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HaTS - Hanover Traffic Scenario for SUMO

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Abstract. Realistic and comprehensive traffic simulations are essential for the effective testing and evaluation of emerging technologies, such as Vehicle-to-X (V2X) communication, and diverse use cases, particularly within complex urban environments. While current traffic scenarios often focus on motorized vehicles, there is a need to address the safety of vulnerable road users (VRUs), such as pedestrians and cyclists. This is especially relevant in light of the European Union's Vision Zero initiative, which aims for zero road fatalities by 2050. Although a few pedestrian-focused scenarios exist, there is no scenario specifically addressing bicycle traffic, despite their status as one of the most at-risk VRUs, with stagnant fatality rates in recent years. To address this gap, this paper introduces the Hanover Traffic Scenario for SUMO (HaTS), a novel traffic scenario including motorized vehicles and bicycles. HaTS provides a detailed and accurate representation of the road network, traffic light systems, and buildings within the city center of Hanover, Germany. A key feature of HaTS is its integration of real-world traffic count data for both bicycles and motorized vehicles, enabling a realistic and representative traffic demand representation. Additionally, a novel metric is employed for the parametrization of the scenario, enhancing the alignment between real and simulated traffic volumes. For the validation we compare the results of the HaTS with the real world traffic counts. HaTS is the first open-source SUMO scenario focused on bicycles, providing a realistic representation of the road network and traffic demand, thereby contributing to the advancement of urban traffic simulations.

Keywords: Traffic Scenario, SUMO, Simulation, Bicycles

1. Introduction

In recent years, simulations have become increasingly important for the development and analysis of various applications and use cases. Real-world testing of various road traffic applications can be both expensive and hazardous, particularly when the applications have not undergone thorough validation and pretesting. For example in autonomous driving functions, where the risks to testers can be significant. Additionally, certain scenarios, such as providing traffic forecasts for large events, are impossible to evaluate in real-world conditions. Simulations are especially important for applications of Vehicle-to-X (V2X) communication. The aim of V2X communication is to enable use cases like collision warnings, cooperative lane merging, overtaking assists, and many others, as outlined in [1]. Testing these newly developed V2X communication applications, especially those focused on safety, in simulations is essential. As a result, various simulators and scenarios have been developed, with the Simulation of Urban MObility (SUMO) [2] being one of the most renowned in research.

While past simulations have primarily focused on motorized vehicles, there is a growing need to include Vulnerable Road Users (VRUs) such as pedestrians and bicyclists. The European Commission's Vision Zero [3] target, which sets the goal of eliminating all road fatalities and serious injuries by 2050, highlights the critical need to incorporate VRU safety into traffic planning and technology development. In particular, the stagnant fatality rates for bicyclists [4], in contrast to the decreasing trends for other road user groups, underscores that especially bicycles could profit from including new technologies like V2X. However, existing simulation scenarios that include VRUs are limited (e.g., [5], [6]) and tend to focus on pedestrians rather than bicycles.

This paper introduces the Hanover Traffic Scenario for SUMO (HaTS), a novel high-density bicycle traffic scenario. HaTS is openly available to the entire research community[1]. Hanover was selected for this scenario due to its high proportion of households with bicycles and its status as one of the cities with the largest proportion of bicycles in the modal split among cities with 500,000 or more inhabitants [7]. HaTS accurately represents the traffic flows of motorized vehicles and bicycles from 6 am to 7 pm in Hanover, Germany, including a realistic representation of the road network, buildings, and traffic lights in the city center. The traffic flows for both vehicles and bicycles are based on seven different real traffic counts at various crossings. To enhance the accuracy of HaTS, we optimized its parameters using a newly introduced metric based on the Normalized Root Mean Square Error (NRMSE), absolute error, and maximum variations per parameter set. This approach significantly improves the representation of traffic demands within the simulation. Additionally, this paper provides a step-by-step description of the scenario generation process, which can serve as a valuable resource for other researchers to create new traffic scenarios. By sharing this methodology, we aim to facilitate further advancements in traffic simulation.

