Improving GIS-based Models for Bicycling Speed Estimations

European Transport Conference 2018

IMPROVING GIS-BASED MODELS FOR BICYCLING SPEED ESTIMATIONS

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ABSTRACT

For reasons ranging from public health to sustainable urban development, traffic planning as well as urban design aim to increase the modal share of bicycling at the cost of fossil fuel based transport. Despite this increasing interest in bicycling, most planning practices handle bicycling schematically, applying methods that rely on fixed speed and distance templates, paying little attention to the fact that bicycling speeds vary a lot depending on bicycle routes and the contexts of these routes. Since travel time is important for both route choice and mode choice, more refined methods for predicting bicycling speeds should be highly useful. This paper presents a bicycling speed model that combines parameters from two recent bikeability modelling studies. One is an urban form based study that identified urban form parameters significant for average bicycling speeds at segments of the bicycle route network. The other study estimated likely speeds based on horizontal and vertical geometry of routes. The latter model used a statistical model to grasp dependence between contiguous road segments; based on so-called Markov-dependence, the model predicted continuous speed profiles along entire routes, and not only average speed levels on road segments seen independently. The new combined model is estimated using GPS tracking of real bicycle trips in combination with GIS-based data of bicycle route networks and of the local urban form parameters along the routes. The covariates included in the model are route geometry, intersection impedances, type of bicycle-route, kind of surface, and density of entrances to buildings along route. The latter is a proxy for slower bicycling due to urban/vibrant context. The new model results in more detailed and realistic speed estimations than the previous models. This paper presents the model and some results from applying the model on bicycle routes in Gothenburg.

1. INTRODUCTION

For reasons ranging from public health to sustainable urban development, traffic planning as well as urban design aim to increase the modal share of bicycling at the cost of fossil fuel based daily transport. In order to achieve this, there is a need for knowledge of the conditions influencing daily commuting in general and bicycling in particular.

In most kinds of travel, both route choice and mode choice depend on time, cost and convenience, therefore reliable measures of these aspects are essential for understanding bicycle travel. In bicycle routing applications, the complexity of bicycle route choice is explicit by offering different options for selecting the route, for example the shortest, the fastest, the simplest, the safest, or the least slope routes. In bicycle planning, the methods of analysis usually apply the measure of distance. Explicitly stated or not, this is obtained by converting travel-time to a measure of travel-distance. Typically, convenient maximal distance of bicycling for daily commuting is considered to be about 3-5 km (Scheiner, 2010; Rietveld, 2000). In cases where speed is constant, this concept of measuring distance rather than time works fine. However, when speeds vary a lot, which is often the case for bicycling, the measure of distance alone is less useful, and even possibly misleading. Bicycling speed depends on the kind of bicycle and bicyclist, as well as on the conditions and the context of the particular bicycle route. The speed, when travelling by bicycle, may range from slower than walking when you have to walk with the bike among a crowd of pedestrians, to the speed of a car when riding downhill. The strong effect of slope implies that even the speed of a specific route, for a particular bicyclist, varies a lot depending on the direction of travel (Arnesen et al., 2017). Due to these variations, methods that grasp speed differences along specific routes will likely be much more realistic than methods measuring distance alone.

Today, identifying most useful bicycle routes in a street network at the city scale relies on comparing distances along numerous different routes, ignoring the effect of different speeds at different parts of the network. The inclusion of an improved speed model in accessibility and transport models, comparing travel time rather than distances, may provide the ground for a new generation of travel mode choice analyses as well as bicycle flow predictions. Such instruments should be highly relevant for planning authorities and consultants evaluating and comparing the likely performance of alternative project proposals within urban planning, urban development and traffic infrastructure.

The aim of the research presented in this paper is to contribute to the development of an improved model for bicycle speed estimation, by estimating speeds along routes at a detailed level and including urban form parameters. In order to be able to analyse large route network systems, such as entire cities, the model should preferable rely on data that is commonly available and can be easily mapped in GIS. This includes geometry of routes, the type of bicycle route, intersection and route surface, as well as the urban context in terms of entrances to buildings along the route. Before presenting the proposed model and its application in the case of Gothenburg, the next sections present the research background on which the new model is based.

2. BACKGROUND

2.1 Urban form and daily travel

Numerous studies have examined the relationship between urban form and travel, from which one can conclude that there is a complex bi-directional interaction between urban form, socio-economic and attitudinal characteristics, and travel outcomes. Daily travel, described in a simple way, involves journeys between an origin and a destination, using a specific travel mode, and following an adequate route. But the components of this complex relationship influence the location and choice of both origin and destination, as well as the choice of travel mode and of travel route. For this reason, richer transport models that incorporate to different degrees these components are being developed. The better we model travel, the better we will be able to predict it, and make informed planning decisions addressing everyone's needs.

Within the field of transport modelling in general, the use of utility functions is essential. In particular, for modelling mode choice and route choice (Ortuzar and Willumsen, 2012), both travel-distance and travel-time are inputs to such functions. However, the latter input demands a considerably more detailed modelling approach given the numerous factors that can impact travel time. Typically, motorized travel modes, such as personal cars, have been devoted a lot of attention in terms of modelling speed as a function of exogenous variables and traffic flow, see for instance the reviews by Hassan and Sarhan (2011), Arnesen and Hjelkrem (2018), and many of the references therein. Walking and bicycling, the non-motorized, active and softer modes of travel have been treated much simpler, often with constant speeds and lesser dependence of environmental parameters. With increased focus on sustainable transport (Russo et al., 2016), more accurate modelling of non-motorized travel is necessary and has therefore been given an increased interest within the field of transport modelling research (see for instance Beheshtitabar et al., 2014; Bernardi and Rupi, 2015; Jiang et al., 2016).

