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## Case Studies on Transport Policy

journal homepage: [www.elsevier.com/locate/cstp](http://www.elsevier.com/locate/cstp)Developing a route calculator for e-bikes based on GPS data<sup>☆</sup>Clémence de Rolland<sup>a,1,\*</sup>, Catherine Morency<sup>b</sup>, Jean-Simon Bourdeau<sup>b</sup><sup>a</sup> Polytechnique Montréal Department of Civil, Geological and Mining Engineering, Montreal, Quebec, Canada<sup>b</sup> Mobilité Chair, CIRRELT / Polytechnique Montréal, Department of Civil, Geological and Mining Engineering, Montreal, Quebec, Canada

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## ABSTRACT

Electric-Assisted bikes, or e-bikes, are a low-carbon mode of transportation. Therefore, they could help in mitigating climate change by reducing greenhouse gas emissions caused by the transportation sector. Indeed, they could replace personal cars for some trips. However, even if the use of e-bikes is developing in Europe, it is less the case in North America. In particular, little information is available regarding the use of e-bikes in Québec (Canada). In order to include them into transportation planning, it would be useful to know more precisely the potential routes that e-bikes could follow. Using GPS data from e-bike trials in the six major regions of Québec (Canada), we develop a route calculator dedicated to e-bikes by computing the cost of each link thanks to the observed speeds in the dataset. This calculator takes into account the slope and road category. The computed itineraries are coherent with the dataset and with another dataset containing trips from the e-bike sharing system in Montreal (Québec Region, Canada).

## 1. Introduction

In the context of climate change, the rapid reduction of greenhouse gas (GHG) emissions is one of the priority issues to limit global average warming IPCC (2022). The transportation sector accounts for 14 % of global GHG emissions Lamb et al. (2021) Minx et al. (2021), and therefore is an area of opportunity for action. The "Avoid, Shift and Improve" strategy Dalkmann and Sakamoto (2011) was adopted by the United Nations Environment Program to this end. As private vehicles account for 45.6 % of transport-related GHG emissions IEA (2020) and can be replaced in many situations by less carbon-intensive modes, they are the focus of most "Shift" strategies. Examples of modes to which car travel can be shifted include walking, cycling, and public transport. An additional option is increasingly being developed: Electrically Assisted Bicycles (or e-bikes). Indeed, while a mid-range combustion-powered car emits on average 0.232 kgCO<sub>2</sub>e/km (including its manufacturing), an e-bike emits on average 0.011 kgCO<sub>2</sub>e/km ADEME (2022). This value depends on the energy mix with which the batteries are recharged but generally stays very small with regards to classic cars. Encouraging the shift from cars to e-bikes would be eased by a better knowledge of the e-bikes uses. Indeed, despite the spread of e-bikes in Asia and their growth in Europe and North America Bourne et al. (2020), there is very

few research on routes taken by e-bikes and travel behaviors.

In the Québec province of Canada in particular, there is little knowledge on the subject, which limits the action of decision makers. To address this issue, the Equiterre association launched the Vélovolt project, which consists of lending e-bikes to volunteers for a few weeks. The goal is to collect their GPS data and their response to surveys to provide a more precise picture of their use and to evaluate the possibilities for e-bikes in Québec and the policies that could be implemented. From these premises, the following research questions arise:

- How can GPS Data be processed to develop a route calculator for e-bikes?
- How to measure the performance of a route calculator?

The aim of the present study is to develop a route calculator for e-bikes by analyzing these GPS data. With further research, such a calculator could be used to forecast how current observed trips would transfer to e-bikes by giving an accurate travel time. Section 2 presents an overview of the literature on the subject, then section 3 describes the methodology that was used to identify trips from the GPS points and to elaborate the route calculators. The results are analyzed in section 4. Finally, section 5 lists the limits and the research perspectives.

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## 2. Literature review

First of all, it should be noted that there are several types of e-bikes on the market. In Asia (and mainly in China), the most common models are the “mopeds”, in which the motor is activated directly from the handlebars with a button or a controller. In this case, gas and energy consumption is higher. In Europe, the only models legally allowed to use bicycle lanes (and therefore the most common) are the “pedelecs”, where the electric assistance only comes into play when the user activates the pedal, and which comparatively use less energy. The regulations limit electric assistance when the speed exceeds 25 km/h. In Canada, the most common models are also of the “pedelec” type. All e-bikes, regardless of type, are limited to 32 km/h and 500 W battery power SAAQ (2021).

### 2.1. E-bikes and their differences with regular bikes

The electric assistance makes the e-bikes easier to ride compared to regular bikes. Therefore, the common hypothesis is that they allow the users to go faster, further, and higher, and are discussed in the following sections. The differences between e-bikes and regular bikes explain why a route calculator dedicated to e-bikes is useful: the parameters mentioned in the following sections should be taken into account in such a calculator.

#### 2.1.1. Going faster

The speeds observed through e-bike use are between 10 and 40 % greater than those obtained with regular bikes Berntsen et al. (2017) Dozza et al. (2016) Fishman and Cherry (2016), although Plazier et al. (2017) notes that this increase disappears in urban contexts. Even in a study led by Edge et al. (2018) that do not measure the actual speed difference but only the perceived speed difference, the e-bikes are described as faster than regular bikes and public transportation.

#### 2.1.2. Going further

The electric assistance also seems to allow e-bike users to travel greater distances. The literature reviews made by Bourne et al. (2020), Cairns et al. (2017) and Fishman and Cherry (2016) all concur on this point, even though their distance values are different. The average distance of an e-bike trip varies between 9.8 km and 11.4 km instead of 6.3 km to 7.1 km for a regular bike Cairns et al. (2017) (38 % to 81 % greater). The traveled distance by e-bike by users owning both regular bikes and e-bikes is larger (9.4 km and 3.0 km) than the traveled distance by regular bike by persons owning only regular bikes (4.8 km and 2.6 km) as observed by Castro et al. (2019) and Kroesen (2017) respectively. Finally, the logistic regression done by Jahre et al. (2019) on a survey shows that the probability to travel distances from 4 to 10 km is higher for e-bike users than regular bike users. This increase in the traveled distance is also perceived by the users, who report that “the motor [is] allowing them to travel further than a regular bike or by foot while using similar levels of exertion” Edge et al. (2018). Among the e-bike users interviewed by Lee et al. (2015) and MacArthur et al. (2014), respectively 56 % and 23 % of the respondents mention “going further” as the reason why they use or bought an e-bike.

#### 2.1.3. Going through hills with more ease

The main hypothesis for the computing of e-bike routes is that e-bike users make fewer detours than regular bike users as they do not avoid hills and positive slopes. A survey by MacArthur et al. (2014) supports this hypothesis: 45 % of their respondents use a different itinerary since they changed to e-bikes, mainly (for 35 % of them) because they “do not avoid hills on their e-bikes like they would on standard bikes”. This ability to go easily through hills is also a reason to buy or to use an e-bike Fyhri et al. (2017) MacArthur et al. (2014). The electric assistance also makes cycling up hills faster Berntsen et al. (2017).

#### 2.1.4. The specific drawbacks of the e-bike

The battery adds weight to the e-bike compared to a regular bike, which is often mentioned as an obstacle Jones et al. (2016) Popovich et al. (2014) MacArthur et al. (2014). It is even more important for those who make multimodal trips as they have to carry the bike Edge et al. (2018). The added weight makes the e-bikes more difficult to use when the battery is dead. This leads to the “range anxiety” observed among e-bike users Jones et al. (2016). The limited capacity of those batteries is therefore another specific drawback of e-bikes Popovich et al. (2014) Söderberg f.k.a. Andersson et al. (2021) Plazier et al. (2017). Then, as e-bikes are technical objects not completely widespread, their maintenance is not as easy and accessible as regular bike maintenance, and its cost is also higher. It is often cited as a day-to-day issue by the users Jones et al. (2016) Fyhri et al. (2017) Popovich et al. (2014) Söderberg f.k.a. Andersson et al. (2021). Their price is also higher, and therefore the fear of having one’s bike stolen is preventing some users from taking it as much as they would want to when a safe storage solution is not available Fyhri et al. (2017) Popovich et al. (2014) Söderberg f.k.a. Andersson et al. (2021) Edge et al. (2018). Moreover, the higher speed of e-bikes can create a new security issue. Indeed, it is harder for the drivers of motorized vehicles to evaluate the speed of e-bikes and therefore to adapt their driving and to avoid accidents Bourne et al. (2020) Dozza et al. (2016) Jones et al. (2016). The increased confidence of e-bike users can also lead them to be less careful Fishman and Cherry (2016). Finally, in places where regular bikes are widespread, e-bike users are sometimes perceived as lazy or categorized as old people Bourne et al. (2020). In these cases, the regular bike will be preferred to avoid “écheating” Jones et al. (2016).