The remainder of this paper is structured as follows: Section 2 provides an overview of existing traffic scenarios. Section 3 details the generation of the HaTS road network, the extraction of traffic demand, and the parametrization process employed to optimize the scenario. Section 4 presents the validation of the HaTS scenario, comparing the simulated traffic demand against real-world traffic counts to assess its accuracy. Finally, Section 5 presents a discussion and conclusion.

2. Related Work

In recent years, much research has focused on creating realistic SUMO city scenarios for various purposes.

Lobo et al. [5] introduced the Ingolstadt Traffic Scenario for SUMO (InTAS), which offers a realistic representation of road networks and traffic flow in Ingolstadt. This scenario includes detailed features such as buildings, bus stops, and realistic traffic light phases, and simulates private cars as well as public transport. The authors compared the simulation results to real traffic data from 24 measurement points, with the scenario representing traffic flows over the course of a full day. Simulated trips were generated based on demographic data and real traffic information. The InTAS exhibits discrep-

[1] https://github.com/boschresearch/HanoverTrafficScenario

ancies between simulated and real traffic in situations with high traffic volumes. A key distinction of our work is the inclusion of a realistic proportion of bicycles, in addition to vehicles, within our simulated scenario. We also strive to achieve a more realistic representation of high traffic demands during peak hours.

The Monaco SUMO Traffic scenario (MoST) [6] captures peak morning traffic in Monaco, offering a 3D representation of Monaco with multimodal traffic. This scenario encompasses private vehicles, commercial vehicles, public transport, pedestrians, and bicycles. Unlike MoST, which derives trips from demographic studies without validation against real traffic flows, HaTS utilizes observed traffic counts to generate a more realistic scenario. Furthermore, our scenario differs in that it not only encompasses morning traffic but also includes evening traffic. Additionally, our scenario features a higher volume of bicycle traffic compared to MoST.

The Luxembourg scenario (LuST) [8] is designed to simulate a complete day of mobility in Luxembourg. It offers a high level of detail, incorporating all buildings, parking lots, and realistic traffic flows. The evaluation of the scenario is based on demographic data and certain measured statistics, such as average speed in specific regions. A key distinction from our scenario is that LuST exclusively includes vehicles and does not account for other road participants such as bicycles.

TAPAS Cologne [9] incorporates a road network imported from OpenStreetMap (OSM) and offers various options for simulating traffic in Cologne. The traffic flows are derived from demographic data and the daily activities of the city's inhabitants. However, a key distinction is that the imported road network is not corrected and may not always accurately represent the real topology of Cologne. Additionally, the representation of traffic lights and buildings is not realistic. Furthermore, the scenario's large scale results in extended computation times.

Schrab et al. introduced the Berlin SUMO traffic scenario (BeST) [10], which simulates the traffic patterns over a full day in Berlin. BeST includes motorized private trips that have been validated against real traffic data. Encompassing an area of $800\,\mathrm{km}^2$ and over 2.2 million trips, BeST is a comprehensive representation of urban traffic. A notable distinction from our scenario is that BeST exclusively focuses on private vehicles and does not consider other road participants such as bicycles.

The Turin SUMO Traffic (TuST) scenario [11] provides a comprehensive representation of realistic traffic within the city of Turin spanning an entire day. The traffic flows and traffic light phases are derived from real traffic data, ensuring a high level of accuracy. The scenario exclusively includes vehicles, which distinguishes it from our work.

To the best of our knowledge, there is currently no SUMO scenario that incorporates a significant volume of bicycle traffic generated through traffic counts. As a result, this research stands out from existing scenarios and offers a unique contribution to the simulation of bicycle traffic in an urban setting.

3. Setup of Scenario

The setup of the HaTS was structured into three distinct steps, each will be explained in this chapter. The initial step involved the development of the map and the road network for the scenario. Subsequently, the second step entailed extracting the traffic demands from the available data. Finally, the third step encompassed the parametrization of the scenario.