2.2 Modelling bicycling in particular

Bicycle speed has to some degree been studied in the transport modelling literature (see for instance, El-Geneidy et al., 2007; Parkin and Rotheram, 2010; Figliozzi et al., 2013; Bernardi and Rupi, 2015; Ryeng et al., 2016; Strauss and Miranda-Moreno, 2017; Manum et al., 2017; Flügel et al., 2018). All the above works do, however, assume constant speed along homogeneous road segments, and do not include speed dependence between contiguous segments, typically resulting in disconnected speed levels between segments and unrealistic speed profiles in terms of variability. For some applications, within the transport modelling field, such simple models might be sufficient, for instance in mode choice models on aggregated level. Other applications, such as route choice models, energy calculations and travel time quotas in denser parts of cities, would benefit from more nuanced modeling approaches.

In Sweden, two of the few municipalities using traffic models that include bicycling are Linköping and Gothenburg. For estimating travel time quotas and aggregated bicycle flows on routes, they both use PTV Visum (http://vision-traffic.ptvgroup.com/en-us/products/ptv-visum/). Linköping uses a speed between 20-25 km/h depending on “experience valuation” along the route. Depending on the type of crossing (signal, no signal, circulation) “time penalties” are then added. In Gothenburg, a speed of 20 km/h is initially assumed on all routes and then differentiated by type of route (commuter route, bicycle track, bicycle and walking track or streets with mixed traffic). Further, impedance is then added for slopes steeper than 4%, and signal crossings are handled with “time penalties”. These examples of transport planning practice include bicycling as a mode of transport, but lean on assumptions of bicycling speeds rather than on empirical research. In Norway, an Arc View application called “ATP-modellen” includes estimation of bicycle speed variation due to slope but not from other route conditions (Miljødirektoratet, 2002).

Aiming at estimating speed variation along a route more in detail, the model proposed in this paper is based on two recent bicycle speed models that take more conditions of bicycle routes into account. The first model, in the following sections termed the average speed regression model or the average speed model (ASR-model), was developed by a study of bicycling speeds in Gothenburg, Sweden, and departs from architectural research studying spatial configurations of urban form and street networks (Manum et al., 2017). The second model was developed by a study of bicycling in Trondheim, Norway, and departs from transport research. By using Markov dependence between closely spaced points on a predefined route, this model, in the following termed the Markov model, estimates model parameters on very detailed GPS data of horizontal and vertical geometry of route (Arnesen et al., 2017). This model estimates very detailed speed variations along routes based on route geometry but does not include environmental covariates such as road surface, city environment and influence by other traffic. The following sections describe these two earlier models in more detail.

2.3 Model I, the average speed regression model (the ASR-model)

The study of bicycling speeds in Gothenburg, carried out on the commission of Gothenburg Traffic Office and initiated by Chalmers Technical University in collaboration with NTNU aimed at examining the relationship between urban form, urban environment and average bicycle speeds at street-segments (Manum et al., 2017). The empirical data collected were bicycling speeds from GPS-tracking of bicycling along eight pre-defined bicycle routes (Figure 1). The routes were selected for providing a representative sample of kinds of bicycle routes in Gothenburg. The bicycle routes were subdivided into segments of constant characteristics (n = 334), based on impedance variables that according to existing research should influence the speeds of bicycling.

Table 1 lists these variables and the units examined for each. In order to grasp the fact that bicycling speeds may differ in different directions on the same route, the route-network was modelled as a bi-directional system (see Figure1). The aim of the model was to estimate median speed in each direction on each of the route-segments.

The GPS-tracking was conducted by 15 bicyclists, cycling in total 875 trips along the selected routes in rush hour traffic on two weekdays in May 2016 (between 07:30-09:30 and 16:30-18:30), using the Traffic Office GPS app “Bicycle City”. The bicyclists were of different kinds regarding gender, self-experienced bicycle type (slow normal, fast) and age group, selected for representing the variation of bicyclists along the selected routes in Gothenburg. The mix of bicyclists was identified by an observation study of 1946 bicyclists. The GPS data showed that median speeds differ significantly between segments on a route as well as between different routes in the city. Median speeds of individual segments range from 6 to 35 km/h (1,5 – 9,7 m/s), whereas speeds of entire routes range from 13 to 21 km/h (3,6 – 5,8 m/s). The total median speed for all segments were 17 km/h. Unfortunately, the GPS app was not able to track exact stop time at intersections. Due to this technical problem, the GPS tracking only resulted in median speed along individual segments.

