The 7th Symposium of the European Association for Research in Transportation (hEART 2018)

Modelling cyclist cruising speed heterogeneity and corresponding delays on bicycle tracks

Mads Paulsen[a*], Otto Anker Nielsen[a], Thomas Kjær Rasmussen[a]

[a] DTU Management Engineering, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark

Abstract

This study proposes an approach to model cruising speed heterogeneity among cyclists. The model let fast moving cyclists be slowed down by slower moving cyclists when there are no free lanes left in which to perform an overtaking. Initial tests on a toy network and Weibull-distributed desired cruising speeds show that the model behaves intuitively when the traffic flow is increased, even though large-scale experiments are still to be conducted.

Keywords: Bicycle Modelling; Speed Heterogeneity; Mesoscopic Simulation.

1. Introduction

The main purpose of transport models are to facilitate appropriate decision making in project appraisal situations. As such they should model all relevant modes of transport reasonably detailed so that all sensible effects of suggested infrastructure changes are included. Commonly, only car traffic and public transport are considered in such models, but for countries like Denmark and the Netherlands with large shares of bicycle trips there is a need to also include this mode in appraisals.

For a number of reasons bicycle traffic differs severely from car traffic, discouraging the use of macroscopic approaches traditionally used for car traffic. Firstly, cars can arguably be assumed to follow the same speed on a given link as all of them would desire to go by the maximum allowed speed, alternatively by the highest possible speed given the traffic circumstances. On the contrary, the desired cruising speed of an individual cyclist is very much dependent on the equipment (e.g., cargo bike, road bike, city cruiser) and the abilities of that individual (e.g. age, gender, physique). As such it seems necessary to assume speed heterogeneity among cyclists, such that each cyclist has its own cruising speed and that these may differ considerably between individuals. Such speed heterogeneity cannot be included using a macroscopic approach.

Secondly, due to the speed heterogeneity, overtaking is much more common for bicycles than for cars. This also means that fast cyclists will be delayed if relatively slow cyclists are currently occupying the left-most part of the bicycle track by overtaking even slower cyclists. This means that delays will occur more often, and that the actual travel time is very much dependent on *who* is on the network and not solely by *how many* are on the network.

* Corresponding author: Tel.: +45 45 25 65 98.
E-mail address: madsp@dtu.dk

Thirdly, using a macroscopic approach would fully ignore travel time variability, whereas such can be extracted directly from a model that takes on a mesoscopic approach.

Modelling bicycle traffic using a mesoscopic approach has been done for over a decade, with the vast majority of models based on extensions of Cellular Automata (CA), originally proposed by Nagel and Schreckenberg (1992), e.g. (Gould and Karner, 2009; Jiang et al., 2017; Jin et al., 2015; Liu et al., 2008; Luo et al., 2015; Ren et al., 2016; Shan et al., 2015; Vasic and Ruskin, 2012; Xue et al., 2017; Zhao et al., 2013). The models touch upon speed heterogeneity by having separate maximum speeds for traditional bicycles and e-bicycles or bicycles and cars, but none of the studies model separate speeds for each individual – likely due to the discrete nature of CA-models.

Shen et al. (2011) do propose a detailed car-following model with individual desired speeds. The model framework, however, does not allow overtaking and is tested in a closed-loop setting.

This study proposes a new and supposedly large-scale applicable mesoscopic model for dynamic traffic assignment of bicycle traffic that takes speed heterogeneity among individuals into account while implicitly dealing with overtaking.

2. Methodology

The proposed model first assigns a desired cruising speed to every cyclist in the population. Secondly every link of the network is split into a number of pseudo-lanes based on the width of the link. When a cyclist enters the link, the cyclist will pick the right-most pseudo-lane where the dynamic maximum speed is greater than or equal to his/her desired cruising speed. If no pseudo-lane with such dynamic maximum speed exists, the cyclist will choose the link furthest to the left.

When a cyclist with a desired cruising speed lower than the dynamic maximum speed enters a pseudo-lane, its dynamic maximum speed is lowered to the cruising speed of that cyclist. The dynamic maximum speed is automatically updated in each time step, so that it corresponds to reaching the end of the link simultaneously with the current speed setter of the pseudo-lane – if the lane is empty the dynamic maximum speed will be reset to infinity.

An explicit algorithm of the proposed model is found in Algorithm 1.

