Modelling Cyclist Delay at Intersections from GNSS Trajectories: Underlying Factors and Behavioural Characteristics

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Short summary

Cyclist delays at intersections strongly affect perceived trip quality and network performance through interruptions, i.e. slowing, stopping, negotiating conflicts, and re-accelerating. We aim to measure these delays consistently through GNSS trajectories by taking into account the cruising conditions of each situation and analysing factors affecting them. Steady-state cruising segments are identified, and a mixed-effects model predicts cyclist-specific cruising speeds based on infrastructure, slope, environment, and rider heterogeneity. Intersection delays are then defined as the ratio of observed crossing time to this personalised cruising-time baseline, with crossing distance extracted through a consistent geometric method. Results of a mixed-effects delay ratio model show that traffic signals, left turns, and peak periods are the dominant sources of delay, whereas right turns and off-peak times reduce them. These findings point to clear intervention priorities: reducing signal-related waiting through improved phase coordination, simplifying left-turn movements, and minimising conflict points through improved intersection layouts.
Keywords: Cyclist delay; Intersection performance; GNSS trajectories; Cruising speed; Urban cycling behaviour; Traffic signal impact

1 Introduction

Cyclist delay at urban intersections is a key yet understudied component of cycling performance and perceived trip quality. While substantial research has measured cycling speeds at the link level and related them to infrastructure characteristics, comparatively fewer studies have isolated how delay emerges at intersections, where slow-down, waiting, conflict negotiation, manoeuvring, and re-acceleration jointly influence travel time and comfort. As cities seek to expand bicycle mode share and deliver low-stress networks, clarifying the magnitude and drivers of intersection delay is essential for evaluating network performance and guiding design and operations.

For motorised traffic, a delay can be inferred by comparing observed travel times with that of the maximum allowed speed, whereas for cycling, it remains a persistent challenge to determine the baseline against which to measure a "delay". Although cycling speed is widely reported, the literature has long struggled to define and disentangle cruising speed from average link speeds contaminated by stops and accelerations. Prior work has relied on heterogeneous proxies (e.g., percentile speeds, free-flow conditions, context-specific thresholds), leading to conceptual and empirical inconsistency (Argyros et al., 2024; Clarry et al., 2019; Flügel et al., 2019; Paulsen et al., 2019; Bigazzi & Lindsey, 2019; Pérez Castro et al., 2025). Recent contributions advance a behaviourally grounded definition: cruising speed as an equilibrium observable in trajectories as sustained, stable-speed segments under fixed local conditions (Berjisian & Bigazzi, 2025). Empirical evidence shows that this equilibrium might vary systematically with infrastructure type, motor-traffic volumes, gradient, and trip purpose (Strauss & Miranda-Moreno, 2017; Argyros et al., 2024; Clarry et al., 2019), reinforcing the need for a segment-level, context-aware definition. Yet many edge-speed models still allow intersection effects to propagate into link estimates (e.g., via link length or control variables), even after stops are filtered (Argyros et al., 2024; Rupi et al., 2020; Maurer et al., 2025).

Intersection delay has likewise been operationalised inconsistently. Fixed buffers (often 20 to 40 m) are commonly used to contrast in-buffer speeds with upstream speeds (Strauss & Miranda-Moreno, 2017; Maurer et al., 2025), but the spatial influence of intersection dynamics might extend beyond such windows. Other approaches isolate waiting time (e.g., speeds below 1 m/s) without capturing the full slow-down–stop–turn–accelerate sequence (Poliziani et al., 2022). A coherent measurement