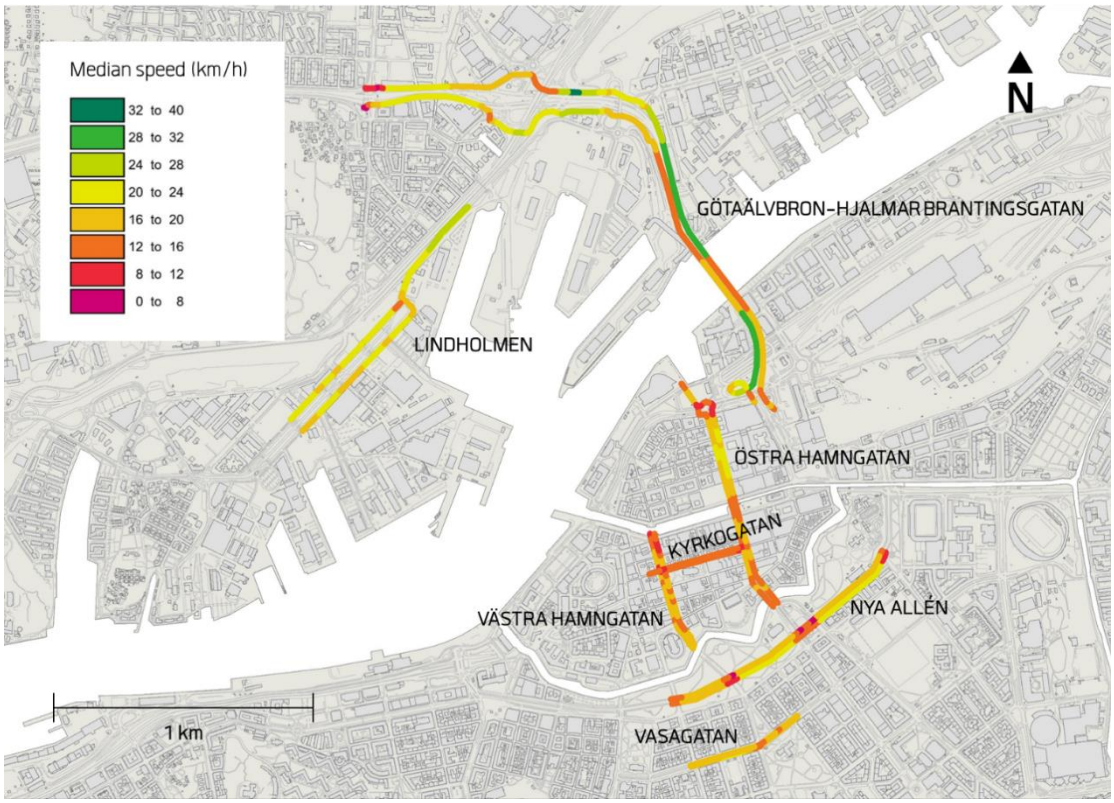

Figure 1. Bicycle routes examined in Gothenburg.
Routes colored by speed (km/h) as mapped by GPS-tracking.

Table 1. Impedance measures assigned to street segments (* included in the model)

	Impedance variable	Categories / Units
1	Kind of route *	• Pedestrian street, (walking and bicycling merged) • Slow Bicycling street • Mixed traffic • Bicycle lane • One-way bicycle track • Two-directional bicycle track
2	Width of bicycle lane	• Metres
3	Kind of bicycle lane surface material *	• Asphalt • Concrete • Cobble stone • Gravel
4	Kind of separation from pedestrians	• Furniture, vegetation etc • Height difference (different level) • Different surfaces
5	Slope *	• Percentage (%)
6	Horizontal curvature (radius) *	• Metres
7	Length of segment *	• Metres
8	Distance between junctions	• Metres
9	Segment connected to junction *	• Yes \ No
10	Entrances along segment, within 15m from segment	• Count / 100 metres (All kinds of entrances to buildings, within straight line distance)
11	Entrances along segment, within 30m from segment *	• Count / 100 metres (as previous)
12	Car parking	• Yes \ No
13	Bus stop	• Yes \ No

All the impedances considered were then added to a statistical model for calculating their impact on median bicycle speeds on route segments. To find the most important independent variables and test their significance a multiple regression analysis (OLS) was performed. A number of significant variables (< 1 %) were identified and kept in the model. These variables were the following: being connected to signal junction (or not); number of entrances along route (within 30 metres from street segment); slope; kind of route (pedestrian street or not, two-directional bicycle track or not); horizontal curvature; length of segment; and route surface (cobble stone or not). Finally, the R2 value was calculated to see how much of the measured variation could be explained by the chosen variables. The model showed good fit in terms of estimating median speed levels (adjusted R2 value of 0.53).

2.4 Model II, the Markov model

As opposed to the previous study, Arnesen et al. (2017) used a large amount of GPS data with little information on each road segment to estimate a model for bicycle speed based on horizontal and vertical curvature (see Figure 2 for an example of a logged bicycle trip). The data were collected from 15 individuals from one particular workplace, where the aim during the logging period was to increase the physical activity of the participants. The purpose of the observed bicycle trips ranges from bicycling for leisure, to bicycling to/from work, or bicycling for training. Although the many different types of bicycling and bicyclists are represented within this data set, this particular group of participants cannot be considered a representative sample for all bicycling in Norway, and there is probably a bias towards fast riding bicycling enthusiasts in the data set. In total, 2085 bicycle trips, consisting of approximately 550 000 GPS observations (see Figure 3) were analyzed to construct a model estimating bicycle speed from the geometric curvature of the road.

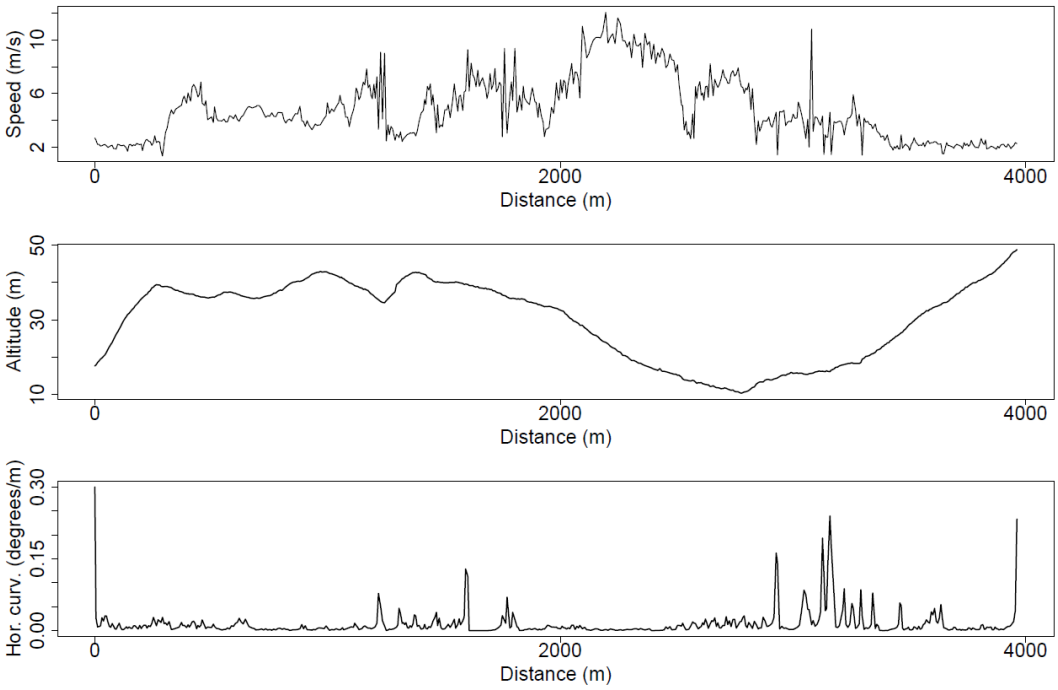

Figure 2. Example of a logged bicycle trip, with the collected covariates.