3.1 Map and Road Network

The area chosen for the HaTS is illustrated in Figure 1, with the simulation area outlined by the red square. The blue triangles indicate the junctions where traffic counts were conducted. This particular area in Hanover was selected due to its high traffic volume and unique topology. It encompasses several of Hanover's primary streets, residential neighborhoods, and is situated near the city center. The waterfront area is a focal point for cyclists, resulting in notable congestion for both bicycles and vehicles.

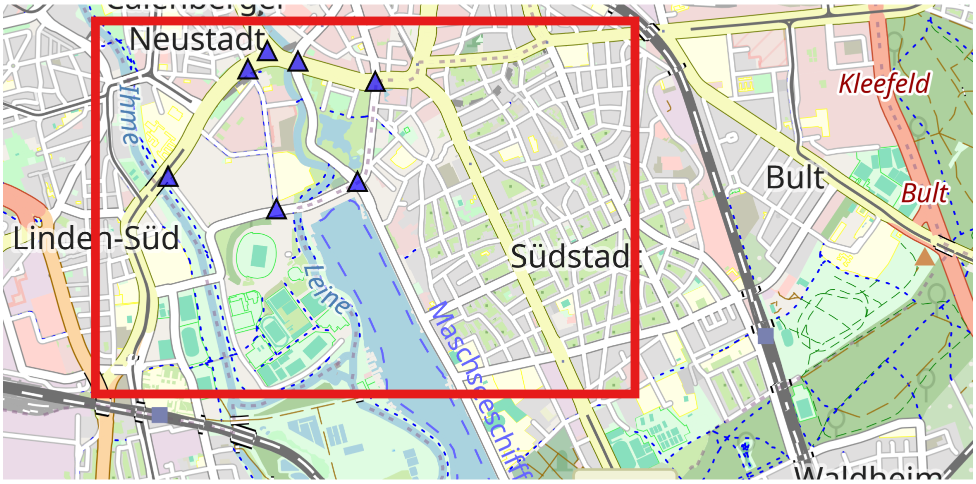


Figure 1. *Selected Scenario Area and Traffic Count Stations. [12]*

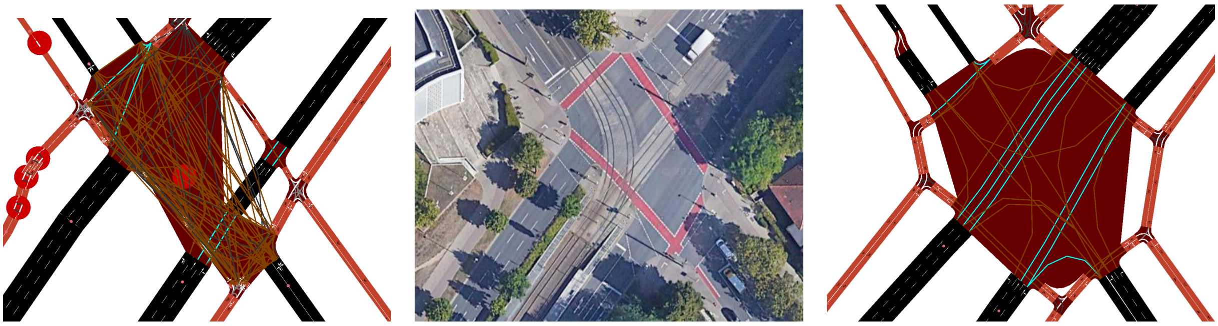
Using the `OSMWebWizard`[2], we generated the SUMO network based on the Open Street Map (OSM)[3] representation of the selected area. Upon exporting the network, we discovered that many streets did not accurately reflect the real world. This was particularly evident in the representation of turning possibilities at intersections, as well as discrepancies in the number of lanes and the placement of traffic lights. These inconsistencies may be attributed to outdated information obtained from OSM. Despite the regular updates on OSM, due to its crowd-sourcing approach, certain areas lack sufficient detail and may only include street segments without specific lane or exclusive lane information.