of cyclist delay, therefore, requires (i) a behaviourally sound cruising baseline and (ii) a consistent and geometry-adaptive representation of the intersection crossing.
To do this, we develop a reproducible, data-driven framework to measure and model cyclist delay at intersections using large-scale GNSS trajectories in Copenhagen. Delay is defined as the excess time relative to cyclist-specific cruising conditions and is linked to intersection geometry, signal control, infrastructure attributes, and temporal context. Our scope combines cruising-speed estimation with systematic extraction of intersection crossings and modelling of normalised delay. Together, these elements enable systematic comparisons across intersections and provide empirical evidence to inform design strategies and control policies aimed at reducing delays.
Overall, the study contributes in four ways: (i) it applies a behaviourally grounded approach to cruising-speed estimation that minimises contamination from intersection influences; (ii) it introduces a consistent geometric method to identify entry, exit, and crossing distance for both straight and turning movements; (iii) it defines intersection delay through a cyclist-normalised travel-time ratio, improving comparability across users, locations, and turning manoeuvres; and (iv) it integrates OSM geometry, intersection attributes, and temporal factors into a unified delay model, quantifying how design and operational characteristics influence cyclist delay.

2 Method

We implement a three-stage workflow: (i) estimate cyclist-specific cruising speeds at the edge-level; (ii) compute intersection delay as the relative deviation from those cruising conditions, and (iii) model its determinants.

Data and Trajectory Pre-Processing

We use pre-processed, map-matched GNSS trajectories, as in Argyros et al. (2024). Each trip k is an ordered sequence of time-stamped positions aligned to network link l. Observed link travel time is:

$$TT_{k,l}^{\text{obs}} = t_{\text{end}} - t_{\text{start}}. \tag{1}$$

To stabilise the identification of steady-state riding, we smooth speed and acceleration time series using Gaussian smoothing (15 s window, $\sigma = 10$ s), following Lißner & Huber (2021). Similar to binning/segmentation strategy in Bigazzi & Lindsey (2019), a point is labelled as "cruising" if its smoothed acceleration lies within $\pm 0.05\,\text{m/s}^2$ and its smoothed speed exceeds 1.38 m/s. To avoid contamination from intersection behaviour (including subtle cautionary decelerations), we exclude all observations within a radius r around each intersection. The radius is set according to the highest-order road category (40 m for primary/secondary; 30 m for tertiary; 20 m for residential or non-motorised links), altering the fixed radius approach in Maurer et al. (2025); Strauss & Miranda-Moreno (2017).

Cruising Speed Estimation

Let $S_{k,l}$ denote the observed cruising speed on link l during trip k. We estimate a mixed-effects model:

$$\ln(S_{k,l}) = \beta_0 + X_l\beta_l + X_k\beta_k + u_{\text{user}(k)} + \varepsilon_{k,l}, \tag{2}$$

where X_l contains link-level characteristics (e.g., infrastructure typology, segment length, land use, elevation) and X_k includes trip-level attributes (e.g., weather, time-of-day). A cyclist-specific random intercept $u_{\text{user}(k)}$ captures persistent heterogeneity in riding behaviour. Predicted cruising speed can then be found as

$$\hat{S}_{k,l} = \exp\Big(\hat{\beta}_0 + X_l\hat{\beta}_l + X_k\hat{\beta}_k + \hat{u}_{\text{user}(k)}\Big), \tag{3}$$

and denoting link length by L_l, uninterrupted (cruising) travel time on link l becomes

$$\widehat{TT}_{k,l}^{\text{cr}} = \frac{L_l}{\hat{S}_{k,l}}. \tag{4}$$

Intersection Crossing Extraction and Distance

For each intersection i, we apply concentric buffers of radii r and $2r$. We retain only trajectories with ≥ 1 points in $2r$, ≥ 1 in r, and ≥ 1 again in $2r$, ensuring complete and consistent crossings.

Entry and exit times are linearly interpolated between the last point outside r and the first point inside (and vice versa on exit). The geometric crossing distance L_i is then computed using the interpolated entry and exit points: if the extensions of the entry and exit segments intersect inside the inner buffer, we use the resulting polyline; otherwise, we approximate the path by the straight-line chord between the two interpolated points. Distances were validated against those obtained by summing distances between all GNSS points inside the buffer, with only small differences observed.