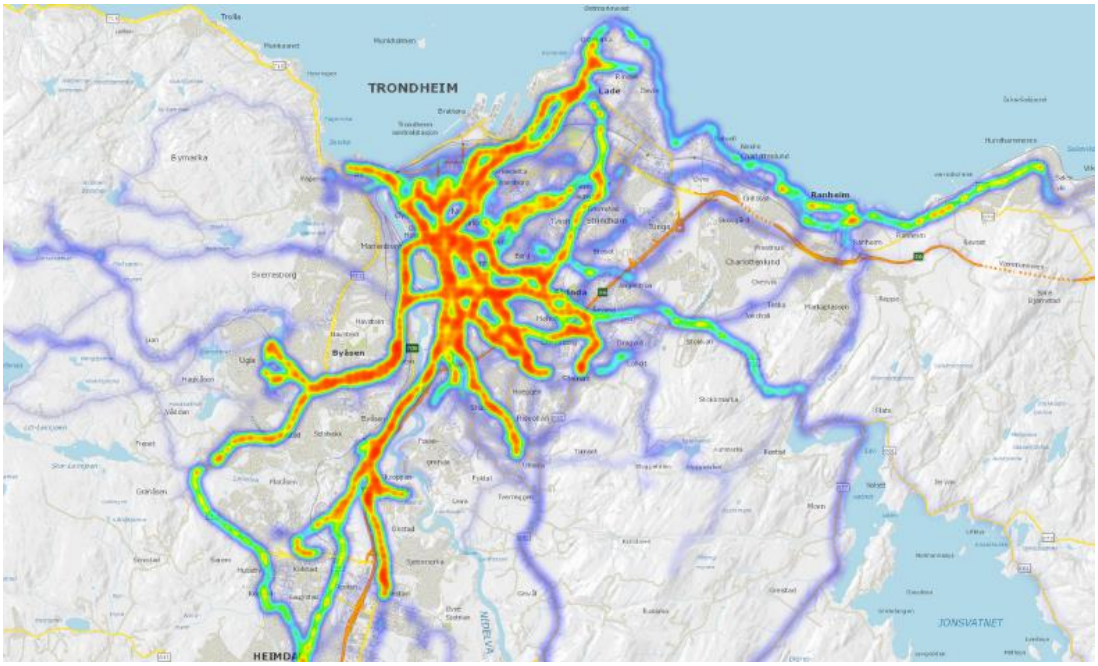

Figure 3. Bicycle GPS-observations examined in Trondheim. The observations are shown as a heatmap, where deeper red represents more observations.

The model takes the speed from previous road segments and the presence of a sharp turn ahead into consideration when estimating the bicycle speed along a predefined route. The following equations denote the horizontal and vertical curvature by h_i and v_i, respectively. First, the authors of the study assume that bicycle speed is dependent on the slope through the regression term

$$r_i = \beta_0 \exp\{\beta_1 v_i I(v_i \geq 0) + (\beta_2 v_i + \beta_3 v_i^2) I(v_i < 0)\}, \quad (1)$$

Where r_i in this framework is the speed a bicyclist will converge to under constant slope and zero horizontal curvature. Secondly, they introduce a Markov dependence in the model. Assuming that the distance between point i and the previous point $i-1$ is defined to be $||w_i||$, they assume the speed at point i to be dependent on the speed in point $i-1$ by

$$v_i = y_{i-1}\alpha_i + (1-\alpha_i) r_i, \text{ and} \quad (2)$$

$$\alpha_i = \exp\{-\omega ||w_i||\}, \quad (3)$$

where $0 < \alpha_i < 1$ acts as a weight between the previous observed speed y_{i-1} and r_i, and where v_i is the speed on a hypothetical road segment with no turnsahead. Moreover, assuming $\omega > 0$, the dependency of the previously observed speed decreases as $\left|\left|w_i\right|\right|$ increases. This intuitively adapts Tobler's first law of geography (Tobler, 1970), as points further apart on the route should be less correlated than points closer to each other.

Finally, the dependency between bicycling speed and horizontal curvature is described by

$$y_i = v_i \exp\{\beta_4 H_i\} + \epsilon_i, \text{ where } \epsilon_i \sim N(0, \sigma^2), \text{ and} \quad (4)$$

$$H_i = h_i + \sum_{\forall j > i : D(i,j) \leq \eta} \frac{h_j}{D(i,j)}, \quad (5)$$

where $D(i,j) = ||w_i|| + ||w_{i+1}|| + \cdots + ||w_j||$, is the total horizontal distance from point i to point j, assuming $j > i$, and where ϵ is assumed to be i.i.d. zero-mean Gaussian noise. Through Equations (4) and (5) an adjustment to the modelled speed without horizontal curvature v_i is introduced, assuming that turns less than η meters ahead influence the speed of the bicyclist ($\eta = 50$). Moreover, it is assumed that this influence is stronger for sharper and closer turns, than for less sharp turns further away.

3. METHOD

The present study proposes a new bicycling speed model resulting from a combination of the ASR and the Markov models. The model is developed and tested based on the data set of Gothenburg GPS traces from Manum et al. (2017). Finally, the speed estimation results of the new model and of the independent models are compared and discussed.

3.1 The new model

To develop a model that unifies both approaches to speed modelling presented in section 2 (ASR and Markov models), and in particular to take advantage of their individual strengths, we propose the following approach.

Using the data set of Manum et al. (2017) we estimate a regression model for bicycle speed with the form

$$y_i = b_0 \exp\{b_1 Entrance_{30m} + b_2 Street_{Pedestrian} + b_3 Street_{DoubleBicycleLane} + b_4 Surface_{NatualStone}\}, \quad (6)$$

including new parameters ($b_1, \ldots, b_4$) estimated for the four covariates - number of entrances on 30 metres, pedestrian street, two-directional bicycle lane, and cobble stone - as these are not included in the model developed by Arnesen et al. (2017). This new model is constructed in this form so that it naturally fits into the regression term in equation 1 from Arnesen et al. (2017).