### 2.2. Route choice models and trip calculators

Route choice models can be used to evaluate the impact of a project on modal share. A “éproject” can be, for example, the creation of new bike lanes. Two types of route choice models exist: stated preferences models and revealed preferences models. The stated preferences models are based on a survey that makes the participants choose their route amongst different propositions. Those propositions can be, for example, an itinerary that goes through a steep slope and the other one with a long detour. The goal is to find out the value assigned to each of those factors by the respondents. Stated preferences data are cheaper and easier to get than revealed preferences but can be strongly biased. Those biases can appear if the participants cannot project into real-life situations or, on the other hand, if they think of real-life routes when answering the survey and therefore take into account variables other than those considered in the question asked. A strategy bias may also arise if participants anticipate the impact of their responses on future transportation policies Broach et al. (2012). For revealed preferences models, the choices are not explicitly presented to those being studied and are only inferred from their behavior as it is observed. The observation is often done thanks to GPS data Broach et al. (2012) Dane (2020), like in this work. Then, the chosen route properties are analyzed and compared to the alternative routes to identify the factors that influenced the users’ choice. The biggest challenge is to list those alternatives. They have to be realistic, attractive, sufficient in number, and reasonable to be the most relevant Broach et al. (2012). Once they are listed, choice models are used to predict the actual trip made. These are typically discrete choice models based on utility maximization which quantifies the satisfaction felt by the user Dane (2020). The utility of alternative  $i$  for user  $n$  is expressed as:

$$U_n(i) = V_n(i) + \epsilon_n(i) \quad (1)$$

where:

- $V_n(i) = \sum_k \beta_{k,n} x_k(i)$  is a deterministic term, in which the  $\beta_{k,n}$  coefficients convert the  $x_k(i)$  variables into generalized cost;

- $\epsilon_n(i)$  is a random error term Dane (2020).

Those models then aim at optimizing the  $\beta_{k,n}$  coefficients so that the generalized cost of the chosen route is the minimum cost among alternative routes, and therefore the route that has the highest probability of being chosen.

### 2.3. Using GPS data

Before being used, the GPS points have to be matched to the bike and road networks. The most straightforward method to do so is by defining a buffer with a fixed radius around each network's links and assigning the points depending on the buffer they belong to Lopez et al. (2017). Allemann and Raubal (2015) define a buffer polygon around all the GPS points, then assign the points using the shortest path on the network that is included inside this polygon. In a similar way, Ton et al. (2017) choose from a list of possible routes the closest one to the GPS points. Finally, Dane (2020) use the *Trace Annotator* software developed by their research group, with parameters such as “the road network topology, distance from trace nodes to road segments, the angle between two lines, direction difference, accuracy of measured GPS log points, and position of roads” Feng and Timmermans (2013). In all of these methods, the main issue is to have an adequate network representation. It is more crucial for cycle networks, as intersections and discontinuities in the cycle network can prevent people from using their bikes Nabavi Niaki (2019). This issue is also identified for pedestrian trips Tal and Handy (2012), and is addressed in the corresponding literature: for example, Kasemsuppakorn and Karimi (2013) gives an algorithm to compute a pedestrian network using only GPS traces.

## 3. Method

### 3.1. Data processing

#### 3.1.1. Data description

The data used in this study comes from the Vélovoit project conducted by the Equiterre association. The project is built similarly to those led by de Kruijf et al. (2018), Moser et al. (2018), and Söderberg f. k.a. Andersson et al. (2021): e-bikes are lent to volunteer employees from eight companies for two to four weeks. The six major metropolitan areas of the Québec Province (Canada) are represented. The e-bikes are provided by the Quantum company. The e-bike model used is the Gazelle Medeo T9. It has a battery capacity of 400 Wh which is enough for up to 88 km Ebikes. Its motor assistance level is 32 km/h, at which point there is no electric assistance and the user must pedal himself, in accordance with Québec laws SAAQ (2021). The GPS points used were collected between the 1st of April 2022 and the 15th of July 2022, from 20 volunteers. Each bike has a GPS provided by the company ConnectedCycle that sends the position, speed and elevation of the bike each

30 s when the bike is turned on, with a spatial precision of up to 10 m. Data analysis was done using the pandas and geopandas libraries in python 3.

#### 3.1.2. Trip identification from the GPS points

ConnectedCycle also provides “trips” data that are identified from the succession of GPS points. The algorithm used to separate those trips and its parameters are adapted in this study to be more relevant. It consists of 3 steps, described in Fig. 1:

1. splitting the points into “trips” based on a time threshold value  $\Delta t$ : if the transmission delay between two points is larger than  $\Delta t$ , another trip starts;
2. eliminating the trips for which all points are located in a predefined  $r_{trip}$  radius: those points were presumably sent at a time when the bike was accidentally turned on but not used, and therefore do not describe an actual itinerary;
3. eliminating the points at the beginning and the end of the trip in a small predefined  $r_{ends}$  radius: the period of time where the user takes its bike or parks, as it is not considered to be part of the trip.

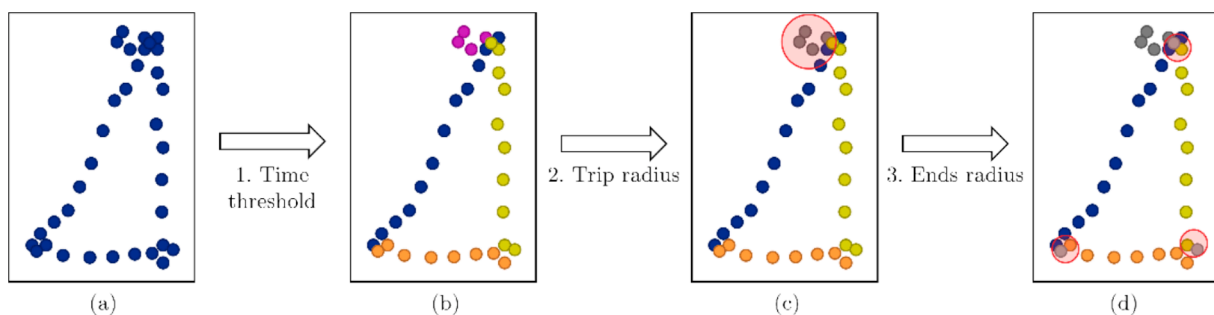
A sensitivity study is done on those parameters to find the best value for each one. To do so, the following relationships are studied one after the other:

- (C1) the total number of identified trips as a function of the time threshold  $\Delta t$ ;
- (C2) the total number of points eliminated in the step 2 as a function of  $r_{trip}$ ;
- (C3) the total number of points eliminated in the step 3 as a function of  $r_{ends}$ .

Then, the inflection points of the curves (C1), (C2) and (C3) are identified and assumed to be the optimal values for each parameter. The inflection point of a curve is the point where the second derivative of said curve is null, and the derivative are computed numerically with a centered difference approximation. Fig. 2 shows (C1), (C2) and (C3), with the red dotted line showing the value on the x-axis of the inflection point. The final values are therefore  $\Delta t = 600$  s (which is the value used by Lopez et al. (2017) in a similar process),  $r_{trip} = 200$  m and  $r_{ends} = 25$  m. After this process 78,522 points are kept after deletion in steps 2 and 3 out of the 99,841 points of the original data set. They are distributed in 1,380 trips.

#### 3.1.3. Elimination of trips made by car

The bikes are sometimes transported by car while being turned on, transmitting GPS data. The trips created in those cases are irrelevant and have to be eliminated. Yet, the speed difference between an e-bike and a car in an urban environment is very small because no “maximum speed



**Fig. 1.** Algorithm used to identify the trips from the GPS points. Points are provided for each 30 s and represented as blue dots in (a). A time threshold is used to separate trips, represented in different colors in (b). A buffer radius is then applied to eliminate hovering trips: it is shown in red (c), and leads to the pink trip being eliminated (represented as turned to gray). Finally, the hovering points at the beginning and at the end of a trip are removed (turned to gray) thanks to an “ends radius” shown in red in (d). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

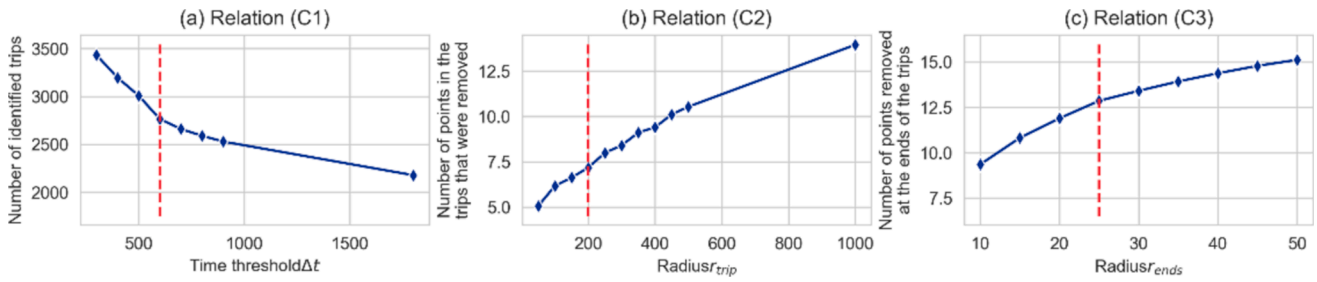


Fig. 2. Determination of the algorithm parameters.

reachable via e-bike” can be defined. Indeed, even if the electric assistance is turned off above 32 km/h, users can still continue to pedal if they wish to go faster and reach high speeds. To eliminate the car trips, a two-steps process is applied. Firstly, for each trip, the proportion of the GPS points that have a speed strictly above 32 km/h is computed. When this proportion is greater than a threshold value, the trip is eliminated. The threshold proportion determined using a sensitivity analysis on the number of trips eliminated, and is set to 29 %. After this first step, 75,798 points remain (96.53 % of the remaining points), split in 1,332 trips. Secondly, there are some points at 50 km/h and more among the remaining trips. This speed is difficult to reach for non-high level athletes [SurDeuxRoues.org](http://SurDeuxRoues.org) (2016). The choice was therefore made to eliminate the 26 trips that contained at least one point with a speed greater than or equal to 50 km/h. It is a rather conservative choice, as one can imagine potentially reaching 50 km/h for instance on a downhill trip. In the end, 73,654 points assigned to 1,306 trips remain in the data set. The distribution of points and trips by region is given in [Table 1](#).