Delay Definition

Intersection delay ($\mathrm{DR}_{k,i}$) is expressed as a travel-time ratio that normalises for cyclist- and segment-specific cruising conditions:

$$\mathrm{DR}_{k,i} = \frac{TT^{\mathrm{obs}}_{k,i}}{\widehat{TT}^{\mathrm{cr}}_{k,i}}. \tag{5}$$

Values above one indicate slower-than-cruising movement (e.g., signal control, conflicting flows, yielding), while values below one may reflect tactical accelerations.
The cruising reference for the crossing is the mean of the predicted cruising speeds on the entry and exit links,

$$\hat{S}^{\mathrm{cr}}_{k,i} = \frac{\hat{S}_{k,l_{\mathrm{entry}}} + \hat{S}_{k,l_{\mathrm{exit}}}}{2}, \tag{6}$$

yielding

$$\widehat{TT}^{\mathrm{cr}}_{k,i} = \frac{L_i}{\hat{S}^{\mathrm{cr}}_{k,i}}. \tag{7}$$

Ideally, a distance-weighted harmonic mean of cruising speeds should be used. For this abstract, we apply the arithmetic mean; given the limited variation in cruising speeds, this choice is unlikely to materially influence the results.

Delay Modelling

We relate the delay ratio to infrastructure and contextual factors by estimating a mixed-effects linear regression model, as:

$$\mathrm{DR}_{k,i} = \alpha_0 + X^{\mathrm{int}}_i \alpha_i + X_k \alpha_k + u_{\mathrm{user}(k)} + \epsilon_{k,i}, \tag{8}$$

where X^{int}_i captures traffic signals and turning manoeuvres; X_k captures trip-level (i.e, length of the trip) and temporal context (i.e., peak, night, weekend, wind, rain, and temperature). The ratio outcome reduces confounding from natural differences in cruising speed and intersection crossing distance, thereby isolating intersection-level effects.

3 Results and Discussion

This section presents the empirical findings from the adapted cruising-speed model and the intersection delay-ratio model. The cruising-speed model is an adaptation of Argyros et al. (2024), here modified to exclude intersection influences, and mainly serving as a behavioural baseline. Accordingly, the empirical focus is on the delay-ratio model, which forms the core contribution of this study and quantifies how intersection design, control, and manoeuvres shape cyclist delay.
Our findings are based on a large-scale GNSS trajectories from the Hövding helmet system in Copenhagen, pre-processed and map-matched to a detailed cycling network (Argyros et al., 2024; Łukawska et al., 2023). OpenStreetMap (OSM) provides the base network graph and attributes used in the study. The resulting dataset supports (i) extraction of stable cruising segments away from intersections and (ii) computation of crossing distances and times within intersection buffers. All delay measures are referenced to cyclist-specific cruising speeds predicted from these map-matched trajectories.

Cruising Speed Model

The cruising-speed model was estimated from more than five million stable-speed cyclist observations across over seven thousand riders (Table 1). Although the model was adapted from Argyros et al. (2024) to represent cruising speed uninfluenced by intersections rather than average edge

Table 1: Edge-level cruising speed model.