Simply combining these two expressions define the first term in the joint model, i.e.

$$r_i = \beta_0 \exp\{\beta_1 v_i I(v_i \geq 0) + (\beta_2 v_i + \beta_3 v_i^2) I(v_i < 0) + b_1 Entrance_{30m} + b_2 Street_{Pedestrian} + b_3 Street_{DoubleBicycleLane} + b_4 Surface_{Cobble\ Stone}\}, \quad (7)$$

where we use the estimates $\beta_1, \ldots, \beta_3, b_1, \ldots, b_4$ as before, but where we estimate $\beta_0$from the Gothenburg data (details below). We use Equation (2) and (3) as defined above also in this joint model.

The route data has coded the route end in crossings with light signals. We adopt the speed reduction on such a crossing with that equivalent of a turn by expanding Equation (4) and (5) in the following way:

$$y_i = v_i \exp\{\beta_4 (H_i + \beta_5 B_i)\} + \epsilon_{i,} \text{ where } \epsilon_i \sim N(0, \sigma^2), \quad (8)$$

$$H_i = h_i + \sum_{\forall j > i : D(i,j) \leq \eta} \frac{h_j}{D(i,j)}, \quad (9)$$

$$B_i = I(signal\ crossing\ at\ i) + \sum_{\forall j > i : D(i,j) \leq \eta} \frac{I(signal\ crossing\ at\ j)}{D(i,j)}, \quad (10)$$

where now β_5 is a parameter that explains how much a bicyclist on average must slow down before a crossing. That is, B_i is a covariate increasing as signal crossings approach and β_5 is a parameter that represents the level of speed reductions, which must be estimated from the empirical data. Using the data set's β_0, the base level of bicycle speed, and β_5 is estimated in the following way. The data set consists of several bicyclists riding a few defined routes, and the mean travelling times are calculated for each route. Using the mathematical optimisation function *optim* from the *stats R package*, β_5 and β_0 can be estimated by comparing the calculated travelling time from the model with the observed travelling time from the data with the square-root error between travelling times.

4 RESULTS

4.1 Estimating the new model

The new model is estimated in two steps, as explained above. First, estimating the parameters $b_1, \ldots, b_4$ using the same data as in Manum et al (2017), next, estimating the speed level β_0 and crossing parameter β_5 by comparing calculated travelling time from the model with observed travelling time for all the available routes. All the resulting parameter values for the new joint model are shown in Table 2.

Table 2: Parameter estimates for the joint model.

Parameter	Associated covariate	Value
β_0	Constant speed level	5.79 [m/s]
β_1	Uphill bicycling	-9.04
β_2	Downhill bicycling	5.66
β_3	Downhill bicycling squared	-1.18
β_4	Horizontal curvature	-10.26
b_1	Number of entrances (30 m)	-0.001
b_2	Pedestrian street	-0.16
b_3	Two-directional bicycle lane	0.07
b_4	Natural stone	-0.07
β_5	Crossing	-0.41

4.2 Results from applying the new model in the case of Gothenburg

This section presents the results from applying the new model on the same bicycle routes in Gothenburg as examined by the average speed model. For location of the different routes, see Figure 1. Figures 4a – 4c show a sample of the routes. For each route, the bottom figure shows the horizontal curvature whereas the top figure shows the slope (gray line), the observed median speeds (blue dotted line), and the speeds estimated by the different speed modelling approaches. The circles indicate signal crossings.

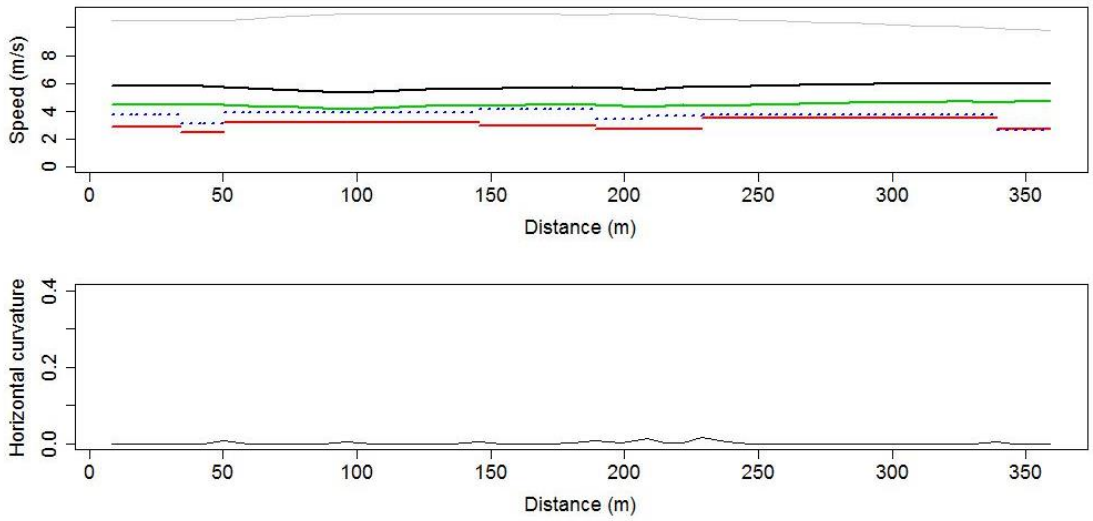

Figure 4a. Route "Kyrkogatan"
(top: slope and speeds, bottom: horizontal curvature)

Legend of top diagram:
Blue dotted line: Median observed speeds
Green line: The new model
Red line: The ASR model
Black line: The Markov model
Gray line: Slope