As a result, it was necessary to make adjustments to the exported network. Figure 2 illustrates such a correction. We compared each lane and intersection in our simulation with satellite images from Google Maps[13] and manually rectified these discrepancies using SUMO's netedit[4] tool. To streamline the scenario and maintain a focused analysis on bicycles and vehicles, we removed all pedestrian paths, private roads, car parking areas, railway tracks, and bus lanes from the simulation. After the optimization, the road network consists of a total length of 224 km, divided between bicycle and vehicle roads. Table 1 provides details about the road network.

Another important consideration is not only the adjustment of lanes and potential turns, but also the management and positioning of traffic lights.

The `osmWebWizard` automatically generates traffic light programs, as OSM only provides the locations of the traffic lights but not the phases. In the area of HaTS 42 traffic lights are included.

[2] https://sumo.dlr.de/docs/Tutorials/OSMWebWizard.html
[3] www.openstreetmap.org
[4] https://sumo.dlr.de/docs/Netedit/



(a) *Before Correction* ***(b)*** *In Google Maps [13]* ***(c)*** *After Correction*

Figure 2. *Crossing exported from OSM before and after manual correction.*

Table 1. *Network Statistics.*

Parameter	**Value**
Total Area	5.5 km^2
Exclusive Vehicle Road Length	48.9 km
Exclusive Bicycle Road Length	107.5 km
Both Allowed Road Length	67.6 km
Nodes	1074
Edges	2503
Traffic Lights	42

By default, all generated programs have a 90-second cycle and are of type `actuated`. Actuated traffic lights respond to traffic demand, with each phase in the program having a minimum and maximum time. Gap-based actuated traffic control, which is supported by SUMO and widely used in Germany, operates by extending traffic phases upon detecting a continuous flow of traffic. It then transitions to the next phase after identifying a suitable time gap between successive vehicles or if the maximum time limit is exceeded. This approach facilitates improved distribution of green time across phases and adapts cycle duration in response to changing traffic conditions. [14]

However, it was necessary to logically verify the assigned phases. Real-world data concerning the actual signal phase plans and timings for the intersections within the HaTS study area were not available for this work. Therefore, we compared the traffic lights with images from Google Street View, particularly for green arrow turns. We also utilized our personal real-world experience of different phases and optimized all traffic light phases to enhance traffic flow. It's important to note that for all traffic lights we maintained the `actuated` mode.

3.2 Traffic Demand

The traffic demand in the scenario is determined by real traffic counts, while the specific routes are constructed randomly. The following section will outline the data set and tools utilized to create the routes and distribute traffic.

3.2.1 Real Traffic Counts

The department of Planning and Urban Development of the city of Hanover has provided comprehensive traffic count data sets for the purpose of this research and we would like to express our gratitude at this point.

The data includes counts from seven distinct crossings (c.f. blue triangles in Figure 1) and was collected in May 2022. Each data set contains detailed information on the volume of vehicles and bicycles that passed through these areas during the hours of 6 AM to 7 PM, with a resolution of 15 minutes. Furthermore, the data sets include turn counts at each crossing, which provide valuable insights into traffic flow patterns. For instance, Figure 3 illustrates an example of turn counts at a T-crossing. Turn counts specifically quantify the number of vehicles utilizing designated entry and exit points at a crossing during a specified time period. In this example, the turn counts indicate that 32 vehicles traveled from south to east, while 44 vehicles moved from south to west. In total, the traffic count data sets comprise 86 distinct turn counts across the seven crossings, offering a robust foundation for analyzing traffic demand.

