

RISK ANALYSIS OF CYCLING ACCIDENTS USING A TRAFFIC DEMAND MODEL

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ABSTRACT:

In Germany, accidents are collected nationwide, including also bicycle accidents. To determine accident-prone locations, it is necessary to not only look at the number of accidents but also in relation to the absolute number of cyclists traversing that location. Thus, this study exploits a collection of bicycle accidents in combination with estimated cyclist volumes on street level in Hanover (Germany). The basis for the generated bicycle volumes is the resulting origin-destination demand for bicycle mode from an agent-based traffic simulation model. A normalization of the accidents by an absolute bicycle volume allows to estimate a risk score and to compare high frequented ways with less popular minor paths in an objective manner. This method is used to show locations with comparatively high risk for cyclists. Besides highlighting these spots on a map, e.g. for city planners, the resulting risk scores can be integrated into bicycle routing to avoid those areas for future trips.

1. INTRODUCTION

Bicycling has experienced increased popularity as transportation mode, especially for shorter everyday trips in urban areas. The support of bike traffic is also becoming a political issue, as it is expected to reduce traffic congestion and have ecological and health benefits (Pucher and Buehler, 2017).

(Ravensbergen et al., 2020) identified distinct factors in their work discouraging people from cycling (on certain trips). A fear of accidents with cars and resulting injuries was mentioned by every participant in their survey. There has already been work from different perspectives on the analysis of cyclists' safety and relevant factors ((Vanparijs et al., 2015), (Johnson et al., 2010), (Jaber et al., 2021)). This includes works to identify general accident causes and aspects on an abstract level, or comparative works on regional differences or influences of specific infrastructure types. These studies of the general factors influencing the risk of cycling are very wide-ranging, but also often without specific geospatial reference.

Consequently, this work will not be further discussed here since the focus of this research relies on integrating reported accidents and their network locations with a corresponding bicycle demand from given origin-destination information. In particular, the spatial location of an accident has to be related to the quantity of bicycles to extract accident spots causing a disproportionately high number of accidents. This methodology allows us to identify accident locations in a network where a traditional analysis would not necessarily reveal them since these spots do not appear to be remarkable due to their absolute frequency. An edge-specific bicycle traffic volume is essential for this approach. This demand can be derived either from real data or from traffic demand models.

Some works like (Wu et al., 2018), utilize surveys to analyze perceived cycling safety for different situations and locations in a city. One recent crowd-sourcing, but more sensor and

data-driven approach by (Karakaya et al., 2020), utilizes smartphones to detect near-accident, which can be observed more frequently than actual accidents. However, a challenge remains to classify the events reported by the participants in a representative and objective manner. Local infrastructure characteristics aside, accidents in absolute terms occur more frequently at high-traffic sites than at low-traffic sites, so the volume of (bike) traffic should be included in comparative analyses. Even though it is now easier than ever to collect mass and diverse movement data, it is primarily commercial data as in (Lee and Sener, 2021) that is still limited in its use and availability. Especially, estimating and adjusting the representativeness in retrospect is challenging. (Medeiros et al., 2021) used a commercial dataset from the provider *BikeCitizens* in their work to determine a detailed bicycle traffic demand.

In addition to real data, there is also a high potential in applying traffic demand models. (Loidl et al., 2015) utilized a specific agent-based bicycle traffic model (Wallentin and Loidl, 2015) with an integrated, explicitly geospatial approach to conduct a bicycle safety and accident analysis. This detailed approach requires a specific bicycle model, which is not always available as the primary focus, especially in field of transport demand modeling, is often on the motorized traffic.

Due to the lack of appropriate real world bicycle volume data or a detailed bicycle model, our work provides its own estimation methodology as a first step. Therefore, this study exploits a collection of actual accidents in combination with bike traffic volumes based on a socio-demographically representative transportation demand model (Bienzeisler et al., 2020). Unlike some bicycle traffic simulations that are limited to a specific roadway like (Grigoropoulos et al., 2021), the demand fully represent the study area of the city of Hanover (Germany) and thus provides an objective overview. The derived absolute bicycle volumes allow to normalize the respective bike accidents to a risk score and to compare highly frequented ways with less used minor paths.