### 3.1.4. Trips assignment to the road network

The road network is extracted from the OpenStreetMap© network for the six Census Metropolitan Areas (CMA) territories and a 20 km buffer around each of them. It is then split in two: a “road network” and a “bicycle network”. The latter contains bike paths, bike lanes and other dedicated bicycle infrastructure. The “road network” gathers the links that do not have dedicated bicycle infrastructure, but can still be used by bikes. Those two networks are separated using the OpenStreetMap keys that describes them: it was decided not to use the automatic categorizations available (like the *clazz* of *osm2po* for example) but to control more precisely the variables. However, the quality of the results still depends on the quality of the OpenStreetMap data, which may vary from region to region. The keys used are *highway*, *cycleway*, *bicycle*, *foot* and *segregated*. As their use is not completely unified in OpenStreetMap, all 551 combinations of the 5 variables present in the data set were classified in 16 final categories presented in [Table 2](#).

Each link of the two networks is split into straight segments, and the azimuth of each segment is computed. The GPS points are then assigned to those segments using the following process for each point (described in [Fig. 3](#)) and each network:

1. the azimuth of the point is calculated thanks to the direction of the segment formed by the adjacent points (if they belong to the same trip);

Table 1  
Distribution of trips and VélovoIt data points in the six regions.

Region	Number of trips	Number of points
Ottawa-Gatineau	194	17,042
Montréal	159	11,747
Sherbrooke	226	12,593
Trois-Rivières	143	7,074
Québec	331	15,737
Saguenay	253	9,461
All regions	1,306	73,654

Table 2

Final categories deducted from the *highway*, *cycleway*, *bicycle*, *foot* and *segregated* keys in OpenStreetMap.

Bicycle network	Road network	Bikes forbidden network
<ul style="list-style-type: none"> <li>• Physically separated cycle track</li> <li>• Marked cycle lane</li> <li>• Cycle path shared with pedestrians</li> <li>• Reserved public transport lane shared with bikes</li> <li>• Cycle track in opposite way</li> <li>• Cycle crossing</li> </ul>	<ul style="list-style-type: none"> <li>• Primary road</li> <li>• Secondary road</li> <li>• Tertiary road</li> <li>• Local road</li> <li>• Residential road</li> <li>• Service road</li> <li>• Other road</li> </ul>	<ul style="list-style-type: none"> <li>• Highway</li> <li>• Link forbidden to bicycles</li> </ul>

2. the segments in a radius of 100 m around the point are extracted;
3. for these extracted segments, only those with similar directions up to an error of more or less 45°;
4. the point is assigned to the closest remaining segment (if the distance between the point and this segment is smaller than an acceptable threshold).

The bicycle network is tested first: it is assumed that the users prefer to use a link from this network than one from the road network. If there is not any segment entering all the conditions, the point is not affected. A sensitivity analysis is done for each network to identify the thresholds for acceptable distances. They are presented in [Fig. 4](#) and [Fig. 5](#) for the bicycle network and the road network respectively. The kept values are  $d_{bicycle} = 35 m$  and  $d_{road} = 70 m$  (for the latter, the real inflection point is at 110 m as shown by the red dotted line, but a first stabilization near 0 is observed at 70 m).

## 3.2. Route calculator elaboration

### 3.2.1. Topology verification

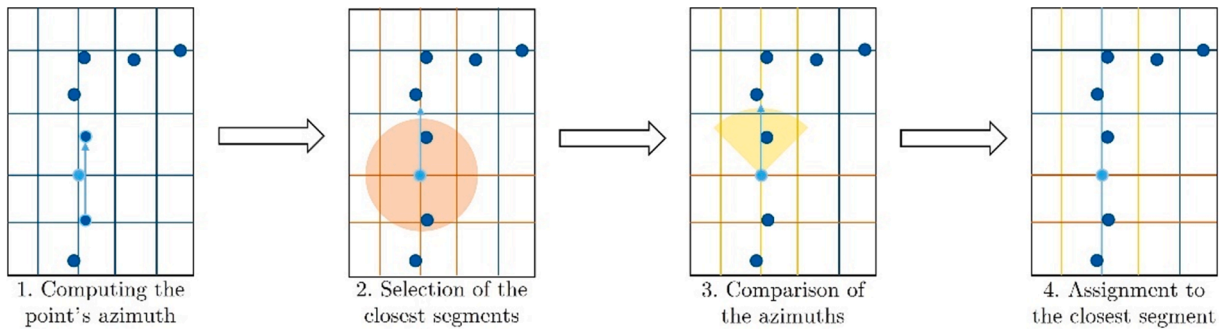
All shortest path calculations were done with the *pgRouting* extension of the PostgreSQL 13.6 database manager. It requires associating the origins and destinations of each trip to a node of the network. By default, it is the nearest node. However, in some cases, the nearest node belongs to a link that is not connected to the rest of the network. In each of those cases, the value of the node is manually corrected before performing the path calculations.

### 3.2.2. Shortest path route calculator

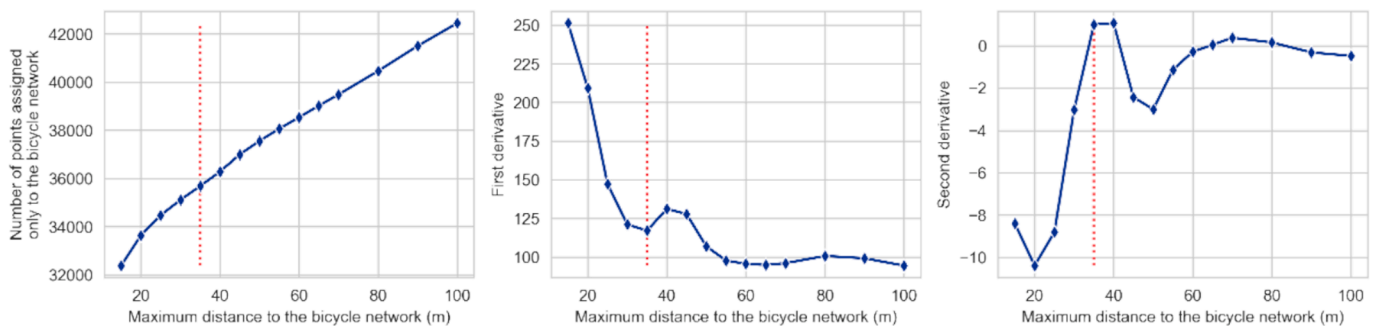
The simplest version of a route calculator gives the shortest path in length from a point A to a point B  $R_{distance}$ , namely the route R that minimizes:

$$\sum_{s \in R} l(s) \quad \text{where } l(s) \text{ is the length of segment } s. \quad (2)$$

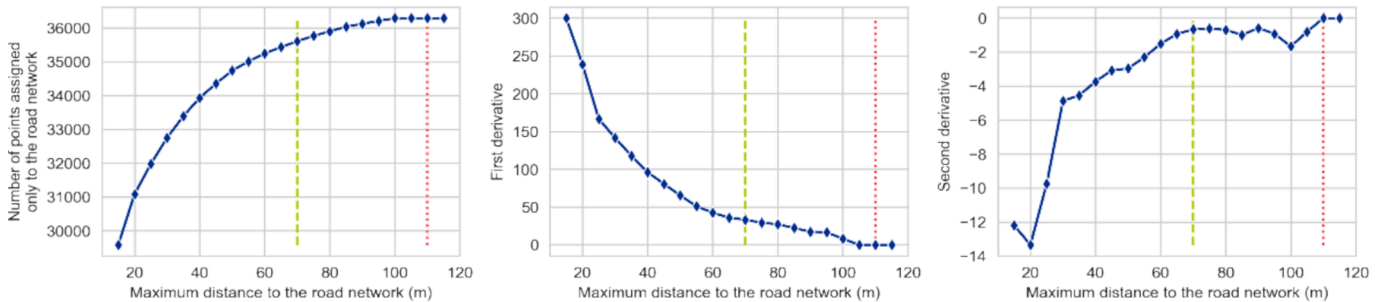
In this case, a segment is the part of a link located between two intersections, created automatically during the import via *osm2po*. Only the segments on which bicycles are allowed to circulate are taken into



**Fig. 3.** Algorithm used to assign the points to the networks. Step 1. consists of computing the azimuth of the light blue point based on the direction of the two adjacent points, represented as a light blue arrow. Step 2. selects the closest segments to the light blue point (inside the orange circle) with a 100 m buffer (circle in orange) around the light blue point. Step 3. adds the condition determined by Step 1. and selects only the segments in the right azimuth (segments represented in green) with a 45° error (green cone). Finally, Step 4. identifies the closest segment (in light blue) and assigns it to the light blue point. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 4.** Results of the sensitivity study on maximum distance to the bicycle network.