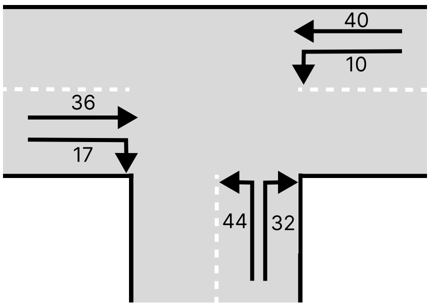


Figure 3. *Example of turn counts at a T-crossing.*

The total number of traces in the data set is illustrated in Figure 4. Vehicles and bicycles exhibit a similar distribution throughout the day, despite the significantly higher volume of vehicles compared to bicycles. The number of bicycle and vehicle traces begins at a low level in the early morning (6 AM) and rises steadily until the morning rush hour, which occurs between 7:45 AM and 8:45 AM. Following this peak, the volume of traces experiences a slight decline until around 11:15 AM. After this point, the number of traces gradually increases again, leading up to the evening rush hour (3:30 PM to 5:30 PM). From 5:30 PM until the end of the scenario the traffic demand decreases again. Overall, the distribution of traces aligns with expectations, reflecting high traffic demand during the morning and evening periods, primarily driven by commuting traffic for both bicycles and vehicles. While there is still some traffic between the rush hours, which is noticeably lower.

3.2.2 Traffic Demand Modeling

In order to model a realistic traffic demand, we used the traffic counts and the `routeSampler`[5] method of SUMO. This method is able to generate traffic demands based on turn count, edge count, and origin-destination count data. To do this, we provided possible routes in the network and the count data, allowing the `routeSampler` to select the appropriate distribution of routes to generate specific traffic demands.

[5] https://sumo.dlr.de/docs/Tools/Turns.html

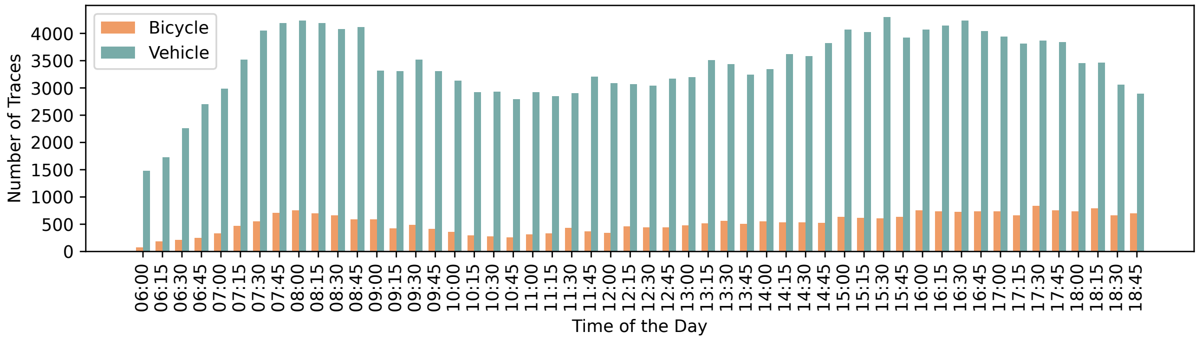


Figure 4. *Traces from real traffic counts for bicycles and vehicles.*

To generate possible routes as input for the `routeSampler`, we utilized the `randomTrips` method[6], which creates random possible trips, in conjunction with the `duarouter` method[7], which generates routes based on those trips. In the context of SUMO, a trip defines the starting and ending points of a road user during the simulation, while a route specifies the exact path, including all roads that will be taken to reach the destination.

The `randomTrips` method selects starting and destination points based on a defined distribution. To better reflect the traffic patterns in the area, we increased the probability of trips originating from or terminating at the fringes of the network, as most traffic in this region consists of through-traffic. The `duarouter` method was then used to create routes based on the trips, utilizing the Dijkstra [15] route-planning algorithm. The Dijkstra algorithm finds the shortest possible route between starting and destination points. We parametrized the `duarouter` to allow also for routes up to 3 times longer than the shortest path, leading to a higher variation of possible routes. This is realistic as drivers may choose longer routes based on traffic conditions or for other reasons, e.g., to pick up additional passengers.