This enables an estimation of the relative risk for cyclists to be

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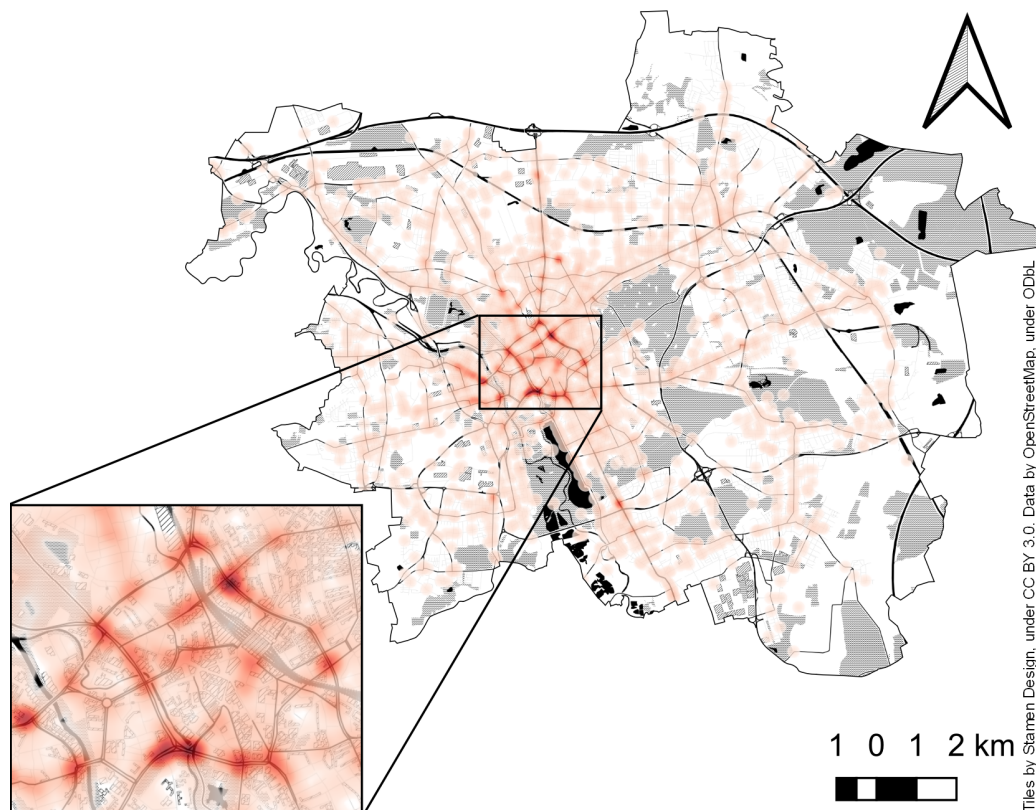


Figure 1. Heatmap of all listed accidents involving cyclists from 2017 to 2020 in Hanover city.

injured on certain streets based on the accident history. The results can be used for the identification and mitigation of comparatively dangerous spots in the network. In addition, it is required to analyze possible reasons for the accidents and to take it into account in further urban planning. Further, derived risk scores can be integrated into bicycle routing to avoid corresponding areas for future trips.

2. STUDY AREA AND DATA

This paper focuses on the city of Hanover as a case study. It is the state capital of Lower Saxony in the north-western part of Germany. The city center is enclosed by a ring of main streets (called *Cityring*), from which other main axes branch off in a star shape. Much of the bicycle traffic is oriented along these. Between them are densely populated neighborhoods adjacent to the center, some of which are separated by large areas of parkland, woodland and water, but which are well accessible for bicycles. Towards the outskirts of the city, large commercial and industrial sites complement the less dense residential use. There are relatively few and only minor hills in the city area.

Specific data sets used for this work are presented in the following subsection.

2.1 Accident History

In our work, the term (traffic) accident is chosen because it describes an undesired incident with negative consequences, although it is explicitly not meant to be read as an unavoidable situation here. The otherwise common term incident seems to be a bit too general in the context of the data used (with personal injury), since near accidents would also be included. These are

of course to be avoided as well, but are not part of the data set used.

In Germany data of accidents is public available for the years 2017-2020 via the *Unfallatlas* (Statistische Ämter des Bundes und der Länder, 2021). Only those resulted in damage to persons and reported by the police are included into this collection. Beside different location and time attributes, further given information on the accident is for example: involved types of road users, maximum severity (slightly/seriously injured or death), incident type and light and road conditions. A full list can be found in the German data information sheet.

According to these criteria, 4 174 entries remain. Of these, 88 % resulted in minor injuries, 11 % in serious injuries and about 0.2 % (10 in total) in deaths. They are distributed over the entire city area in figure 1, but are concentrated especially towards the edge along the main axes and intersections. Further they are categorized by *UART* and *UTYPE1*, so types of accidents. For *UART*, 48 % are group 5 (collision with turning/crossing vehicle), 26 % are group 0 (other), and groups 1, 3, 4, 6 are assigned around 5 % each. For *UTYPE1*, 33 % type 3 (entering/crossing accident), 23 % type 2 (turning accident), 13 % type 7 (other), 12 % (driving accident) type 1 and the rest are represented by 3-8 % each.

As can be seen in figure 1, most of the accident hotspots for cyclists in absolute terms are located along the main roads and intersections around the city center. However, as in the case of motorized traffic, these also have a significantly higher cyclist frequency than minor streets or paths, so the relative accident risk of individual cyclists may have to be allocated differently.