Algorithm 1.		
1.	For each cyclist in the population, $n \in \mathcal{N}$, draw a desired cruising speed from a distribution, $\mathcal{D}^0$, $v_n^0 \sim \mathcal{D}^0, \quad \forall n \in \mathcal{N}.$	
2.	Divide each link, $l \in \mathcal{L}$, of the network into Ψ_l pseudo-lanes from right to left, $\psi_l^{(1)},\ \psi_l^{(2)}, \dots, \psi_l^{(\Psi_l)}$, based on the width of the link.	
3.	Initialise the dynamic maximum speed of all pseudo-lanes of all links to infinity, $v^m_{\psi_l^{(i)}} = \infty, \quad \forall l \in \mathcal{L},\ \forall i \in\ 1, 2, \dots, \Psi_l.$	
4.	Every time a cyclist enters a link, select the right-most pseudo-lane that allows travelling by his/her cruising speed (if no such pseudo-lane exists, choose the left-most link) and adjust the cyclist speed and pseudo-lane speed accordingly.	> $i \leftarrow 1$ > **while** $v_n^0 > v^m_{\psi_l^{(i)}}$ & $i < \Psi_l$ **do** $i \leftarrow i + 1$ > **if** $v_n^0 < v^m_{\psi_l^{(i)}}$ **then do** $v^m_{\psi_l^{(i)}} \leftarrow v_n^0$

		> $v_n \leftarrow v^m_{\psi_l^{(i)}}$
5.	After each time step of size τ, update the dynamic maximum speed of each pseudo-lane of each link.	> $D \leftarrow \frac{L_l}{v^m_{\psi_l^{(i)}}} - \tau$ > **if** $D > 0$ **then do** $v^m_{\psi_l^{(i)}} \leftarrow \frac{L_l}{D}$ > **else do** $v^m_{\psi_l^{(i)}} \leftarrow \infty$

Notice that besides the initial assignment of desired cruising speeds (step 2) the algorithm is fully deterministic. It is suggested that the number of pseudo-lanes of a link with width W_l, is given as $\Psi_l = 1 + \left\lfloor \frac{W_l - 0.40}{1.25} \right\rfloor$, where 0.40m and 1.25m are parameters derived from Buch and Greibe (2014).

3. Case Study

Analysis of 490,062 GPS traces of 146 cyclists in Copenhagen (Halldórsdóttir et al., 2014) shows that if the 95th percentile speed of every individual is used as an indicator for desired cruising speed, then the corresponding distribution has a high resemblance to a Weibull distribution, see Table 1.

Table 1. Distribution of 95%-percentile speeds (within each cyclist) of 146 cyclist in Copenhagen and the corresponding best fit Weibull distribution.

[m/s]	Mean	Standard Deviation	Mode	5th Percentile	Median	95th Percentile
Data	*5.99*	*1.24*	*6.4 - 6.6*	*3.75*	*6.07*	*7.80*
Weibull(*6.48*, *5.09*)	*5.96*	*1.34*	*6.21*	*3.62*	*6.03*	*8.04*

In this present analysis a toy network (Figure 1) consisting of three consecutive links each with a length of 100m has been used for initial tests. The first two links have three pseudo-lanes, whereas the last has two. All tests simulate one hour of traffic with cyclists entering from the left by a homogenous Poisson point process with mean arrival rate equal to the stated flow.

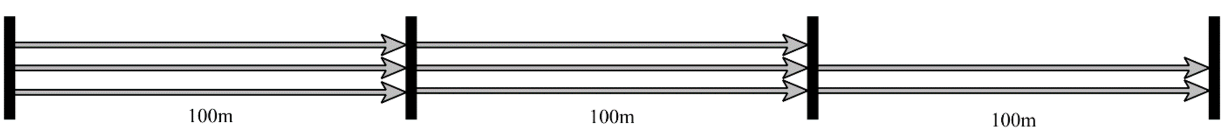

Figure 1. Toy network used for initial tests with grey arrows representing pseudo-lanes.

These small-scale experiments show that the proportion of cyclist that are slowed down on at least one of the three links increases noticeably with an increase in flow, see Figure 2. The opposite effect is seen on space mean speed (Figure 3), although to a less degree than the effect on the minimum speeds of cyclists, that are clearly seen (Figure 4) to be drastically shifted to the left as the arrival rate of the Poisson process is increased.