**Fig. 5.** Results of the sensitivity study on maximum distance to the road network.

account for the path calculations.

### 3.2.3. Shortest duration route calculator

A first possible improvement is to compute the shortest path in duration from point A to point B, by assuming that the speed of the e-bikes is the same on all segments of the same type. In this case, knowing the length  $l(s)$  and the type of link  $\tau(s)$  of a segment, the time required to go through the segment  $t(s)$  can be given by:

$$t(s) = \frac{l(s)}{v(\tau(s))} \quad \text{where } v(\tau(s)) \text{ is the speed on the links of type } \tau(s). \quad (3)$$

Then, the shortest path in duration  $R_{duration}$  is the route  $R$  that minimizes:

$$\sum_{s \in R} t(s) = \sum_{s \in R} \frac{l(s)}{v(\tau(s))} \quad (4)$$

The type of link  $\tau(s)$  is defined by two variables: the link category  $c(s)$  as defined in 3.1.4 and the slope category  $p(s)$  of the link the segment

belongs to. The slope categories are taken from the work done by Grante et al. (2020) and derived from the work by Broach et al. (2012):  $]-\infty; 2\%]; [2\%; 4\%]; [4\%; 6\%]; [6\%; +\infty[$ . For each segment, the slope is defined as the average slope between the initial point and the final point of the segment. It is computed by retrieving the elevation of each intersection point from the API made available by Natural Resources Canada. The speed of the type of link  $\tau$  is computed as following:

$$v(\tau(s)) = \left[ \frac{v(p(s))}{v(p_0)} \right] v(c(s)) \quad (5)$$

where:

- $v(c(s))$  is the median of the speeds of the points in the data set that are assigned to a link of category  $c(s)$ ;
- $v(p(s))$  is the median of the average speed between two points separated by a slope belonging to the category  $p(s)$ ;

- $v(p_0)$  is the median of the average speed between two points separated by a slope belonging to the category  $p_0 = ] - \infty; 2 \%]$  which is taken as the reference slope.

This expression assumes that both variables are independent: the speed is mainly defined by the link category and is then modulated by a coefficient  $v(p(s))/v(p_0)$  quantifying the reduction of the speed due to a positive slope. The pair of points for which the average speed is null (the bike did not move) are removed from the medians' calculation. Calculators using only one of those two variables (either the slope or the type of link) were also studied but are not described in this paper, as they did not perform as well as the one taking into account both parameters.

### 3.2.4. Smallest generalized cost calculator

When choosing a route, users do not base their decision on the traveling time only, as presented in 2. Among the parameters taken into account, convenience and security are the first two mentioned by cyclists Fyhri et al. (2017), as 5 min spent next to a very busy road or climbing a steep slope can seem to last 10 min to the user Wardman (2004). Therefore, it is interesting to turn the effective travel time into perceived travel time by weighting it with perception coefficients. In the previous example, the perception coefficient would be 2. Grante et al. (2020) developed a trip calculator for regular cycling using such preference coefficients for slope categories and link categories taken from the work done by Broach et al. (2012). The values found for the link categories by Broach et al. (2012) are presented in Table 3. The values used by Grante et al. (2020) are the minimum coefficients.

In this work, the assumption is made that the slope does not induce a discomfort, and therefore that the perceived time does not have to be weighted by a slope perception coefficient. The generalized cost used for the calculator only uses a link category perception coefficient. The minimum, average, and maximum values of the preference coefficient from Broach et al. (2012).

### 3.2.5. Indicators used to qualify the route calculators

Several route calculators were designed and the routes they provide were compared to the GPS data. The GPS data used for this comparison is the same as the one used for the elaboration of the route calculator, which is not optimal.

Nevertheless, it was chosen to do so as the GPS dataset is not large enough to be split in a training and testing dataset, and that several itineraries could be observed for the same origin and the same destination, adding variability to the itineraries dataset. To compare objectively the quality of the route calculators we designed, three indicators

**Table 3**  
Link categories and corresponding coefficients determined by Broach et al. (2012).

Link category as identified by Broach et al. (2012)	Minimum coefficient	Maximum coefficient	OpenStreetMap keys used to define the link categories as done by Grante et al. (2020)
Physically separated cycle track or cycle lane	1.00 (reference)	1.00 (reference)	highway in pedestrian, track, path cycleway or cycleway in track, opposite track.
AADT: 10,000 to 20,000	1.22	1.368	highway in living street or cycleway in lane, opposite lane, shared busway, opposite shared busway, shared lane.
AADT: 20,000 to 30,000	2.373	2.40	highway in tertiary, residential, road, unclassified, service.
AADT: 30,000 to 40,000	7.194	8.715	highway in primary, secondary.

\*AADT: "Annual average daily traffic", annual average daily volume on the lane in number of vehicles.

were used (see Fig. 6):

1. a detour indicator, defined as the ratio of the calculated route length (or duration) to the GPS route length (or duration), which target value is  $i_{detour} = 1$ , reached when both routes are the same length (or duration);
2. an overlap indicator, defined as the percentage of the GPS route length that is in common with the computed route, which target value is  $i_{overlap} = 100 \%$  when both routes overlap perfectly;
3. an average distance indicator, defined as the ratio between the area of the polygon formed by the two routes and the length of the GPS routes, which describes the average distance difference between the two routes, and which target value is  $i_{av.distance} = 0 m$ .

## 4. Results and Discussions

### 4.1. Assignment to the network

#### 4.1.1. Points assignment

Among the 73,654 points of the data set, 35,689 were assigned to the cycle network (48.45 %), 35,606 were assigned to the road network (48.34 %) and the remaining 2,359 points were not assigned (2.3 %). The unassigned points are either isolated points or points grouped together far from the network. The latter are probably points corresponding to the "test sessions" organized by Equiterre as part of the Vélovolt project, where e-bikes are lent to passers-by so that they can test them quickly.

#### 4.1.2. Computation of the trips

The path calculator fails to give solutions for the origin-destination pairs that correspond to a loop. Those loops can be either "recreational" loops made by a user, or "trial" loops related to the e-bikes trials organized by Equiterre and mentioned above. These pairs are subsequently removed from the analyses. Secondly, in the initial calculations of the shortest routes in Quebec City, the computed routes did not go through the Quebec City Bridge, even though it was noted as being open to bicycles. Indeed, there was a topology issue in the network, as the pedestrian and cyclist part of the Quebec Bridge were not correctly included in the OpenStreetMap network. A new link connecting the two "nodes" of the network was therefore manually added to the Quebec City network database before recalculation. Its geographic properties are identical to those of the parallel link describing the Quebec Bridge, and its lane category is set to "Cycle path shared with pedestrians".

#### 4.1.3. Users behavior analysis

For a first analysis, the shortest path in distance is computed for each origin-destination pair observed in the Vélovolt data set (this calculator is from now on called  $C_{distance}$ ). Those calculations show that individuals do not always use the same GPS route for the same origin-destination pair, and that those routes sometimes do not overlap for the majority of the trip. One explanation could be that the trial period is short (2-4 weeks) and may not be long enough to reach an "equilibrium state" where each individual almost always uses the route that they consider optimal. Since the calculated paths are always identical for the same origin-destination pair, the overlap indicator for  $C_{distance}$  takes on relatively low values, as shown in Fig. 7. Those values vary greatly by region: for Saguenay and Trois-Rivières, where the choice of routes is less extensive because the network is less dense, the overlap is much higher than in Montreal, where there are many more options. The detour indicator is quite close to 1, which shows that the alternative trips made are not much longer than the shortest route. For regular bicycles, this value would probably be lower as the users would potentially avoid steep slopes with detours. Finally, for the average distance indicator, the value of Ottawa-Gatineau is very high compared to the others. After checking the trips, it would appear that one of the study participants used their e-bikes extensively as a leisure tool, with trips that take very

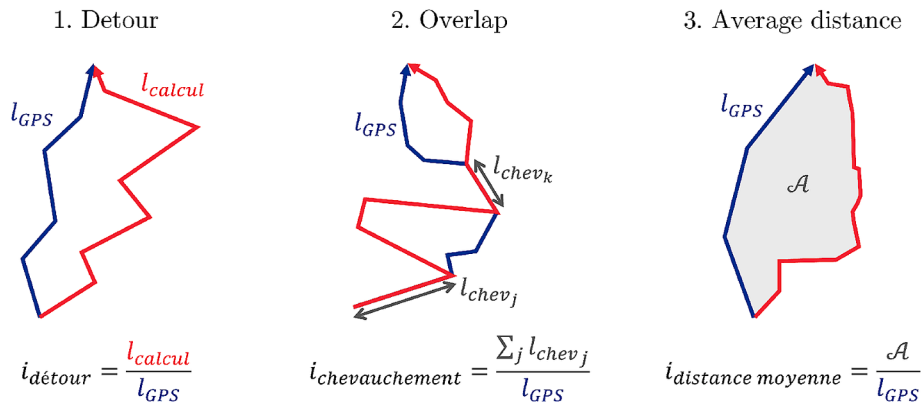


Fig. 6. Illustration of the indicators used to characterize the calculators.