	Coef.	Std.Err.	z	P>|z|		Coef.	Std.Err.	z	P>|z|
Intercept	2.862	0.002	1485.2	0.000					
Road Roughness Indicator									
ln(DCI)	0.075	0.001	102.8	0.000					
Elevation (ref. flat)									
ln(Very steep uphill (in m, >35 m/km))	-0.176	0.001	-135.2	0.000	ln(Steep downhill (in m, 10 – 35 m/km))	0.014	0.000	188.0	0.000
ln(Steep uphill (in m, 10 – 35 m/km))	-0.024	0.000	-344.8	0.000	ln(Very steep downhill (in m, >35 m/km))	0.025	0.002	15.7	0.000
Infrastructure (ref. cycleway)									
ln(Length (in m))	0.029	0.000	197.9	0.000	Footways	-0.054	0.001	-81.5	0.000
Living streets	-0.108	0.001	-77.4	0.000	Shared paths	-0.046	0.001	-86.0	0.000
Pedestrian zones	-0.176	0.001	-126.8	0.000	Medium roads w/ painted bicycle lanes	0.028	0.001	44.4	0.000
Residential roads w/o bicycle infrastructure	-0.052	0.000	-119.8	0.000	Medium roads w/ protected bicycle tracks	0.051	0.000	134.5	0.000
Residential roads w/ painted bicycle lanes	-0.028	0.001	-22.7	0.000	Large roads w/o bicycle infrastructure	0.036	0.001	41.0	0.000
Residential roads w/ protected bicycle tracks	0.015	0.001	23.4	0.000	Large roads w/ painted bicycle lanes	-0.022	0.001	-21.7	0.000
Medium roads w/o bicycle infrastructure	-0.012	0.001	-19.4	0.000	Large roads w/ protected bicycle tracks	0.052	0.000	126.7	0.000
Trip Caracteristics									
Short trips (<1 km)	-0.084	0.001	-157.5	0.000	Medium trips (5-10 km)	0.026	0.000	108.9	0.000
Long trips (>10 km)	0.044	0.000	89.4	0.000					
Seasonal and Time									
Weekend	-0.027	0.000	-100.6	0.000	Is spring	-0.004	0.000	-12.1	0.000
On peak period	0.016	0.000	81.9	0.000	Is winter	-0.028	0.000	-76.3	0.000
During night	-0.021	0.000	-42.8	0.000					
Weather									
ln(Wind speed (in km/h))	-0.023	0.000	-113.9	0.000	Temperature 0-10 °C	-0.016	0.000	-64.6	0.000
Temperature below 0 °C	-0.046	0.001	-86.6	0.000	Temperature above 20 °C	-0.002	0.000	-4.9	0.000
Land Usage (ref High-rise urban areas)									
Green areas	0.013	0.000	60.5	0.000	Low-rise urban areas	0.008	0.000	40.7	0.000
Industrial areas	-0.010	0.000	-42.4	0.000					
Random error									
User variance	0.019	0.002							
No. Observations				5512940	Log-Likelihood				-926416
No. Unique Links				16788	R-squared				0.36

speed, the coefficients remained nearly the same. Interestingly, the intercept increased, reflecting the higher baseline of cruising speeds. Overall, the model reveals substantial cyclist-level heterogeneity, indicating meaningful differences in individual riding tendencies, alongside a set of infrastructure and environmental factors that strongly shape cruising behaviour.

Despite Copenhagen's generally flat landscape, the model detects clear speed responses to grade. Uphill segments were associated with noticeably lower cruising speeds, while downhill movement increased speed. Moreover, cruising speeds were highest on segregated, protected cycling facilities and lowest in pedestrian-oriented or shared environments. Dedicated cycling infrastructure on larger roads supported the most stable and efficient riding conditions, while footways, pedestrian streets, and mixed-traffic residential streets consistently produced lower cruising speeds. These patterns align with prior research showing that infrastructure affects unconstrained cycling behaviour (Clarry et al., 2019; Flügel et al., 2019; Berjisian & Bigazzi, 2025). Modest temporal variation was observed, whereas longer trips tended to exhibit higher steady-state speeds. Weather conditions had measurable effects, with cold temperatures and wind reducing cruising speed, while movement through green or open land-use areas slightly increased it.

Overall, these results show that cruising speeds are shaped by infrastructure, slope, and local conditions, with additional variation across riders and time periods. This supports the use of predicted cruising speeds as intersection-specific baselines, ensuring that measured delay reflects intersection interactions rather than underlying differences in cruising behaviour.

Intersection Delay Model

The delay model, estimated on more than one million intersection crossings, reveals much stronger variation than the cruising-speed model, underscoring that intersections, not links, are the primary source of cycling disruption (Table 2). The presence of traffic signals stands out as one of the strongest determinants of delay. Signalised intersections consistently produced substantially longer crossing times, reflecting red-phase waiting, queue formation, and start-up delays. The scale of this effect is large compared to temporal, weather, or trip-related variables, confirming that intersection control mechanisms play a central role in shaping cyclist delays.

Table 2: Intersection delay ratio model.