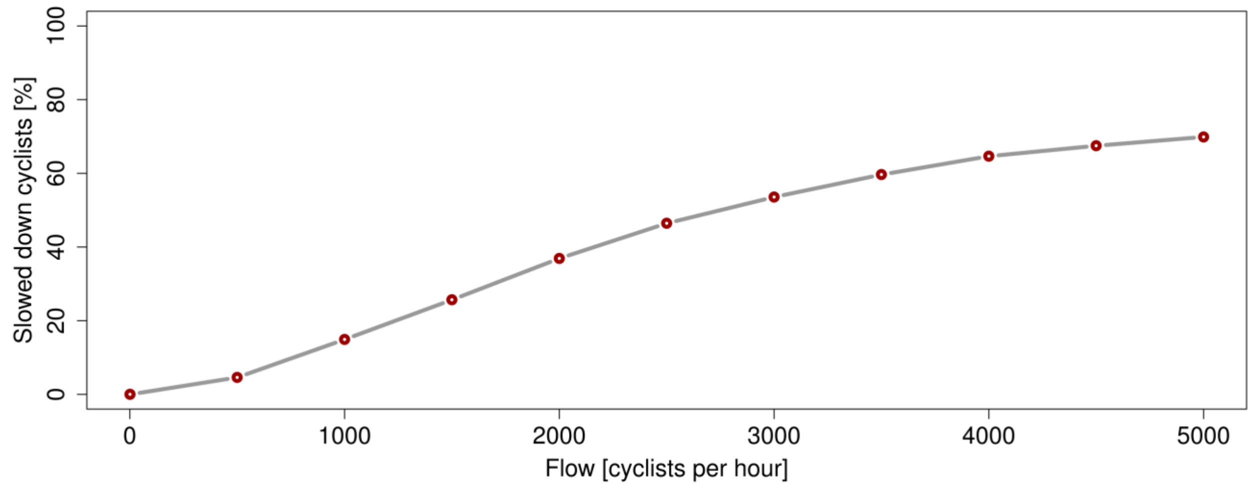

Figure 2. Proportion of cyclists that are slowed down as a function of traffic flow.

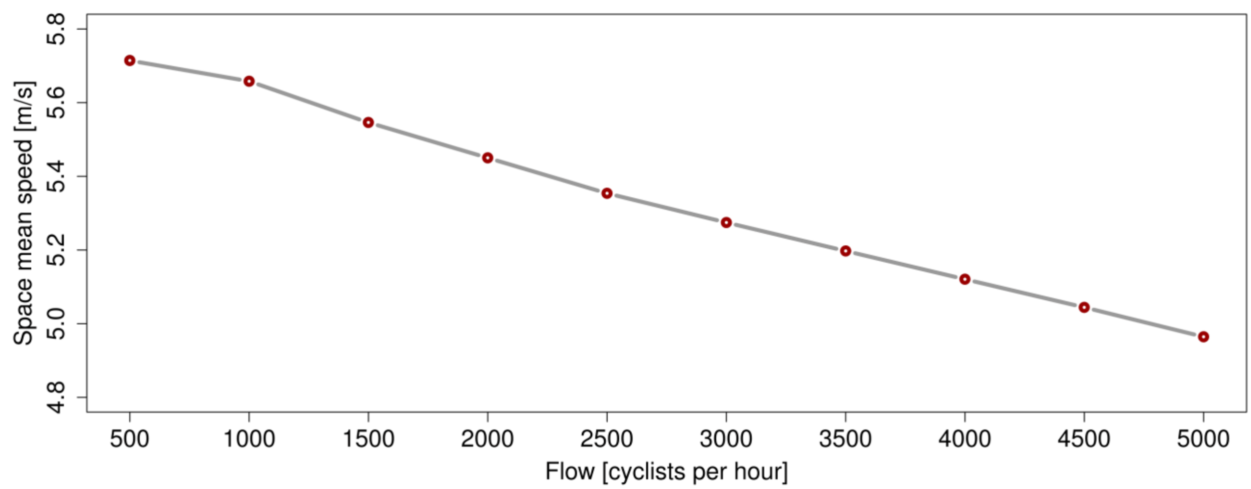

Figure 3. Space mean speed of cyclists as a function of traffic flow.