3.3 Scenario Parametrization

A SUMO simulation provides the possibility to set different parameters based on the specific scenario. These parameters define the handling of different situations and specific behaviors. The most important parameters set for HaTS are summarized in Table 2.

Table 2. *Simulation Parameters.*

Parameter	Value
start	0 s
end	46,800 s
step-length	0.1 s
ignore-junction-blocker	15 s
lateral-resolution	0.3
routing-algorithm	Dijkstra
device.rerouting.probability	0.22
device.rerouting.period	300 s

[6] https://sumo.dlr.de/docs/Tools/Trip.html
[7] https://sumo.dlr.de/docs/duarouter.html

Two necessary parameters are the `start` and the `end` time of the simulation. We set the `start` time to 0 which is representative for 6 AM, the `end` time is set to 46800 s, i.e., 7 PM.

The simulation `step-length` defines how often a simulation is updated. We set it to 0.1 s but it could also be adjusted to a shorter or longer value between 0.05 s and 1 s if necessary.

By default, SUMO assumes that driving in parallel on a single lane is not possible. For motorized vehicles this is true most of the time, but for bicycles it does not represent the reality. In most cases bicycles drive next to each other, wait next to each other at a traffic light or overtake without leaving a specified lane. For this reason we decided to acitvate the SUMO `SublaneModel`[8]. The `SublaneModel` subdivides a lane into multiple sublanes, allowing road users to drive adjacent to one another within a single lane, provided there is sufficient space.

In some situations in a simulation it is possible that vehicles block an intersection. This behavior causes large traffic jams and unrealistic behavior. The parameter `ignore-junction-blocker` allows road users to ignore such an junction blocking road user after a specific time. This simulates realistic behavior like "finding a way around the offending vehicle that is blocking the intersection"[9]. We selected a time of 15 s to minimize the impact due to such junction blockers.

Another important parameter for the vehicles and bicycles is the car following model. The default model is the Krauss model [16]. For the vehicles we therefore choose the Krauss model. For bicycles, it is recommended to use the Realistic Bicycle Dynamics Model (RBDM)[10], as described in [17], which aims to capture realistic bicycle behavior. In this study, we will proceed with the Krauss model for both vehicles and bicycles, as it is part of the official version of SUMO. Nonetheless, all analyses conducted are applicable to the RBDM as well, ensuring that our findings remain relevant regardless of the model used.

3.3.1 Optimizing the Rerouting Probability

The last parameter we defined is the `device.rerouting.probability`. This parameter allows road users to reroute their planned routes based on knowledge about the road network if they for example face traffic jams on their initial routes. This parameter effectively addresses traffic congestion in a realistic manner, similar to how a real-time traffic navigation app, such as Google Maps [13], operates, without the need of teleportation in the simulation. Figure 5 illustrates the simulated volume of vehicle traces compared to the expected volume based on traffic counts, without defining a rerouting probability. In the absence of this rerouting probability, the scenario experiences significant traffic jams at certain points during the simulation. This highlights the critical importance of this parameter in accurately modeling traffic dynamics and preventing congestion.

As this parameter is very scenario-dependent, it is necessary to define a metric with which this parameter can be optimized. For this purpose Lobo et al. [5] introduced to use the Normalized Root Mean Square Error (NRMSE):

$$NRMSE = \frac{\sqrt{\frac{\sum_{n=1}^{N}(x_{r,n}-x_{s,n})^2}{N}}}{\overline{x}}$$

[8] https://sumo.dlr.de/docs/Simulation/SublaneModel.html
[9] https://sumo.dlr.de/docs/Simulation/Intersections.html
[10] https://github.com/boschresearch/RealisticBicycleDynamicsModel