	Model I				Model II			
	Coef.	Std.Err.	z	P>|z|	Coef.	Std.Err.	z	P>|z|
Intercept	0.961	0.021	44.953	0.000	0.623	0.035	17.926	0.000
Seasonal and Time								
Wind speed above 5 km/h	-0.002	0.010	-0.210	0.833	0.027	0.009	2.942	0.003
Rainy day (precipitation >0 mm)	-0.001	0.003	-0.366	0.715	-0.004	0.003	-1.231	0.218
Temperature below 0 °C	-0.082	0.006	-14.456	0.000	-0.085	0.005	-17.707	0.000
Temperature 0-10 °C	-0.043	0.003	-15.473	0.000	-0.047	0.002	-20.190	0.000
Temperature 10-20 °C								
Temperature above 20 °C	0.019	0.006	3.368	0.001	0.025	0.005	4.849	0.000
Weekend	-0.054	0.004	-15.075	0.000	-0.040	0.003	-12.811	0.000
On peak period	0.034	0.003	13.035	0.000	0.025	0.002	10.937	0.000
Night	-0.195	0.006	-32.266	0.000	-0.209	0.005	-38.560	0.000
Trip Caracteristics								
Short size trips (less than 1 km)	-0.092	0.008	-12.054	0.000	-0.025	0.007	-3.643	0.000
Short-medium trips (1-5 km)	-0.011	0.003	-3.637	0.000	-0.025	0.002	-10.174	0.000
Medium size trips (5-10 km)								
Long size trips (above 10 km)	-0.007	0.006	-1.170	0.242	-0.013	0.004	-3.059	0.002
Cruising speed (km/h)	0.011	0.001	11.500	0.000	0.025	0.000	55.129	0.000
Intersection and movement								
Traffic lights	0.611	0.004	168.372	0.000	0.577	0.037	15.456	0.000
Left turn	1.755	0.004	438.482	0.000	1.656	0.004	419.767	0.000
Right turn	-0.085	0.004	-19.906	0.000	-0.160	0.004	-38.134	0.000
Random error								
User variance	0.042	0.001						
Intersection variance					0.166	0.007		
No. Observations				1357875				
No. Intersection				664				
Log-Likelihood				-2310757				-2241195
R-squared				0.167				0.22

Peak periods showed clear increases in delay, likely due to higher mode-interaction density caused by intensified traffic during this period. Conversely, night-time and weekend crossings experienced significantly lower delay, consistent with lower traffic volumes, shorter queues, and more permissive interactions. These temporal distinctions indicate that delay is not simply a geometric attribute; it is strongly tied to demand patterns and operational conditions.

Left-turn movements exhibited the largest increase in delay among all predictors. This outcome reflects the structure of two-stage left-turn manoeuvres in Copenhagen, which typically require cyclists to cross two different traffic streams, reposition within the intersection, or wait for alignment with signal cycles. The magnitude of the effect suggests that left turns represent a key friction point in the cycling network. Therefore, alternative signal strategies, such as allowing cyclists to complete the left turn in a single stage or providing dedicated left-turn phases, may offer substantial potential for reducing delay at these movements. On the other hand, right turns consistently reduced delay relative to straight movements. This reflects design conventions in Denmark that allow right turns to proceed more freely, with fewer conflict points and often without direct exposure to signal phases. Potentially, it might also reflect a higher degree of red-light running for right turns.

As expected, trip-related variables (e.g., trip length categories) contributed only small adjustments to observed delay. Very short trips experienced slightly less delay, while long trips experienced slightly more, but these differences were minor compared with turning and control effects. Cruising speed also showed a modest association with delay: higher predicted cruising speeds were linked to slightly higher delay ratios, likely reflecting that faster riders lose proportionally more time when forced to slow down at intersections. Weather effects were similarly small; temperature and precipitation produced slight differences in delay, but wind had virtually no effect. The small magnitude of these variables supports the interpretation that intersection geometry and control dominate over user or environmental characteristics.