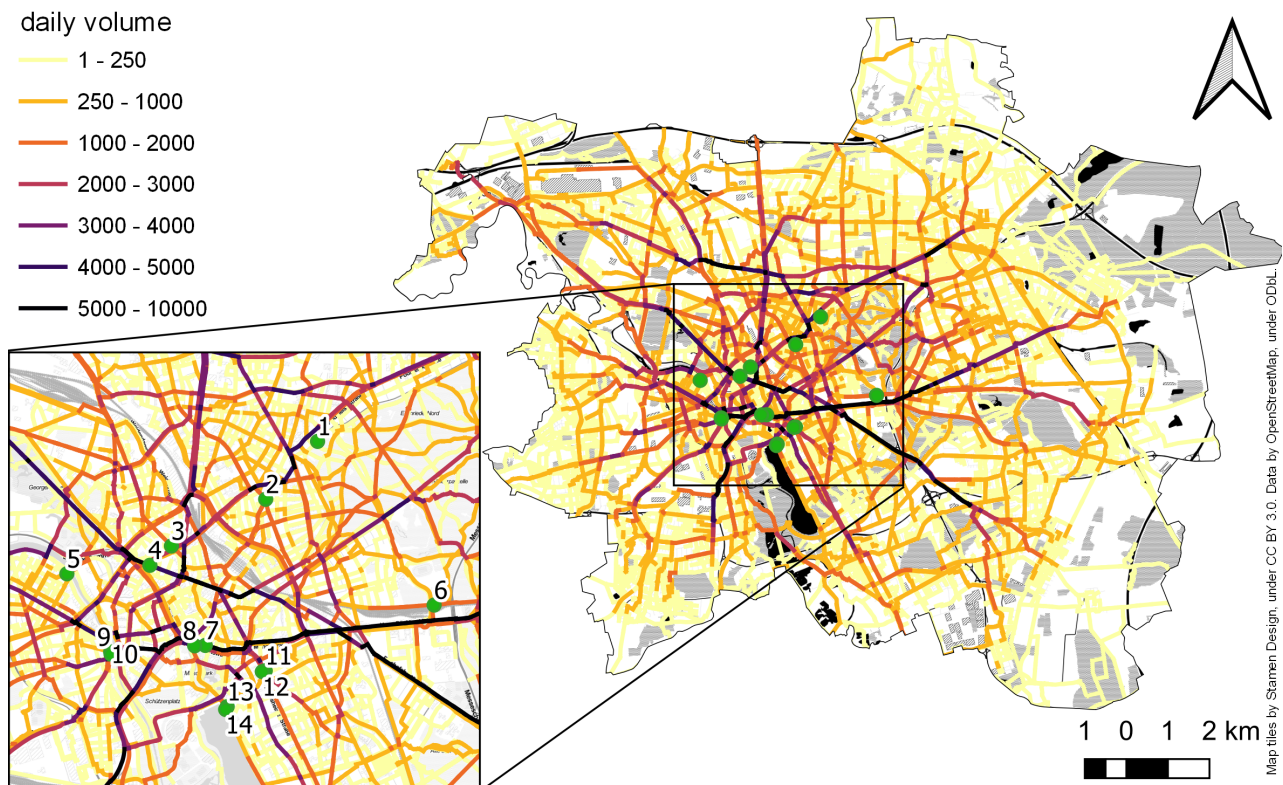


Figure 2. Simulated cyclist volume in the study area (Hanover, Germany), symbolized by light yellow (low volume) to dark black (high volume). Bicycle counting stations are marked with dots.

2.2 Bicycle Demand

The used bike demand is derived from a transportation simulation of Hanover by (Bienzeisler et al., 2020). A city wide multi-modal traffic demand model was implemented based on the agent-based simulation framework MATSim (Horni et al., 2016). It adapts peoples' day schedules and trip chains from the German mobility survey *Mobilität in Deutschland 2017* with specific data and was calibrated to Hanover traffic data. As in many other transportation simulations, the focus was on motorized traffic and no specific bike routing or scoring was implemented. For this study, only the resulting demand of bike trips (origin-destination pairs) is exploited, representing a 10 % sample of daily mobility in the city of Hanover. Simulating only a fraction of the total population is a common practice to reduce the required computing power when running complex MATSim models. In this way, a total of 31627 trips were obtained for the exemplary weekday of 2017.

Other sources of origin-destination data would also be possible, such as from bike or e-scooter sharing services (Heumann et al., 2021), to bypass the effort to create an own complex traffic model. However, these samples must be assumed to have specific usage behavior and therefore lack representativeness for bicycle trips in general. Due to the population generation in the simulation, a demographical representativeness for Hanover can be assumed in the data used here.

Around the city center in Hanover are installed 14 permanent bike counting stations (dots in figure 2) at traffic arteries. Latest counts are accessible via the web portal (VMZ Ni and Region Hannover, 2021), but daily ones only for 30 days and monthly ones for two years. Relevant variations can be seen in the daily ones by day of week and weather, but also in the monthly ones

based on season and continuous changes in peoples' behavior during the Corona pandemic and related constraints. However, no detailed values are available for the reference year, only total sums at (Landeshauptstadt Hannover, FB Planen und Stadtentwicklung, 2021). Due to the lack of station-wise values from the simulation year, counts for four weeks at the end of October 2021 are selected. The median of the weekdays Tuesday to Thursday is formed in order to smooth short-term variations. In comparison, the values are in the annual average and in total no significant increase to 2017 can be identified. The set of counts is selected as reference for section 4.1.