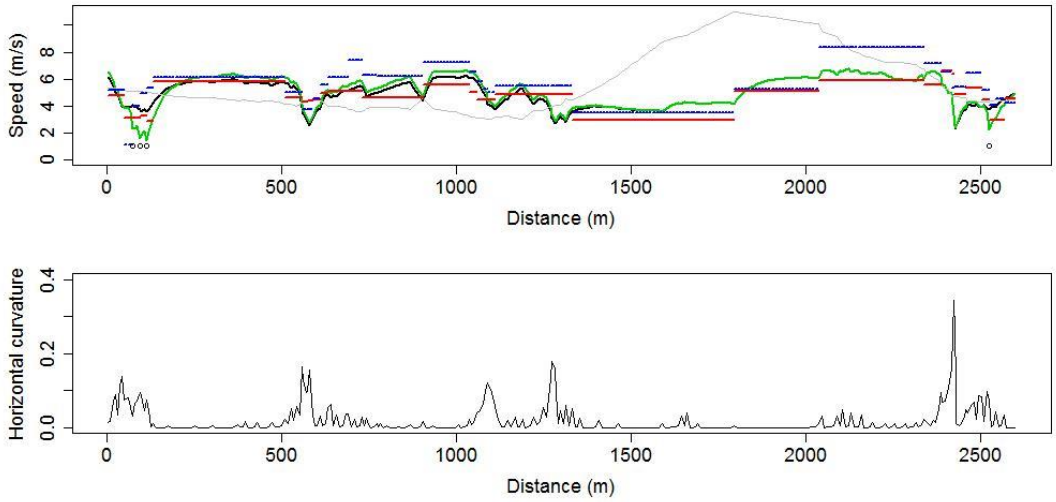

Figure 4b (above). Route "Götaälvbron"

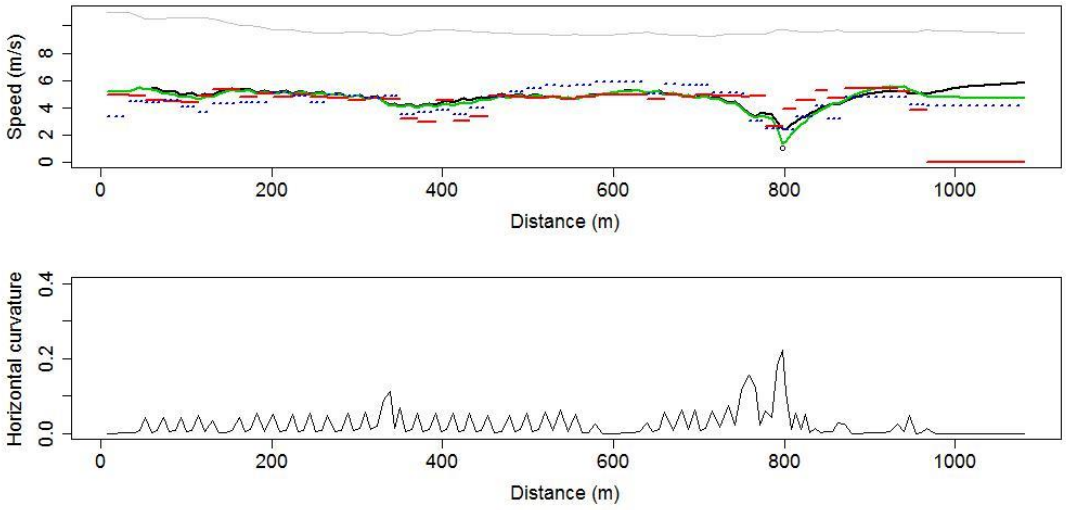

Figure 4c (above). Route " Östra Hamngatan"

Legend of top diagrams:	Blue dotted line:	Median observed speeds
	Green line:	The new model
	Red line:	The ASR model
	Black line:	The Markov model
	Gray line:	Slope
	Circles:	Signal crossings

As we can see from the Figures 4a-4c, the green line represents a more nuanced and realistic speed profile in comparison to the mean speed levels for each segment. In addition, the diversity of speed parameters from the ASR model seem too often to adjust the speed levels to more realistic values compared to the Markov model that just includes geometric dependence. Also, the addition of a signal crossing parameter seems to improve the overall performance, suggesting more refined speed modelling of crossings to be an interesting topic for further research. The models are compared and discussed further in the next section.

4.3 Comparing the models in the cases of particular routes

Taking a closer look at some modelling results of different routes, this section compares the models and highlights particular issues in more detail.

4.3.1 Kyrkogatan

Kyrkogatan is a straight route without any slope. On the one hand, this creates a potential for fast bicycling. On the other hand, the streets are covered with cobblestone and there are many entrances along the route, which reduces bicycling speeds (Manum et al., 2017). At Kyrkogatan, the median speed according to the GPS-data is 16 km/h, which is just below average (17km/h, see section 2.3).

Figure 5. Kyrkogatan (after 200 metres in the direction of figure 4a).

As expected, due to the constant properties of the route, the speed at Kyrkogatan is continuous with small differences between the different street segments (see figure 4a). Comparing the models, we see that the new model estimates speeds similar to the ASR model and is significantly better than the Markov model, since the new model includes environmental characteristics. Looking closely at the Markov model results (black line in the top diagram of Figure 4a), the speeds are significantly faster than the observed speeds, which will likely have two reasons. One is that the speed reduction due to cobble stone is not included in the Markov model; a second is that the Markov model is estimated from the speeds of commuter bicyclists in Trondheim that are faster than the more diverse sample of bicyclists mapped in Gothenburg.

4.3.2 Götaälvbron

This route includes the bridge over the river (Figure 6) and continues in a more traffic segregated environment with few stops and a separate bicycle track on each side of the road. The route has long parts without intersections but also wide horizontal turns and signal crossings. Overall, speed is affected by many variables.