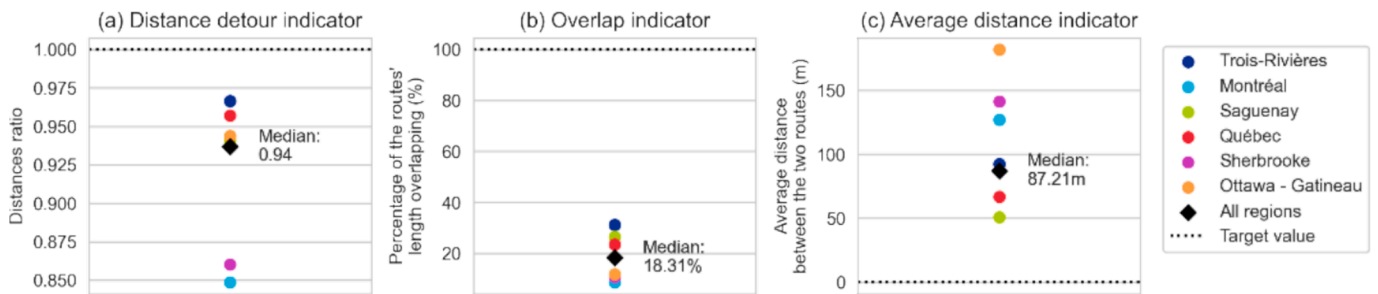


Fig. 7. Indicators for the calculator computing the shortest route in distance.

large detours from the shortest route.

4.2. Shortest duration route calculator results

4.2.1. Median speeds by link category

The distribution of the speeds according to networks where the point belongs is presented in Fig. 8. The median is the value indicated by the black line, and the ends of the box correspond to the first and third quartiles. The speeds on the bicycle network appear to be slightly higher than those on the road network. A Kolmogorov-Smirnov test is performed to validate that the two distributions are indeed statistically different. The results of this test yield  $D = 0.125$  and  $p - value = 1.310^{-244}$ . Thus, the probability that the distributions are similar is almost zero, which validates their difference. Next, the median speeds by link category are presented in Fig. 9. The variations from one link category to another are quite low, except for the *Bicycle crossings* where bicycles are likely to be waiting for a green light or safe passage, which may account for much lower speeds; the *Service roads* which may be places where bicycles are parked; and the *Unknown* lane types, which

may be private lanes where bicycles arrive at their destination and therefore slow down, or places that are not very suitable for cycling. A Kolmogorov-Smirnov test is performed to compare the speed distributions for each pair of link categories. In the vast majority of cases the velocity distributions are statistically different, so the differences in median velocities make sense. The only pairs that show similarities are tests performed with the “Unknown type of cycle path”, which have only 7 points in the sample. The impact on the rest of the study is therefore very small.

4.2.2. Median speeds by slope category

A first analysis is on the pairs of points  $(x_i, x_{i+1})$  by differentiating those for which the slope is negative (downhill trip) and those for which the slope is positive (uphill trip). Fig. 10(a) shows the frequency distribution of average speeds between  $x_i$  and  $x_{i+1}$  as a function of the sign of the slope. The speeds observed are slightly higher for negative slopes, which seems logical: it is natural to be faster when going downhill. A Kolmogorov-Smirnov test yields  $D = 0.07$  and  $p - value = 1.3910^{-64}$  so the two distributions are indeed statistically different and it is relevant

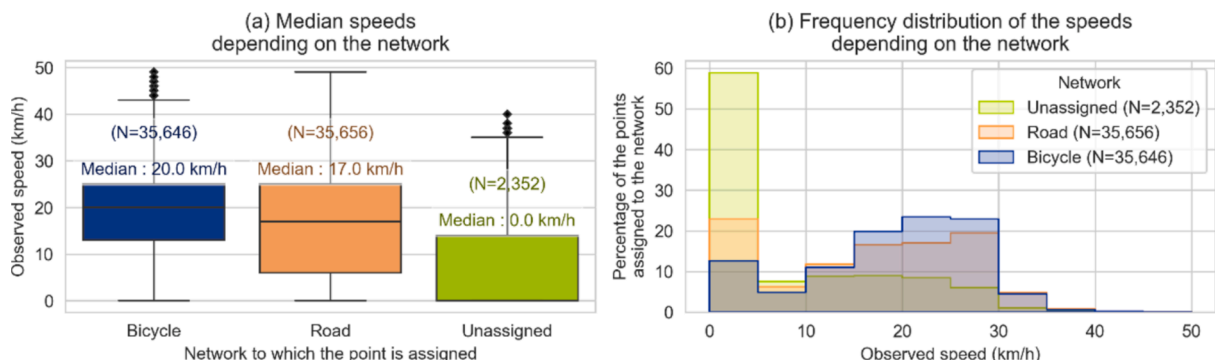


Fig. 8. Observed speeds according to the network.

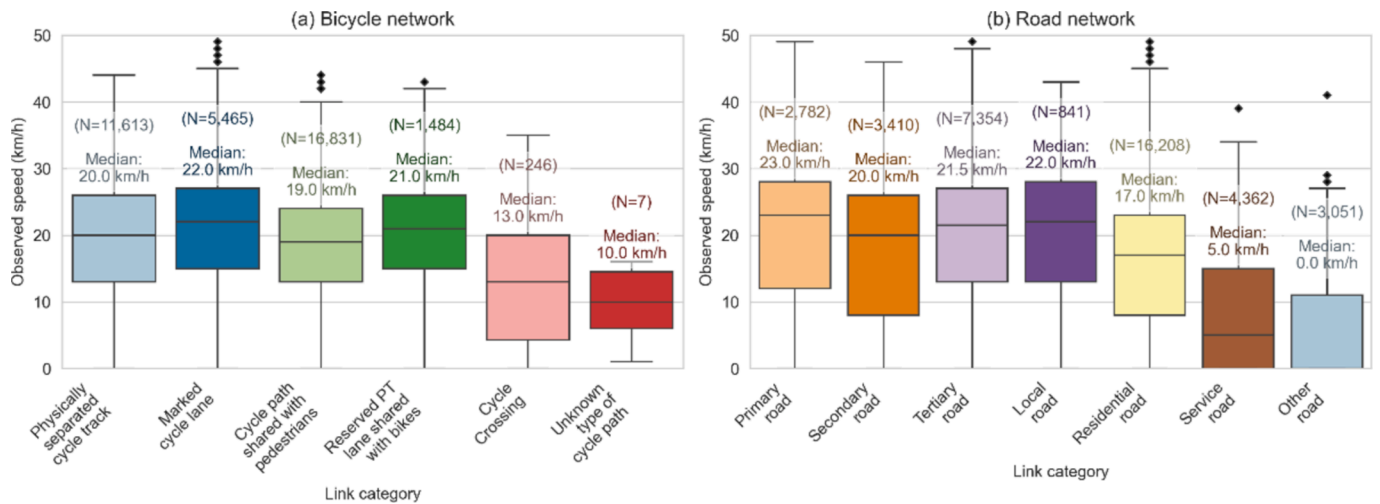


Fig. 9. Observed speeds according to the link category.

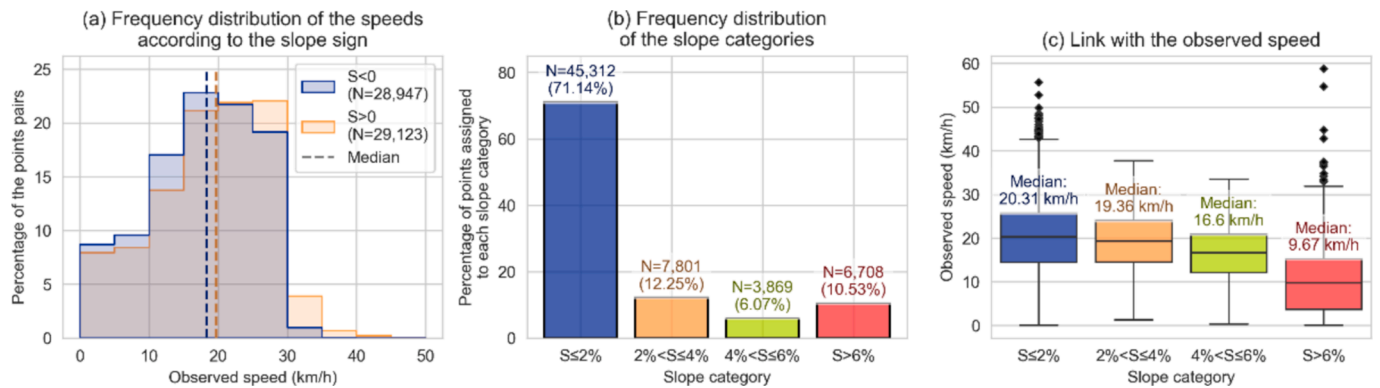


Fig. 10. Observed speeds according to the slope category.

to compare them. To go further, the median velocity as a function of the slope category is presented in Fig. 10(b,c). Naturally, the speed observed decreases when the slope increases. Nevertheless, this decrease in speed only occurs in a very steep slope (greater than + 6 %). Below this, there is a strong overlap of the speeds between the slope categories. This suggests that while the slope does have an effect on the speed practiced, the effect is quite small.