2.3 Way Network

The popular open-data platform OpenStreetMap is used to extract bikeable way geometries based on related tags characterizing those segments and transform it to a routable network graph via the tool *osm2pgrouting*. Further, the result was inspected and adjusted manually. The network is interpreted bidirectionally, as large parts of the infrastructure are open for bicyclists in both directions and otherwise less attention is paid to this in practice.

In addition, the slope of all paths was calculated from the digital terrain model (Landeshauptstadt Hannover, Bereich Geoinformation, 2021) with a high ground resolution of one meter. The slope of a segment results from its height difference in relation to the segment length.

3. METHODOLOGY

Figure 3 gives an overview of the workflow. Accidents are to be filtered and matched and bicycle volumes to be estimated as components of the final risk score.

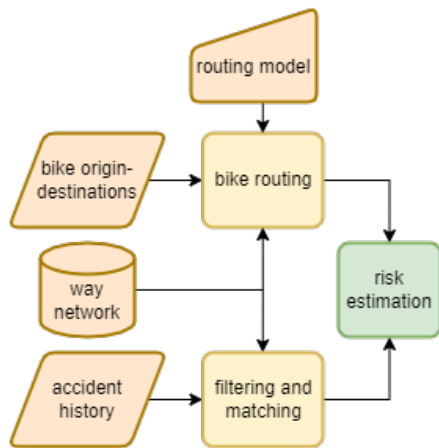


Figure 3. Data processing diagram.

3.1 Accident Processing

As a first step, the accidents are filtered to those within the Hanover study area and with bike involvement. No general weighting of the accidents according to their severity is applied, because the focus in this study lies on accident-prone areas. Thus, each accident counts equally.

Next, based on the given location, they are matched to the neighboring (within 20 m) network segment with highest bicycle volume. This prevents accident hotspots on main roads from spreading to low frequented side roads. To include also intersection points into the study, the accidents of adjacency edges are additionally assigned to each node to include them as well.

3.2 Bicycle Volume Estimation

Due to another focus of the original MATSim simulation, the bike trip demand has not been routed and only their origin-destination pairs were output. First, this must be realized in order to derive a representative daily bicycle traffic per network segment. In a first version this is done with shortest-paths, simply optimized by segment lengths. Since the simulation represents a 10 % sample of agents, each segment pass is weighted accordingly as ten.

In a second version, the ten shortest routes for each origin-destination pair are calculated and a weighted choice is realized. The probability for each route alternative is derived from estimated utilities, based on the proposed route choice model of (Huber et al., 2021). Via ten draws with replacement a upscaling to 100 % is simulated, while preventing exaggeration of picked routes like in version 1.

3.3 Risk Score Definition

In general, risk describes the number of incidents in relation to the number of opportunities. So transferred to this case

$$\text{risk} = \frac{\text{accidents}}{\text{volume}}, \quad (1)$$

analogous crashes by exposure in (Molino et al., 2009).

For better clarity and transferability, it is convenient to normalize the values used to a consistent period of time. In this case,

the number of average accidents per year (data are from four years) is calculated and the bicycle volumes are also extrapolated to a year, so an accident probability by passing cyclist can be derived. The previous mid-week day bicycle volumes are projected to a year using the average weekly distribution from (Landeshauptstadt Hannover, FB Planen und Stadtentwicklung, 2021) and 365 days.

4. RESULTS

Following the procedure described above, the data discussed at the beginning were prepared and processed for the city of Hanover. First, the cyclist traffic volumes were generated in order to be able to use them for normalizing the accidents to risk scores.

4.1 Bicycle Volume

The resulting bike volumes of both approaches (version1 and version 2) are compared against the values of permanent bike counting stations in table 1. In total, the overall sum of simulated volumes differs by 153 % in version 1 and by -8 % in version 2 from the ground truth sum at the counting stations. Significant deviations arise when looking at individual counting stations. Version 1 obviously performs worse, compared to version 2, whose route variation seems to lead to a more realistic distribution. Thus, version 2 is visualized in figure 2 and used for further analysis. At six stations the deviation is below 50 %, at five others below 80 % and at three others up to several factors. Station 1 is almost ignored in the simulation. For stations 7 and 10, on the other hand, the volume was estimated to be two to three times too high, whereas their respective stations across the street show hardly any deviation from the target. Possible reasons for this deviations are discussion in section 5.1.

4.2 Risk Score

The resulting bicycle volumes for each way segment are used to normalize the matched accidents based on the risk score definition in section 3.3. In order to smooth the results and not pay excessive attention to individual underrepresented outliers, only segments with a minimum volume of 100 and more than one accident are further taken into account.

