport models. It explores the availability of a new data source that can overcome data collection challenges, typical in macroscopic models. It also complements the work done on delay modelling for different transport modes, which focuses on the operational needs. It was found that crowd-sensed GPS data are suitable to estimate intersection movement delays at the intersection movement level. The case study examined traffic signal-controlled arterial-arterial and arterial-collector type intersections. Average speeds were found to be different for left turns, right turns, and through movements, justifying the importance of considering turn penalties. These speeds were then used to propose a method to integrate them back into macroscopic transport models to improve travel time estimation and consequently improve route choice.

The proposed method can be further improved by increasing the automation of the procedure, allowing for the rapid treatment of many GPS trajectories. This, in turn, will increase the sample size of the observations and allow to estimate different turn penalties per peak period or per hour. Moreover, an extension of this work can examine different methods to address the length variable to ensure that no bias is introduced since different road segments can have different lengths, which can in turn influence the calculated turning speed. Furthermore, if more intersection variables are available, such as the number of lanes, the number of conflicts per movement type, the possibility to turn right on red, the presence of dedicated turning lanes, or other intersection control variables, they can be included to classify turning movement to improve turn penalty estimation accuracy.

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Data availability

The GPS trajectory dataset used for this research was available for public for a period on the municipality website; however, it has now been removed from the website and therefore unavailable.

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Formal analysis: AB
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Investigation: AB, AE, LMM
Methodology: AB, AE, LMM
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Supervision: AE, LMM
Validation: AB, AE, LMM
Visualization: AB
Writing – original draft: AB
Writing – review & editing: AB, AE, LMM

Competing interests

The authors declare there are no competing interests.

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