4.2.3. Median speeds by region

Finally, those median speeds are studied according to the region to check the consistency of the results and to investigate their variability by

region. Fig. 11 shows that for the lane categories (left), the variability is much higher than for the slope categories (right), where the values are almost identical for all regions. The trends are still quite similar to the median speed for all regions. Two explanations can be given for the high variability of the median speeds of the lane categories depending on the region: (1) the large number of link categories could lead to categories with few points observed that do not allow the extreme values to be absorbed; (2) the points may not be distributed evenly in the link categories across regions, leading to some categories with few representatives per region. For instance, for the Cycle crossing category, there are 203 points in Montreal and only 0 to 14 in the other regions: even

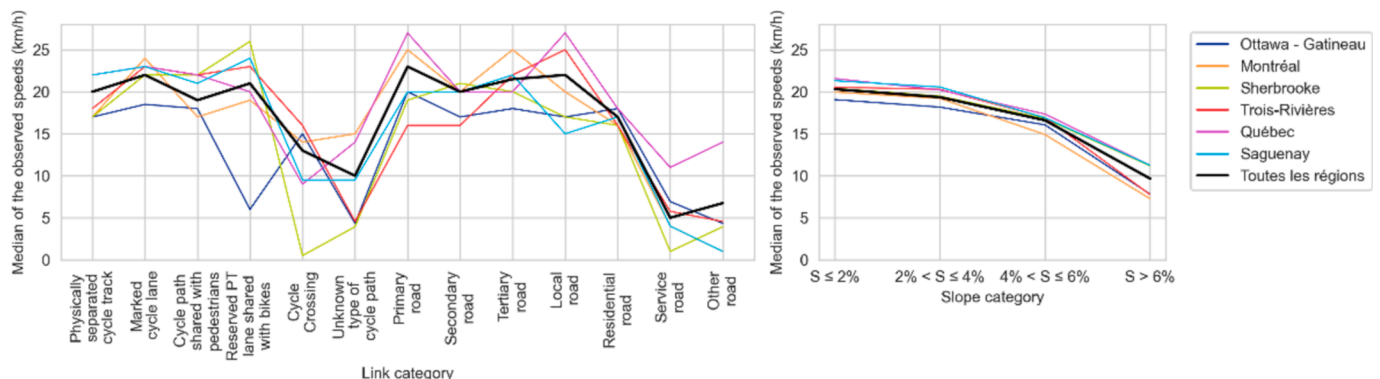


Fig. 11. Observed speeds according to the slope category and link category across regions.

though in total the number of points in this category is important, the distribution across the regions leads to great differences. Because of this variability, it seems more relevant to work with the median speeds of all points to calculate the time costs on the segments and not the median speeds of only the considered region.

#### 4.2.4. Application of the calculator

The shortest duration route is then computed for each origin–destination pair present in the Vélovoit data set (calculator  $C_{duration}$ ). The indicators defined in 3.2.5 are used to compare the results of this route calculator with the results of the shortest distance route calculator  $C_{distance}$ . Their values are shown in Fig. 12. According to them, the calculator  $C_{duration}$  does not perform much more than the calculator  $C_{distance}$ : in median, the overlap and mean deviation indicators are further from their optimal values in the duration calculator than the distance calculator; only the distance ratio indicator is slightly improved. This observation justifies the development of another calculator, which also takes into account preference coefficients, in order to get closer to the GPS paths. The value of the detour indicator in duration for  $C_{duration}$  is  $i_{detourdur}$  = 0.86 < 1, which means that the real time cost from the calculator is less than the real time spent to travel. This is logical since the path calculator simply adds up the time spent on each segment, without taking into account the time at intersections for example.

A comparison can be made with a calculator using the speeds specific to each region  $C_{region}$ . Its indicators are shown in Fig. 13 compared to the indicator using the global values. As expected, the indicators' values are closer to their target values for the region-specific calculator. The improvement is mainly visible for the overlap indicator, which is this time better than the indicator for the shortest distance calculator. The differences in indicator values between the global and specific calculators remain quite small. In order to have a tool that can be easily applied, the choice was made to use only the first one in the rest of this work.

### 4.3. Smallest generalized cost route calculator results

#### 4.3.1. Determination of the best preference coefficient

Finally, the results for the calculators using preference coefficients to convert the effective duration of a segment into perceived duration are compared to the shortest path calculator. Three calculators are studied:  $C_{GC,min}$  using the minimal coefficients found by Broach et al. (2012),  $C_{GC,avg}$  using the average coefficients and  $C_{GC,max}$  using the maximal coefficients. Their indicators are shown in Fig. 14. The calculator which has both the highest overlap indicator and the lowest average distance indicator is  $C_{GC,min}$ , the one using the minimal coefficients. It will therefore be kept for the next analysis.

#### 4.3.2. Comparison with the previous calculators

To study the improvement of the performances using preference coefficients, the results of the calculator  $C_{GC,min}$  are compared to those of  $C_{duration}$  and  $C_{distance}$  and presented in Fig. 15. This improvement is very visible for all three indicators, and particularly for the overlap indicator

that was previously very low.

#### 4.3.3. Comparison with a control calculator based only on preference coefficients

It is important to verify that the calculator  $C_{GC,min}$  has an added value compared to a calculator that would only consider the variation in preferences according to the type of link. To do so, a control calculator  $C_{pref,min}$  is used. For each segment  $s$ , the cost is defined as:

$$C(s) = \alpha(s)t(s) = \alpha(s)l(s)v_{ref} \tag{6}$$

where:

- $\alpha(s)$  is the minimal preference coefficient as defined by Broach et al. (2012);
- $l(s)$  is the length of the segment;
- $v_{ref}$  is a reference speed via e-bike which value is set at 20 km/h Dozza et al. (2016) (and does not impact the computed route).

The comparison of the indicators for  $C_{GC,min}$  and  $C_{pref,min}$  is presented in Fig. 16. The detour indicator is roughly similar for both calculators, but the overlap and average distance indicators have more optimal values for the calculator  $C_{GC,min}$ . This justifies the preliminary study of shortest duration calculators and the use of not only preference coefficients, but also slope-weighted speeds calculated for each link category.

### 4.4. Application to the computation of the travel times

#### 4.4.1. Comparison of the travel times observed in the GPS data of the Vélovoit project and the computed travel times

To go further, the link between the travel time computed with the median speeds for the paths of the calculator  $C_{GC,min}$  and the actual travel time based on the GPS data is shown in Fig. 17. A subset of points describing the “short” trips (30 min and less) is also shown, with the associated linear regression equation. A correlation is clearly visible in these figures, although it is not very strong. The y-intercept would correspond to the time spent at intersections or stops along the route. For the smallest computed travel times, the actual duration is generally longer (points are above the identity line in bright outline), which is consistent with the fact that the detour indicator in distance is also larger than 1. For larger travel times, the trend is reversed, which explains why the slopes of the linear regressions are less than 1. Finally, it seems that the calculator predicts smaller travel times better than larger travel times: the linear regression coefficient is higher in the subset than in the full data set.

#### 4.4.2. Application to the Bixi trips in Montréal

Bixi is a station-based bike sharing service present in the Montréal region that offers e-bikes. The Bixi transaction data set contains for each transaction the timestamp of the beginning and the end of the trip as well as the origin and the destination station. Both e-bike and regular bike transactions are present in the data set and can be identified with a

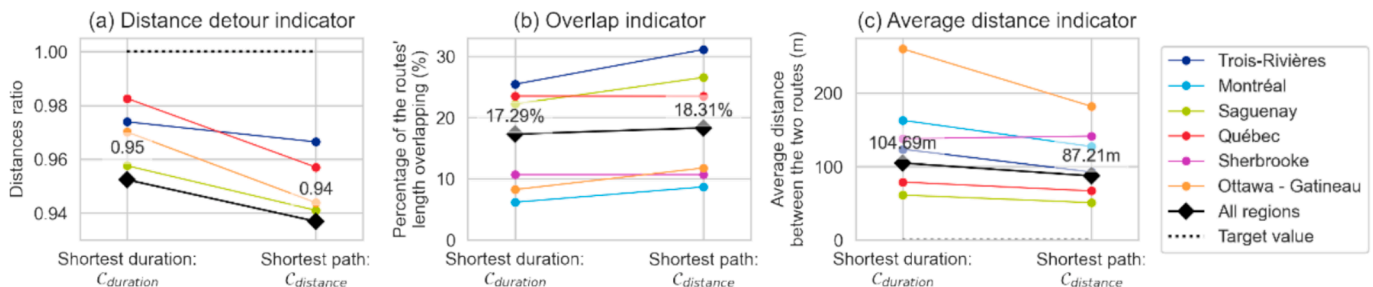


Fig. 12. Comparison of the indicators for the shortest duration routes (on the left of the graphics) and the indicators for the shortest distance route (on the right of the graphics).