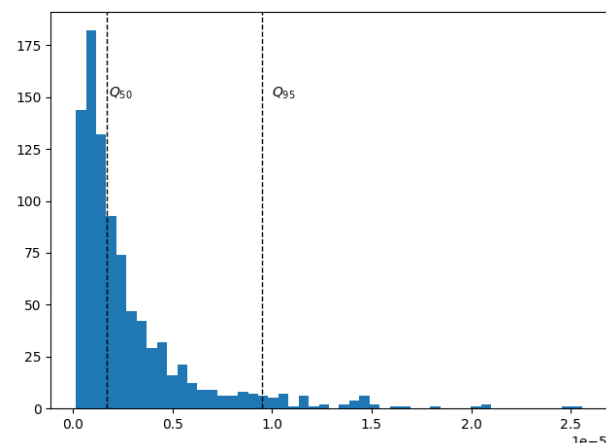


Figure 4. Histogram of the risk score distribution and marked median at 0.17e-5 and 95-quantile at 0.95e-5.

The resulting distribution of risk scores is given in figure 4, with the median at 1.7e-6 and the 95-quantile at 9.5e-6. In other

Reference			Simulated Volume			
ID	Station Name	Count	v1	Δ [%]	v2	Δ [%]
1	Walderseestraße	3 251	180	-94	50	-98
2	Lister Meile	3 739	6 950	86	2 744	-27
3	Klagesmarkt	2 724	5 330	96	1 717	-37
4	Lange Laube	2 786	11 110	299	4 489	61
5	Justus-Garten-Brücke	4 321	3 870	-10	1 166	-73
6	Stadtparkweg	2 461	3 750	52	1 532	-38
7	Friedrichswall Nord	2 003	15 740	686	5 803	190
8	Friedrichswall Süd	2 182	6 830	213	2 634	21
9	Schwarzer Bär Nord	2 724	9 040	232	2 636	-3
10	Schwarzer Bär Süd	1 408	16 970	1 105	6 232	343
11	Hildesheimer Str. Ost	3 552	7 340	107	2 885	-19
12	Hildesheimer Str. West	2 272	3 120	37	1 088	-52
13	Rudolf-v.-B.-Ufer Ost	635	770	21	219	-66
14	Rudolf-v.-B.-Ufer West	3 389	3 850	14	1 362	-60
	Sum	37 444	94 850	153	34 557	-8

Table 1. Overview of bike counts at the reference stations and the two simulated versions with volume per day (v1 & v2) and relative error (Δ) to the reference.

words, for bicyclists, the estimated chance of an accident at half of the spots considered (i.e. spots with more than one accident and 100 bicyclists per day) is less than 1:600 000. At nearly 5 % of the spots, it is more than 1:100 000.

However, the results also allow a look at individual sections based on their risk score. Figure 5 shows the resulting 5 % spots with the highest ratio of accidents to cyclists with crosses. The top ten riskiest spots are highlighted in green. Additionally, the heatmap of figure 1 is given for direct comparison of the identified relative spots to the previous absolute accident spots.

The ten most risky spots are listed in table 2 with more details. It can be seen that some of them are located in the city center, but others are as well located in places on the periphery.

5. DISCUSSION

In the following discussion, the results shown are put in context and limitations of the presented approach are pointed out.

5.1 Bicycle Volume

The sum of counted bicycles at all stations differs in estimation v2 by the experience-based uncertainty range of the counting stations of a few percent. Furthermore, relatively large fluctuations are to be assumed for bicycle traffic due to external influences such as the temperature and rainfall. Thus, the generated volumes can be considered valid as an approximation of the total scale.

There are two different explanations for the particularly large deviations at the three individual stations 1, 7 and 10.

Case one refers to station 1. The station is located on a well-traveled and attractive bikeway. This is not fully taken into account by the routing model and a shorter alternative is picked. In reality, cyclists often accept the detour for the attractive route.

Case 2 refers to stations 8 and 9: Given the moderate deviations at both stations from the reference, the significant overestimation at Stations 7 and 10, which are on the opposite side, indicates that the incoming demand on the east-west axis is too

high in the original model, as there are no convincing alternative routes either.

The problem of case 1 could be addressed by a more sophisticated route-choice model that includes large-scale alternatives. On the one hand, this requires a sufficiently reliable and transferable model such as the applied by (Huber et al., 2021), where however no universal one has been established for bicycles yet. On the other hand, the model requires suitable and sufficiently reliable data for the study area, which was unfortunately not available everywhere for Hanover at the time of the study with regard to the bicycle infrastructure.

In order to address the second case, it is necessary to start one step earlier and to calibrate the actual traffic model more specifically for bicycle traffic in order to achieve a more suitable (spatial) distribution of demand and which would additionally allow a temporal calibration. The underlying demand model from (Bienzeisler et al., 2020) was developed and calibrated with a focus on motorized transport and the accuracy of the model suffers when considering individual road segments (Bienzeisler et al., 2022). Due to these limitations, the temporal dimension was omitted and only average daily volumes of bicycle traffic were considered. There are existing bike contributions for MATSim (Ziemke et al., 2017), but they have to be implemented separately. In current simulation models, the cyclists are merely teleported between start and destination, as in (Bienzeisler et al., 2020), without concretely interacting with the network.