The intersection-level random-effects specification (Table 2 - Model II) reveals substantial unobserved heterogeneity across intersections, with intersection variance far exceeding user variance. This indicates that most remaining variation in delay stems from intersection-specific characteristics rather than cyclist-level differences. Thus, including intersection random effects markedly improves model fit and highlights the role of unobserved geometric and operational factors. Importantly, the fixed-effect estimates remain broadly stable across specifications, with traffic lights and left-turn movements continuing to dominate delay, demonstrating the robustness of the results.

Looking across cruising speeds and intersection delays, the two models reveal a clear behavioural distinction. Cruising speeds vary mainly across cyclists and reflect individual riding tendencies and link conditions. In contrast, intersection delays vary primarily across intersections and are shaped by signal control, geometry, and manoeuvre complexity. This distinction highlights that delays arise from intersection-specific factors rather than underlying differences in cruising behaviour.

Sensitivity Analysis

To ensure that estimated delay patterns were not influenced by omitted spatial structure, model residuals were tested for spatial autocorrelation using a standardised 4-nearest-neighbours weights matrix with 999 permutations. Both Moran's I and Geary's C were close to their expected values under spatial randomness, and neither indicated significant spatial clustering. We also assessed the robustness of the delay estimates under a range of alternative preprocessing and modelling choices. Delay was recalculated using both smaller and larger buffer sizes ($0.5r$ and $1.5r$), and stable-speed segments were re-identified using alternative acceleration thresholds (0.028 and $0.039\,\mathrm{m/s^2}$).
These modifications changed the number of observations but did not alter the qualitative pattern of the delay results. Across all specifications, the main delay determinants remained consistent in both sign and relative magnitude. The largest deviations occurred when altering the intersection radius: enlarging the buffer ($1.5r$) slightly reduced the magnitude of manoeuvre effects, while shrinking it ($0.5r$) amplified them. This behaviour is expected. Larger radii add more approach and exit riding, which mildly dilutes movement-specific delay, whereas very narrow radii truncate the deceleration and re-acceleration phases, inflating the normalised ratio. Importantly, the implied travel-time penalty for left turns remains similar for the base and $1.5r$ radii (18.9 and 19.5s), with the $0.5r$ case underestimating delay (14.6s) due to missing the propagation of slowdown. Overall, the findings appear robust, indicating that the core behavioural and design-related conclusions are not sensitive to reasonable spatial, preprocessing, or modelling choices.

Future Work

The current results already offer a strong foundation for understanding cyclist delay at intersections, but several potential extensions that could improve it even further remain. As a direct improvement, prior to the conference, we plan to model interactions between control type and manoeuvre, particularly turning movements at signalised intersections, to capture structural effects beyond the main effects presented here. We also intend to incorporate higher-resolution vehicle-flow data to better assess demand-delay feedback and congestion influence. In parallel, we will implement the distance-weighted harmonic mean of cruising speeds for intersection baselines, replacing the interim arithmetic-mean simplification used in this version, and test more advanced models that include both random error terms for users and intersections.
Further work could integrate more detailed intersection-design features, e.g., potentially derived from image-based geometric data, which will increase explanatory power and address remaining variability in delay patterns. In addition, conducting cost-benefit analyses of alternative intersection designs and control strategies would support evidence-based decisions aimed at reducing cyclist delay and improving overall network performance.

4 Conclusions

The study shows that most cyclist delays occur at intersections rather than along links. Cruising speeds are relatively stable across link characteristics, while intersection delays vary strongly with control mechanisms and turning manoeuvre complexity. Distinguishing steady-state cruising from intersection-induced disturbance helps identify where cyclists experience disproportionate time losses.
The findings show that cyclist delays are driven mainly by intersection design, control type, and manoeuvre, rather than by rider traits or broader environmental conditions. Signalised intersections and left turns consistently generate the greatest delays, while right turns and off-peak periods support smoother, less interrupted crossings. These patterns remain stable across different buffer sizes, cruising-speed definitions, and modelling choices, underscoring the robustness of the results. Overall, the results highlight a targeted set of levers for reducing delay: improving left-turns, refining signal strategies, and designing intersections that reduce conflict, ultimately supporting more efficient cycling travel.

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