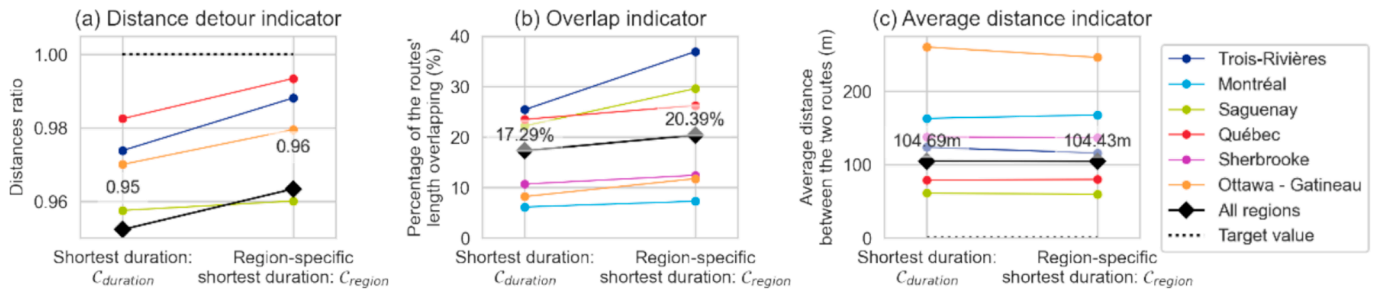


Fig. 13. Comparison of the indicators for the shortest duration routes using the global median speeds (on the left of the graphics) and region-specific median speeds (on the right of the graphics).

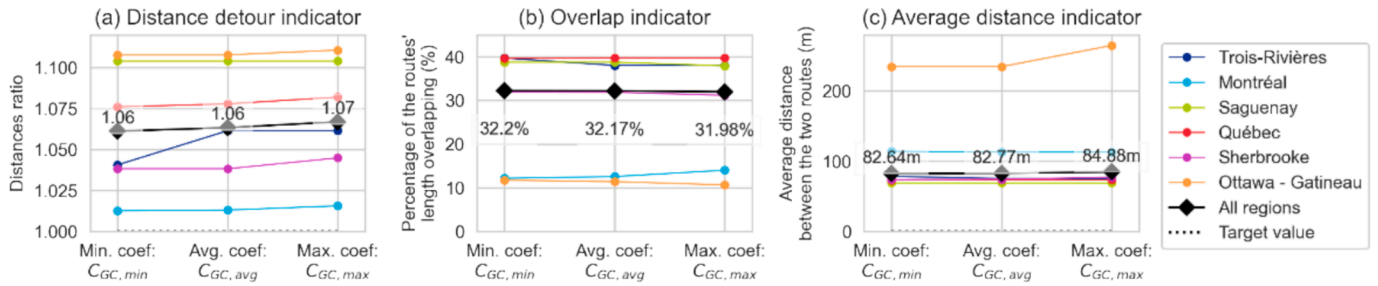


Fig. 14. Comparison of the indicators for the calculator using a generalized cost computed with the minimum (left of the graphics), the average (center of the graphics) and maximum (right of the graphics) preference coefficients determined by Broach et al. (2012).

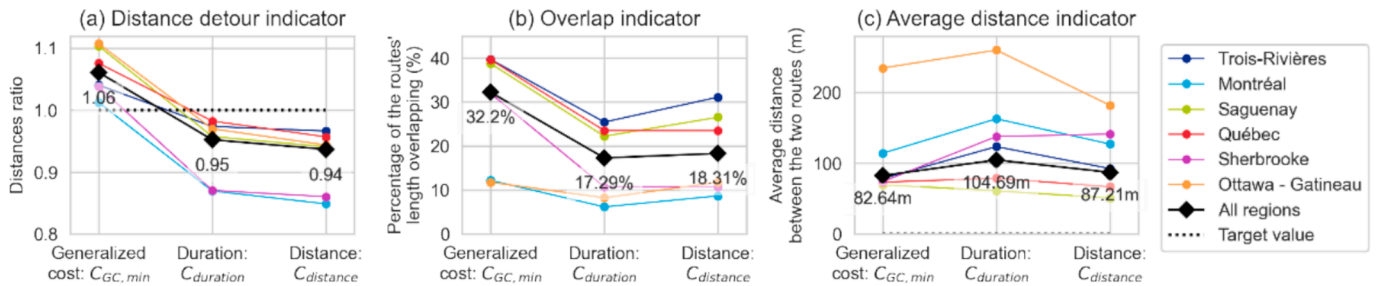


Fig. 15. Comparison of the indicators for the calculator using a generalized cost computed with the minimum (left of the graphics), the average (center of the graphics) and maximum (right of the graphics) preference coefficients determined by Broach et al. (2012).

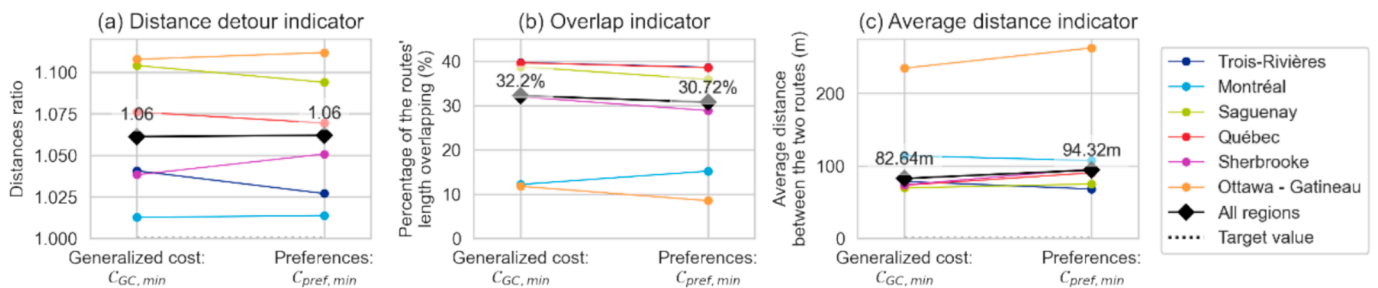


Fig. 16. Comparison of the indicators of the calculator computing the effective travel time with a link-specific speed (left on the graphics) and a calculator computing the effective travel time with a unique speed (right on the graphics). In both cases, the travel time is converted into a generalized cost by weighting it by the preference coefficients.

dummy variable. For this work, the Bixi transactions data of the year 2020 are first processed to eliminate the loops and irrelevant rides. To do so, the average speed of a trip is computed using the Manhattan distance. Then, the trips with an average speed below 6 km/h are removed. This value was determined with a sensibility analysis on the number of trips eliminated as a function of this average speed. After removing those trips, the data set contains 2,802,636 transactions

including 183,862 e-bike trips (6.56 %). Among these e-bike trips, 143,544 (78.07 %) were made by users who had yearly or half-yearly subscriptions to the BSS, and could therefore be considered as “experienced” users. For the e-bike trips, the correlation between the travel time  $t_{computed}$  computed with the calculator  $C_{GC, min}$  and the actual travel time  $t_{transaction}$  computed with the timestamps is shown in Fig. 18. The linear regression equation obtained is:

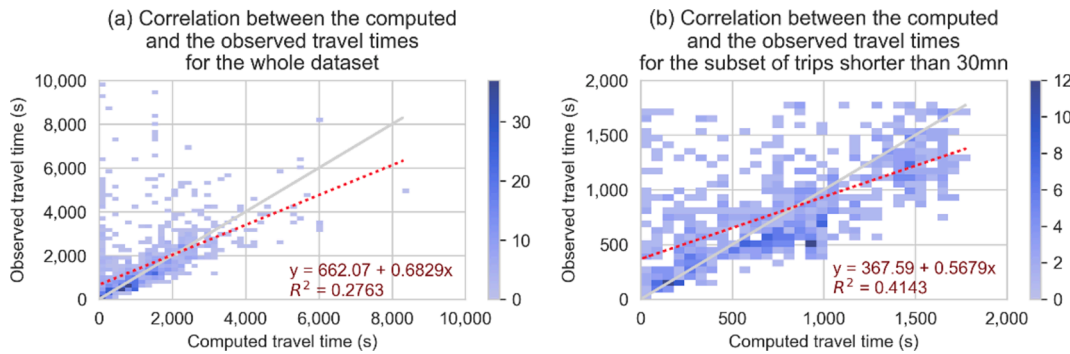


Fig. 17. Correlation between the observed travel time and the computed travel time using the calculator  $C_{GC,min}$  for the Vélovolt trips.