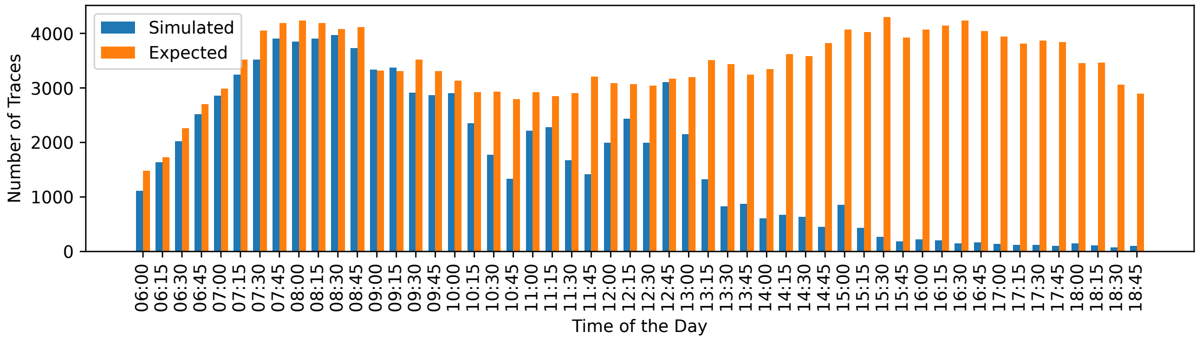


Figure 5. *Comparison between real and simulated traces of vehicles without a rerouting probability.*

where $x_{r,n}$ represents the real amount of road users at timestep n, $x_{s,n}$ represents the simulated amount of road users at timestep n, N represents the total number of samples and $\overline{x}$ is the mean value of the measured data.

In our study, we observed that optimizing solely with NRMSE resulted in a rerouting probability that accurately represented most of the scenario. However, during the evening rush hours when the traffic volume was high, especially for vehicles, significant traffic jams occurred, leading to a large number of vehicles being rerouted through smaller streets. This led to a substantial disparity between real traffic and simulated traffic, as illustrated in Figure 6. This behavior was also observed in the InTAS [5] scenario, where the main issue was the mismatch between real and simulated traces, particularly in dense traffic situations.

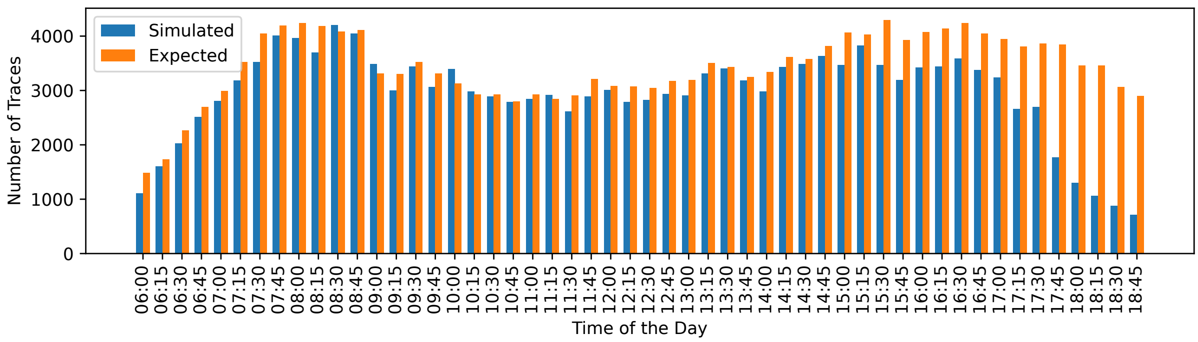


Figure 6. *Comparison between real and simulated traces of vehicles for best NRMSE case.*

To address the optimization challenge of selecting the best rerouting probability, we have developed a novel scoring system based on several distinct metrics. The first metric is the Normalized Root Mean Square Error (NRMSE), as previously explained. The second metric measures the absolute difference in the number of traces throughout the entire simulation scenario. This metric aims to minimize significant discrepancies between simulated and expected values. Unlike the NRMSE, which averages the error over the entire scenario, this metric sums the errors across the whole simulation. The final metric, the maximum difference, captures the largest variation between expected and simulated traces at any point during the simulation. This difference is calculated for each time slot, and the time slot with the highest discrepancy is used to represent the specific rerouting value. A lower value is considered better, as this metric was chosen to avoid high deviations in individual time slots, which is not taken into account in the previous metrics. Therefore, it contributes to a more realistic representation of the entire day.