5.2 Risk Score

In figure 4 it can be seen that a (small) part of the locations have a comparatively high risk value. Since the peak values are several factors larger than the median, sufficient sensitivity can be assumed despite the underlying volumes being subject to uncertainty. An increased accident risk for cyclists compared to the average can be assumed for those.

A direct comparison of the spatial distribution of the riskiest spots in figure 5 with the heatmap of the absolute hotspots shows that the first supposedly risky locations have shifted. The spots, which are normalized by bicycle volume, are no longer located in the intersections of the main roads near the center, but often in the area of minor roads.

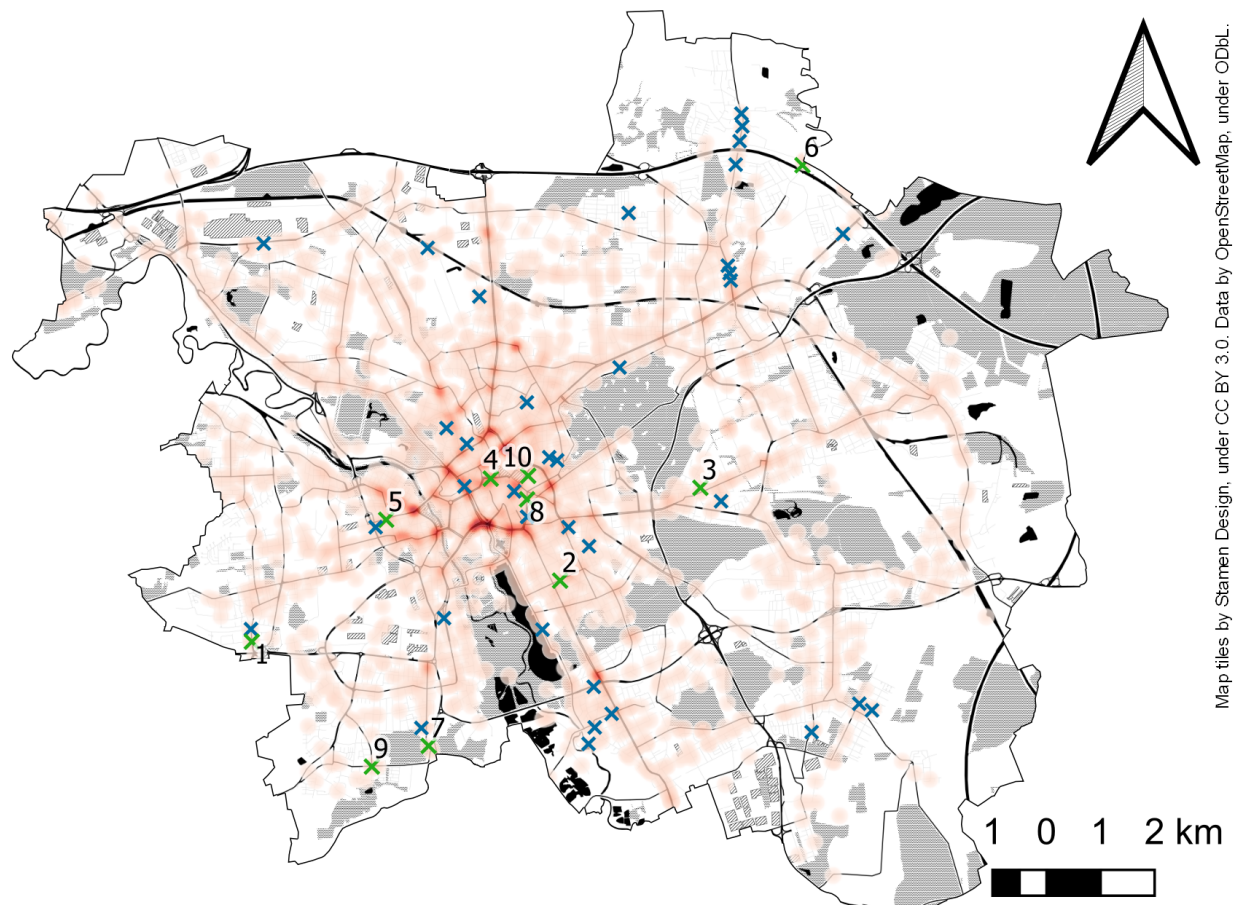


Figure 5. Overview of 5 % (crosses) and top ten (green crosses with labels) riskiest accident spots. The heatmap of absolute accident spots is in the background from figure 1 for comparison.

rank	accident risk	accident chance	focus object	accident count	bike volume [daily]	severity count			accident type count (UTYP1)						
						1	2	3	1	2	3	4	5	6	7
1	2.6e-5	1:39 107	node	4	120			4			4				
2	2.5e-5	1:40 085	node	4	123		1	3	1		1				2
3	2.1e-5	1:47 798	edge	3	110			3	2		1				
4	2.1e-5	1:48 511	node	14	521		2	12	11	1					2
5	2.0e-5	1:49 536	node	8	304		1	7		3	4			1	
6	1.8e-5	1:54 750	edge	5	210			5	1	1	3				
7	1.7e-5	1:59 182	edge	5	227		2	3	1	2				2	
8	1.6e-5	1:61 920	edge	4	190			4	3						1
9	1.5e-5	1:65 504	edge	4	201			4	1		3				
10	1.5e-5	1:66 482	node	5	255			5		2			3		

Table 2. Listing of the spots with ten highest risk scores, the respective chance and their key indicators. Focus object indicates whether the focus is at an intersection or on the road. The severity goes from dead (1) to slightly injured (3). The accident types are driving accident (1), turning accident (2), entering/crossing accident (3), passing accident (4), accident by stationary traffic (5), longitudinal traffic accident (6) and other (7). Their locations are marked in figure 5.