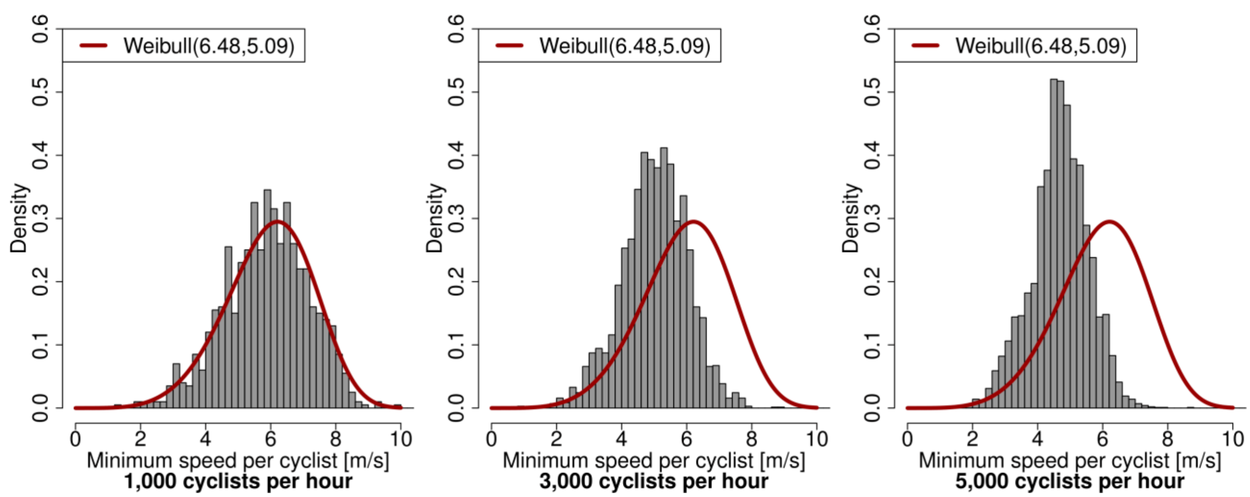

Figure 4. Minimum speed across the three links for each cyclist using 1,000, 3,000, and 5,000 cyclists per hour, respectively, depicted together with the Weibull distribution found to fit the observed cruising speeds the best.

Overall, the small-scale experiments behave intuitively. That being said, various aspects of the proposed model still needs to be examined. For instance the model will most likely be sensitive to how finely the network is digitalised as cyclists' speeds are fully determined when entering the link but lasts for the entirety of the link. Furthermore, the model does not yet include any sort of storage capacity restrictions. Extending the model to consistently obey such simple spatial limitations of the infrastructure would be of great relevance.

Application-wise, future work includes a large-scale implementation of the model, namely for all cyclists in the Greater Copenhagen area, and comparing the modelled travel speeds with observed data from selected streets of Copenhagen.

References

Buch, T.S., Greibe, P., 2015. Analysis of Bicycle Traffic on One-Way Bicycle Tracks of Different Width, in: European Transport Conference 2015. Association for European Transport (AET), Frankfurt, Germany.

Gould, G., Karner, A., 2009. Modeling bicycle facility operation: Cellular automaton approach. Transp. Res. Rec. https://doi.org/10.3141/2140-17

Halldórsdóttir, K., Rieser-Schüssler, N., Axhausen, K.W., Nielsen, O.A., Prato, C.G., 2014. Efficiency of choice set generation methods for bicycle routes. Eur. J. Transp. Infrastruct. Res. EJTIR Issue 14, 332–348.

Jiang, R., Hu, M.-B., Wu, Q.-S., Song, W.-G., 2017. Traffic Dynamics of Bicycle Flow: Experiment and Modeling. Transp. Sci. 51, 998–1008. https://doi.org/10.1287/trsc.2016.0690

Jin, S., Qu, X., Xu, C., Ma, D., Wang, D., 2015. An improved multi-value cellular automata model for heterogeneous bicycle traffic flow. Phys. Lett. A 379, 2409–2416. https://doi.org/10.1016/j.physleta.2015.07.031

Liu, H., Wang, H., Feng, Y., 2008. Bicycle flow modeling based on cellular automata, in: 2008 27th Chinese Control Conference. IEEE, pp. 527–531. https://doi.org/10.1109/CHICC.2008.4605463

Luo, Y., Jia, B., Liu, J., Lam, W.H.K., Li, X., Gao, Z., 2015. Modeling the interactions between car and bicycle in heterogeneous traffic. J. Adv. Transp. 49, 29–47. https://doi.org/10.1002/atr.1257

Nagel, K., Schreckenberg, M., 1992. A cellular automaton model for freeway traffic. J. Phys. I, EDP Sci. 2, 2221–2229. https://doi.org/10.1051/jp1:1992277

Ren, G., Jiang, H., Chen, J., Huang, Z., Lu, L., 2016. Heterogeneous cellular automata model for straight-through bicycle traffic at signalized intersection. Phys. A Stat. Mech. its Appl. 451, 70–83. https://doi.org/10.1016/j.physa.2015.12.159

Shan, X., Li, Z., Chen, X., Ye, J., 2015. A Modified Cellular Automaton Approach for Mixed Bicycle Traffic Flow Modeling. Discret. Dyn. Nat. Soc. 2015, 1–11. https://doi.org/10.1155/2015/213204

Shen, F., Wang, H., Liu, H., 2011. A Mesoscopic Model for Bicycle Flow, in: Proceedings of the 30th Chinese Control Conference. Yantai, China, pp. 5574–5577.

Vasic, J., Ruskin, H.J., 2012. Cellular automata simulation of traffic including cars and bicycles. Physica A 391, 2720–2729. https://doi.org/10.1016/j.physa.2011.12.018

Xue, S., Jia, B., Jiang, R., Li, X., Shan, J., 2017. An improved Burgers cellular automaton model for bicycle flow. Phys. A Stat. Mech. its Appl. 487, 164–177. https://doi.org/10.1016/j.physa.2017.05.036

Zhao, D., Wang, W., Li, C., Li, Z., Fu, P., Hu, X., 2013. Modeling of Passing Events in Mixed Bicycle Traffic with Cellular Automata. Transp. Res. Rec. https://doi.org/10.3141/2387-04