Figure 6. Götaälvbron (after about 2 200 metres in the direction of figure 4b)

Not surprisingly, the GPS-tracks show a relatively high average speed with large local variations along the route (blue dotted line in figure 4B, top). The median observed speed is 21 km/h, significantly faster than the 17km/h average. Looking at the other speed estimates (Figure 4b), the results of the new model are generally in line with observed median speeds. Looking more closely, for instance at about 80, 600 and 2400 meters along the route (Figure 4b), there are some exceptions. Here, similarly to the case of Kyrkogatan, the new model seems to overestimate speed reduction due to horizontal curvature. The differences between the Markov model and the new model are small, the reason being that slope and horizontal curvature together with signal crossings strongly affect the speed on this route and these variables are already included in the Markov model. The new model differs from the observed speeds also on the first part of the route. This is likely due to the presence of signal crossings for which waiting times (i.e. stop-times) are not included in the GPS-speed data (see Manum et al. (2017) for more on this). Comparing the three models, the new model and the Markov model provide the most realistic speed profiles, see for instance how the speed gradually increases downhill from the top of the bridge at about 1800 meters along the route (Figure 4b).

4.3.3 Östra Hamngatan

Östra Hamngatan is a central street in Gothenburg with bicyclists in a mixed traffic environment (Figure 7) including many pedestrians along as well as crossing the street. The speed limit is 30 km/h.

Figure 7. Östra Hamngatan (after 600 metres in the direction of figure 4c)

The median speed of observed bicyclists is as low as 14 km/h, which is the lowest of the routes here compared (see Figure 1 and Figure 4a-c). The low speed is likely due to the urban environment of Östra Hamngatan highly reducing speeds of bicycling. For the same reason, since “urban context” is included in the ASR-model by the “number of entrances variable” (variable no. 11 in Table 1), the ASR-model here generally performs better than in Kungsgatan and Götaälvsbron. Comparing the three models, the new model seems to best match the observed bicycle speed, but here again it slightly overestimates the effect of horizontal curvature in slowing down bicycle speeds.

5. DISCUSSION

5.1 Average speeds with the new joint model

Even though the Gothenburg data set was originally sampled as high-resolution GPS traces, sampling error near intersections resulted in only aggregated median speed levels for each segment. Therefore, it is not straight forward to quantitatively compare this with our new model, which predicts speed on segment vertices (or in general every defined point on a route), i.e. at a higher resolution than the segment level. As a check, however, we compare the ASM model, the (high-resolution) joint model, and a version of our joint model where the predicted speeds are aggregated to the segment level, to the ground truth segment level data, see table 3.

Table 3: Sum of square error when comparing the ASM model estimates, the estimates from the new joint model, and a mean on each segment version of the new joint model to the calculated segment mean speeds from the Gothenburg study.

Route	ASM model	Joint model	Mean joint model
Gota Alvbron 1	490	497	432
Gota Alvbron 2	271	608	535
Linholmsallen 1	156	61	57
Linholmsallen 2	53	38	30
Ostre Hamngatan 1	138	58	56
Ostre Hamngatan 2	80	69	65
Kyrkogatan 1	20	33	32
Kyrkogatan 2	6	27	26
Vestre Hamngatan 1	72	39	38
Vestre Hamngatan 2	16	37	36
Nya Allen 1	25	79	47
Nya Allen 2	147	172	155
Hagaparken 1	57	90	90
Hagaparken 2	24	66	65
SUM	1555	1874	1663

As we can see, the increase in error with new the joint model when compared to the segment means is about 17 %. This result seems reasonable, given that 1) the Gothenburg model is specifically designed to fit this dataset, and 2) the joint model inherits the segment variability form the Trondheim model in its estimates, and would naturally by punished when compared to mean calculations. To try to compensate for point 2) we have added the estimation result when the estimated speeds for the joint model are aggregated to mean speeds on each road segment, giving only a 6% increase in error compared to the Gothenburg model. All in all, we can conclude that the new model is comparable to the median speed observations for each segment, but the detail and realism level of the speed variability along the routes is increased.

5.2 Variables not included in the new model

The environmental covariates included in the new joint model are route geometry, intersection impedances, type of bicycle-route, type of surface, and density of entrances along route. This implies that the model does not include the following variables that are relevant for bicycling speeds: weather and climate conditions, in particular winter with snow, but also local wind conditions; maintenance/standard of routes; impedances at intersections in greater detail, including variation of stop times at signal crossings, and variations of intersection-layouts and kind of streets; and type of bicycle and bicyclist, including e-bikes as separate category..

In relation to speed variations due to bicyclist or kind of bicycle, the new model works as a kind of average speed model. The model predicts speed variation along a bicycle route but not how those speeds depend on the bicycle and the bicyclist. For studying route choice or accessibility on an aggregated level, this is not a problem as long as the populations of bicyclists and bicycles in the sample examined correspond with the samples applied for calibrating the model. In other cases, where one is studying specific bicyclists or bicycles, these differ systematically from the average of the sample applied for calibrating the model.

5.3 Bias of sample of bicyclists

The new joint model is partly based on the Markov-model where the sample of bicyclists is not representative of an average bicyclist, but instead they are mainly fast riding bicycling enthusiasts. The implication is that the speed estimated in the Markov-model is higher than for the average bicyclist. In the new joint model, this is to some degree compensated for when using the speed data from Gothenburg to re-estimate this speed level. However, since the Gothenburg data set provides no GPS tracking of speed variation along segments, the parameters associated to geometric curvatures, see Equations (7)-(10), are still based exclusively on the Markov-model and not re-estimated. How well these parameters translate to the bicyclists in Gothenburg is therefore an unanswered question, requiring more GPS-data for being examined. For instance, the effect of reduced speed due to an uphill climb might be larger for the urban bicyclist in Gothenburg, compared to the fit bicycling enthusiasts represented in the GPS data set of the Markov-model. As previously mentioned, it can also be assumed that a faster bicyclist reduces speed more at sharp curves than a slow bicyclist does. To address this bias, the new joint model should be re-estimated using a new set of detailed speed data mapped from GPS.

5.4 Further research

As highlighted in previous the paragraph, further development of the proposed model would benefit from new data collection. In this data collection, one should create a large GPS based data set ensuring that the right level of detail, with respect to number of covariates, becomes available. With such a data set, the

proposed model can be estimated more carefully, obtaining higher precision and an expanded range of parameters.