In addition to the map, table 2 provides a more detailed description of the ten riskiest spots. Most of them had about four accidents and a daily bicycle traffic volume of a just few hundred was estimated. Therefore, for the most part, these are indeed places that do not have an outstandingly high accident frequency in absolute terms, and therefore would not receive special attention. However, since they are also relatively little frequented by cyclists, they have an increased risk in relative terms, i.e. per cyclist. In this way, therefore, the view for danger spots in side streets can be increased, even if these do not stand out in absolute numbers. A look at the other indicators also

shows that, as in the overall data set, minor injuries dominate, but serious injuries also occurred in some cases. There were no deaths in accidents at these ten locations. Among the accident types, intersection/turning situations (2 & 3) are frequently represented and driving accidents (1), i.e. loss of control (due to obstacles).

To put the highest estimated accident risk (roughly 1:40 000) in a nutshell, commuting through this section on a regular basis (500 times a year) is not unlikely to get involved in an accident once in a lifetime of 80 years.

6. CONCLUSION AND OUTLOOK

This paper shows how bicycle origin-destination demand from traffic simulations can be used to normalize accident data into a risk score based on the resulting volumes per road segment. This can be used to identify high risk locations without focusing only on absolute accident hotspots, or as a factor for route optimization to avoid such spots.

Estimating realistic bicycle volumes at street level proves to be an existing challenge. The comparison to reference counts unfolds deviations of the presented estimation at single locations, but confirms the general magnitude. Compared to the weaknesses in representativeness of work with real routes mentioned in (Lee and Sener, 2021), a weakness in the identification of realistic routes based on representative demand is indicated here. Well-generalized and transferable approaches have already been established for motorized vehicles, which would also be desirable for bicycles in the future. However, in order to apply more comprehensive bicycle routing models, appropriately detailed and accurate data on the way network is also required. During this work, respective weaknesses in the available OpenStreetMap data for Hanover have been noticed.

In general, it was shown that when considering bicycle accident hotspots, in addition to the absolute values, these should also be set in relation to the volume of bicycles. Thus, in addition to (expected) absolute clusters at main intersections, there are also risk spots in relation to the volume of bicycles, which are often located on minor roads and thus might otherwise have received less attention, but also represent a risk. The developed methodology allows to convert any kind of origin-destination matrix (maintained by many municipalities) into a routed bicycle demand. Thus, it can be adapted and applied to different input data determining a risk score for other cities.

Even if the resulting accident risks should not be taken with too much precision due to the uncertainty of the volumes, it is still feasible to identify points of increased risk. Thanks to the continuous scale, they can be transferred to other use cases, such as the (down) weighting of respective route sections for navigation.

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REFERENCES

Bienzeisler, L., Lelke, T., Wage, O., Huck, L.-M., Friedrich, B., 2022. Uncertainty and Variability Analysis of Agent-Based Transport Models. *Transportation Research Procedia*, 62, 719–726. <https://doi.org/10.1016/j.trpro.2022.02.089>.

Bienzeisler, L., Lelke, T., Wage, O., Thiel, F., Friedrich, B., 2020. Development of an Agent-Based Transport Model for the City of Hanover Using Empirical Mobility Data and Data Fusion. *Transportation Research Procedia*, 47, 99–106. <https://doi.org/10.1016/j.trpro.2020.03.073>.

Grigoropoulos, G., Hosseini, S. A., Keler, A., Kath, H., Span-
gler, M., Busch, F., Bogenberger, K., 2021. Traffic Simulation
Analysis of Bicycle Highways in Urban Areas. *Sustainability*,
13(3), 1016. <https://doi.org/10.3390/su13031016>.

Heumann, M., Kraschewski, T., Brauner, T., Tilch, L., Breit-
ner, M. H., 2021. A Spatiotemporal Study and Location-
Specific Trip Pattern Categorization of Shared E-Scooter Us-
age. *Sustainability*, 13(22), 12527. <https://doi.org/10.3390/su132212527>.

Horni, A., Nagel, K., Axhausen, K. W., 2016. *The Multi-Agent
Transport Simulation MATSim*. Ubiquity Press, London, GBR.

Huber, S., Liner, S., Lindemann, P., Muthmann, K., Schnabel,
A., Friedl, J., 2021. Modelling bicycle route choice in German
cities using open data, MNL and the bikeSim web-app. *2021
7th International Conference on Models and Technologies for
Intelligent Transportation Systems (MT-ITS)*, 1–6.