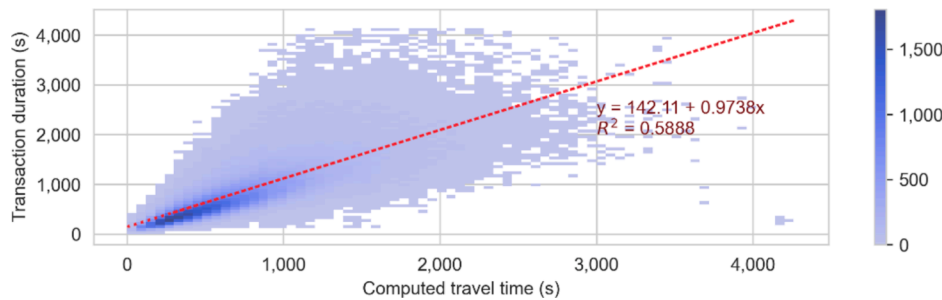


Fig. 18. Correlation between the observed travel time and the computed travel time using the calculator  $C_{GC,min}$  for the Bixi e-bike transactions.

$$t_{transaction} = 141.11 + 0.9738t_{computed} \quad (7)$$

with a satisfactory linear regression coefficient  $R^2 = 0.5888$ . The vertical intercept can be interpreted as the lost time at intersections added to the time spent to lock or to unlock the bikes, as they are not computed by the calculator. The slope is very close to 1, which shows that the calculator gives a pertinent estimation of the travel time by e-bike.

#### 4.4.3. Application to three major origin–destination pairs in Montréal

In order to verify that the results obtained with the calculator are realistic, a qualitative comparison is also made for three major origin–destination pairs in Montréal, each having the Central Business District for destination. Each origin and destination is identified to a Bixi station. For each origin, the Bixi station within a 500 m radius around the point that has the most transactions is chosen. For the Central Business District, the Bixi station within the CBD perimeter as defined in [CityOfMontréal \(2002\)](#) that has the most transactions as destination with the three “origins” stations is chosen (station 52). For each pair, the travel time obtained with the calculator is compared to the travel time computed by Google Maps for bikes, as well as to the average transaction time for Bixi and for Bixi e-bikes. The results are presented in [Table 4](#). In the three cases, the average transaction time for all bikes is longer than the average transaction time for e-bikes, which is consistent with the literature review. The Google maps travel time is smaller than the average transaction time for all bikes: the difference could be interpreted as the time spent to park or to start the bike (as mentioned in section 4.4.2). For the first two origins (Mont Royal and Jean Talon), the computed travel time is smaller than the other travel times; whereas for the third one (Côte-des-neiges), the computed travel time is larger than the Google Maps and Bixi e-bikes travel times. There is no obvious explanation to this difference but it is coherent with the slope found in section 4.4.2: this slope is lower than 1, which means that the calculator may be underestimating the travel time for longer trips. Nevertheless, in all three cases, the computed travel time has the same order of magnitude than the Bixi and Google Maps travel times, which supports the

Table 4

Travel times obtained for three origin–destination pairs in Montréal and corresponding average Bixi transaction times.

Origin (Bixi station)	Destination (Bixi station)	Calculator (s)	Google maps	Bixi (all bikes) (s)	Bixi (e-bikes) (s)
Metro Mont Royal (184)	Eaton Center (52)	608	780	941	710
Metro Jean Talon (246)	Eaton Center (52)	1,163	1,260	1,646	1,380
Metro Côte-des-Neiges (317)	Eaton Center (52)	1,669	1,440	1,688	1,244

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reasonableness of the calculator.

## 5. Discussions

First of all, the GPS data present intrinsic limits: the dataset used for this study consists only of a small part of the data that will eventually exist for the Vélovolt project. As a result, there is an important variability in the median across the observed speeds across the regions due to the small number of points. When more data are available, it may be possible to adapt these values to be more relevant. Moreover, the short duration of the current trials of the Vélovolt project does not seem to be long enough for the participants to stabilize their route. This duration will possibly be increased, leading to better quality data. Another limit is that this work uses the OpenStreetMap network data. As seen with the Quebec Bridge, this data is not perfect and can sometimes be incomplete. There may be other problems that are not as glaring as the one with the bridge that have not been detected. The categorization of links in the paper’s networks also depends on the quality of the link labeling in OpenStreetMap. However, these labels can also contain errors, like a

“crossing” value instead of a “crossing” value. Those errors were taken into account as much as possible but if some new labeling appears in the future, the link categorization could become less accurate. Therefore, the results could be improved by using better quality data when available. Beyond the limits of the data characteristics, the method used here also presents limits. The determination of the slope for each segment is not optimal. Indeed, it is deduced from the difference in elevation between the two ends of the link (the nodes of the network), so there may be intermediate slope variations that are neglected. The slope values also depend on the data available online, which may not be perfect. Secondly, the route calculations are done from one node of the network to another, while the origin and destination of the trip are not always located exactly at an intersection. This leads to a loss of information: if the accessibility is poor between the origin (or the destination) and the network nodes, the additional travel time is not considered in the route calculation. Finally, the calculator presented here was not calibrated according to a discrete choice model based on the trips observed for the Vélovoit project. It is based on median speeds and preference coefficients from the literature. Those coefficients are therefore not optimal for describing the trips made in this particular case. Further work could focus on identifying the possible alternatives for each origin–destination pair via e-bike, and then applying a discrete choice model. However, the variability of the routes taken by the participants for the same origin–destination pairs may complicate the calibration.

## 6. Conclusion and research perspectives

This paper presents the elaboration of a route calculator specific to e-bikes using GPS data from e-bike trials in Québec. To do so, the network links are categorized according to two variables: (1) the slope of the link and (2) the type of link (type of bike lane or type of road). For each of those categories, the median observed speed is computed. The effective time needed to go through each link is computed using these median speeds. It is then converted into a perceived time using preference coefficients for each type of link. Those perceived time can be used as a cost to compute the optimal e-bike itinerary for a given origin–destination pair, which answers our first research question. To solve our second research question, we suggest three indicators to determine the best calculators among the ones we tested: a detour indicator, an overlap indicator and an average distance indicator. The “best” calculator is the one taking into account both the road category and the slope, which shows both variables were relevant and is consistent with the literature review. The characteristics of the calculator itself therefore seems to be coherent. In the end, this calculator has an overlap indicator of 32.2 %, with a detour ratio of 1.02 and an average distance between the computed route and the GPS route of 82.64 m. The detour ratio is very close to one, which shows that the calculator performs well to compute the distance. The overlap indicator is still slightly low, but this value could be explained by the absence of stability in the itineraries chosen by the users. Moreover, even though the calculator route is not perfectly overlapped with the GPS route, the average distance between the two routes is only 1.57 % of the median length of the trips (5.265 km), which is very small. This leads us to think that the calculator can sometimes leads to a route that is very close but parallel to the one observed (highly possible in grid cities like Montréal). Therefore, we can conclude that the calculator performs well.

The travel time estimated using this calculator shows a correlation with the observed travel time in the GPS data. The correlation coefficient is  $R^2 = 0.2763$  and  $R^2 = 0.4143$  for short trips (less than 30 min). These relatively low values can be explained by the detours or stops that users of a new mode generally make, as in this case where the users are e-bike novices. A better correlation is obtained with the observed travel times in the Bixi data set, with  $R^2 = 0.5888$  and a slope of 0.9738 that is very close to the expected value of 1. This evolution could be explained by a dataset with more experienced users (78.07 % of the trips) and less noise in relative terms in the data due to a larger sample.

To the knowledge of the authors, no similar calculator dedicated exclusively to e-bikes exists. This tool could firstly be useful for e-bike users, not only because it gives adapted itineraries but also travel times specific to e-bikes. The calculator could also be used to develop new multimodal transport models including e-bikes for transport planning. Such models could be useful to improve knowledge of the existing use of e-bikes, which is a foundation for every policy decision regarding transport planning. Moreover, as the calculator computes the cost of the link based on the link category and the slope, it could also be used to investigate the impact of new cycling infrastructure such as the creation of a cycle track on the e-bike travel times: for policymakers, it could be a decision-making tool to prioritize between projects. More generally, having a dedicated calculator encourages considering e-bikes as a travel mode per se, different from classic bikes, and therefore helps take into account the possibilities it offers when developing transport policies.

In future research perspectives, other works could enrich the analysis thanks to the survey that was answered by the participants. This survey gives socio-demographic information, the purpose of the most frequent trips, as well as perception indicators for the e-bike. Those answers could be used to nuance the results of this paper and the perception coefficients based on age and gender for example. The GPS data and the survey also allow for computing the maximum threshold distances for e-bike trips by age and gender in each region, as defined by Morency et al. (2020). Knowing these, it would be possible to estimate the proportion of the car trips found in the OD-survey that could be transferred to e-bikes. This proportion could represent potential for modal shift to e-bikes in Québec Morency et al. (2020), and therefore for avoided CO<sub>2</sub> emissions.

## CRediT authorship contribution statement

**Clémence de Rolland:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Catherine Morency:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Jean-Simon Bourdeau:** Visualization, Software, Methodology, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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