Preferably, the data set on bicycling speeds should be subdivided into two sets, one for calibrating the model and one for testing the model. The current dataset, which is the GPS-mapped bicycling speeds along a few routes in Gothenburg, does not contain sufficient data for doing this. Therefore, both the Gothenburg model and the new joint model are tested on within sample data, possibly resulting in overfitting the model estimates, compared to a more realistic case of using the models to predict speeds on new routes, for instance to evaluate planned routes.

A refined model should preferably include input options for specifying different kinds of bicycle and bicyclist, either for modelling speeds for particular groups of bicyclist, or more comprehensively for being able to model average speeds of different bicyclist-populations. An example of the latter is to calculate bicycle flow of scenarios with different shares of electric-bicycles, where speed profiles are very different from traditional bicycles, which is a relevant issue in current planning for bicycling.

Another point requiring further research is the speed reduction at crossings. Here we have adopted a bicyclist behaviour equivalent to a sharp turn to model the speed reduction around crossings, estimating a single parameter representing the level of speed reduction. However, there is no evidence that a bicyclist has the same speed reduction before, and acceleration strategy after, a crossing, compared to when doing a sharp turn. Especially, one should consider different types of crossings, where there can be different types of crossing manoeuvres (i.e. straight ahead crossing, left turn, right turn). In addition, one should consider waiting times at crossings. The proposed model looks at average speeds at every point of a route, and complete stopping at crossings is not an option. Therefore, one should estimate the waiting time of stopping completely at crossings, from this one would calculate the total travel times, then, finally, the average speed for the route segments.

6. CONCLUSION

A new proposed bicycling speed model, considering route geometry and a selection of variables representing quality and context of routes, provides detailed and realistic estimations of speed variation along routes. The model is an inspiring basis for further research along several tracks. For developing the model, larger empirical studies of bicycle speeds should be carried out and more variables relevant for bicycling speeds should be examined and included. Regarding application of the model, its potential for modelling accessibility by travel time should be explored, very likely leading to improved traffic models dealing with travel modes, route choice and aggregated bicycle flows. By including variables of explicit route layout as well as context of routes, the model also has potential to become a tool shared between traffic planners, urban planners and architects, and in that way inspire for stronger collaboration and mutual understanding of how urban form influences bicycle traffic.

REFERENCES

Arnesen, P., Malmin, O. K., and Dahl, E. (2017) A forward Markov model for predicting bicycle speed, Under review at *Transport Science*, second revision.

Arnesen, P. and Hjelkrem, O. A. (2018) An estimator for traffic breakdown probability based on classification of transitional breakdown events, *Transportation Science* **52** (3) 593–602.

Beheshtitabar, E., Rios, S., Konig-Hollerwoger, D., and Svaty, Z. (2014) Route Choice Modelling for Bicycle Trips*, International Journal for Traffic and Transport Engineering* **4** (2) 194–209.

Bernardi, S. and Rupi, F. (2015) An analysis of bicycle travel speed and disturbances on off-street and on-street facilities, *Transportation Research Procedia* **5** 82–94.

El-Geneidy, A. M., Krizek, K. J., and Iacono, M. (2007) Predicting bicycle travel speeds along different facilities using GPS data: a proof of concept model, *Proceedings of the 86th Annual Meeting of the Transportation Research Board*, paper #07-2971.

Figliozzi, M., Wheeler, N., and Monsere, C. (2013) Methodology for estimating bicyclist acceleration and speed distributions at intersections, *Transportation Research Record: Journal of the Transportation Research Board* **2387** 66–75.

Flügel, S., Hulleberg, N., Fyhri, A., Weber, C., and Ævarsson, G. (2018) Empirical speed models for cycling in the Oslo road network, *Transportation*, 1–25. (paper accepted, not yet published)

Hassan, Y. and Sarhan, M. (2011). Modeling Operating Speed: Synthesis Report, *Transportation Research E-Circular*, E-C151.

Jiang, R., Hu, M.-B., Wu, Q.-S., and Song, W.-G. (2016) Traffic Dynamics of Bicycle Flow: Experiment and Modeling, *Transportation Science* **51** (3) 998-1008.

Manum, B., Nordstrom, T., Gil, J., Nilson, L., and Marcus, L. (2017) Modelling bikeability; Space syntax based measure applied in examining speeds and flows of bicycling in Gothenburg, *Proceedings of the 11th Space Syntax Symposium*, paper #89.

Miljødirektoratet (2002) *Samordning av arealbruk og transport, verktøy for planlegging. Utprøving av ATP-modellen i fire fylker, erfaringer og eksempler*, Miljødirektoratet, Oslo.

Ortuzar, J. d. D. and Willumsen, L. G. (2002) *Modelling transport*, John Wiley & Sons, Sussex.

Parkin, J. and Rotheram, J. (2010) Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal, *Transport Policy* **17** (5) 335–341.

Russo, F., Rindone, C., and Panuccio, P. (2016) European plans for the smart city: from theories and rules to logistics test case, *European Planning Studies* **24** (9) 1709–1726.

Ryeng, E. O., Haugen, T., Grønlund, H., and Overå, S. B. (2016) Evaluating bluetooth and wi-fi sensors as a tool for collecting bicycle speed at varying gradients, *Transportation Research Procedia* **14** 2289–2296.

Strauss, J. and Miranda-Moreno, L. F. (2017) Speed, travel time and delay for intersections and road segments in the Montreal network using cyclist Smartphone GPS data, *Transportation research part D: transport and environment* **57** 155–171.

Rietveld, P. (2000) The accessibility of railway stations: the role of the bicycle in The Netherlands *Transport and Environment* **5** (1) 71-75.

Scheiner, J. (2010) Interrelations between travel mode choice and trip distance trends in Germany 1976-2003, *Journal of Transport Geography* **18** (1) 75-84.

Tobler, W. (1970) A computer movie simulating urban growth in the Detroit region, *Economic Geography* **46** (Supplement) 234-240.