Jaber, A., Juhasz, J., Csonka, B., 2021. An Analysis of Factors
Affecting the Severity of Cycling Crashes Using Binary Re-
gression Model. *Sustainability*, 13, 6945. <https://doi.org/10.3390/su13126945>.

Johnson, M., Charlton, J., Oxley, J., Newstead, S., 2010. Natur-
alistic cycling study: identifying risk factors for on-road com-
muter cyclists. *Annals of advances in automotive medicine. As-
sociation for the Advancement of Automotive Medicine. Annual
Scientific Conference*, 54, 275–283.

Karakaya, A.-S., Hasenburg, J., Bermbach, D., 2020. SimRa:
Using crowdsourcing to identify near miss hotspots in bicycle
traffic. *Pervasive and Mobile Computing*, 67, 101197.

Landeshauptstadt Hannover, Bereich Geoinformation,
2021. Digitales Geländemodell (DGM1). *Hannover.de*.
<https://www.hannover.de/Leben-in-der-Region-Hannover/Verwaltungen-Kommunen/Die-Verwaltung-der-Landeshauptstadt-Hannover/Dezernate-und-Fachbereiche-der-LHH/Stadtentwicklung-und-Bauen/Fachbereich-Planen-und-Stadtentwicklung/Geoinformation/Open-GeoData/3D-Stadtmodell-und-Gel%C3%A4ndemodell/Digitales-Gel%C3%A4ndemodell-DGM1>. Requested 2022-03-14.

Landeshauptstadt Hannover, FB Planen und Stadtentwicklung,
2021. Radzählstellen - Radverkehr und Fahrradfahren - Kommt
gut an! *Hannover.de*. <https://www.hannover.de/Leben-in-der-Region-Hannover/Mobilit%C3%A4t/Hannoversch%C3%B6nste-Radtouren/Lust-auf-Fahrrad/Radverkehr-und-Fahrradfahren-Kommt-gut-an>. Re-
quested 2022-03-21.

Lee, K., Sener, I. N., 2021. Strava Metro data for bicycle mon-
itoring: a literature review. *Transport Reviews*, 41(1), 27–47.
<https://doi.org/10.1080/01441647.2020.1798558>.

Loidl, M., Wendel, R., Zagel, B., 2015. Spatial analysis and
modelling of bicycle accidents and safety threats. *International
Cycling Safety Conference*.

Medeiros, R. M., Bojic, I., Jammot-Paillet, Q., 2021. Spa-
tiotemporal Variation in Bicycle Road Crashes and Traffic
Volume in Berlin: Implications for Future Research, Planning,
and Network Design. *Future Transportation*, 1(3), 686–706.
<https://doi.org/10.3390/futuretransp1030037>.

Molino, J. A., Kennedy, J. F., Johnson, P. L., Beuse, P. A., Emo, A. K., Do, A., 2009. Pedestrian and Bicyclist Exposure to Risk: Methodology for Estimation in an Urban Environment. *Transportation Research Record*, 2140(1), 145–156. <https://doi.org/10.3141/2140-16>.

Pucher, J., Buehler, R., 2017. Cycling towards a more sustainable transport future. *Transport Reviews*, 37(6), 689–694. <https://doi.org/10.1080/01441647.2017.1340234>.

Ravensbergen, L., Buliung, R., Lalibert, N., 2020. Fear of cycling: Social, spatial, and temporal dimensions. *Journal of Transport Geography*, 87, 102813. <https://doi.org/10.1016/j.jtrangeo.2020.102813>.

Statistische Ämter des Bundes und der Länder, 2021. Unfallatlas | OpenData. *Unfallatlas*. https://unfallatlas.statistikportal.de/_opendata2021.html. Requested 2021-11-02.

Vanparijs, J., Panis, L. I., Meeusen, R., Geus, B. d., 2015. Exposure measurement in bicycle safety analysis: A review of the literature. *Accident Analysis & Prevention*, 84, 9–19. <https://doi.org/10.1016/j.aap.2015.08.007>.

VMZ Ni, Region Hannover, 2021. Stadt Hannover Radzähler. *VMZ Niedersachsen*. <https://www.v mz-niedersachsen.de/stadt-hannover/radzaehler>. Requested 2022-01-11.

Wallentin, G., Loidl, M., 2015. Agent-based Bicycle Traffic Model for Salzburg City. *GI-Forum*, 1, 558–566. <https://doi.org/10.1553/giscience2015s558>.

Wu, J., Hong, L., Frias-Martinez, V., 2018. Predicting Perceived Cycling Safety Levels Using Open and Crowdsourced Data. *2018 IEEE International Conference on Big Data (Big Data)*, 1669–1676.

Ziemke, D., Metzler, S., Nagel, K., 2017. Modeling bicycle traffic in an agent-based transport simulation. *Procedia Computer Science*, 109, 923–928. <https://doi.org/10.1016/j.procs.2017.05.424>.