To determine the overall score, each individual metric is first normalized using the following formula:

$$score = 1 - \frac{value - x_{min}}{x_{max} - x_{min}}$$

where $value$ is the current value, x_{min} is the lowest value and x_{max} is the highest value observed. Subsequently, each metric is weighted equally, and a combined score is generated. To ensure equal weighting for bicycle and vehicle traffic, we calculated the score separately for both. If we calculated a combined score directly, the bicycles would have a much lower weight due to the lower amount of traces. This approach was chosen to achieve a balanced representation of the full traffic, as we aim for the most realistic depiction. The results of this separated evaluation are plotted in Figure 7.

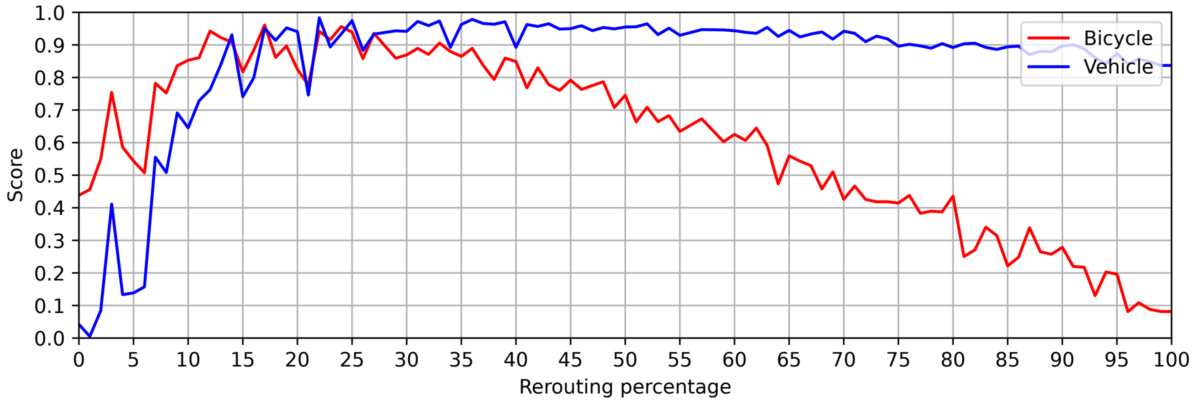


Figure 7. *Score of bicycle and vehicle traces.*

For rerouting probabilities ranging from 0 to 10, both bicycles and vehicles exhibit low scores. However, for rerouting probabilities above 10 a score between 0.8 and 1 is consistently observed for vehicle traces, indicating relative stability. This stability arises from the fact that even with a low number of vehicles opting for rerouting, the resulting traffic jams are either resolved or not critical enough for rerouting to be advantageous.

Conversely, the situation is different for bicycles. For rerouting probabilities between 10 - 40, the score fluctuates between 0.8 and 1. However, beyond that range, the score begins to decrease, reaching a score near 0.1 with a rerouting probability of 100.

To determine the best rerouting probability, both scores need to be combined and normalized. The result of this normalization is depicted in Figure 8.

It is evident from the plot that the score is lower for low values of the rerouting probability, increases with the probability until it reaches the maximum score value, and then decreases again towards higher probabilities. The optimal value for **device.rerouting.probability**, which yields the highest score, is 0.22, with a score of 0.96.

4. Validation of Scenario

The HaTS scenario validation utilizes the traffic count data that was also used to generate the traffic demand. To conduct a comprehensive analysis of the differences between real measured and simulated traces, we separated the bicycle and vehicle traces for validation. The traffic count data included turn counts at the included intersection, as detailed in Section 3.2.1. For a highly detailed validation, we compared these turn

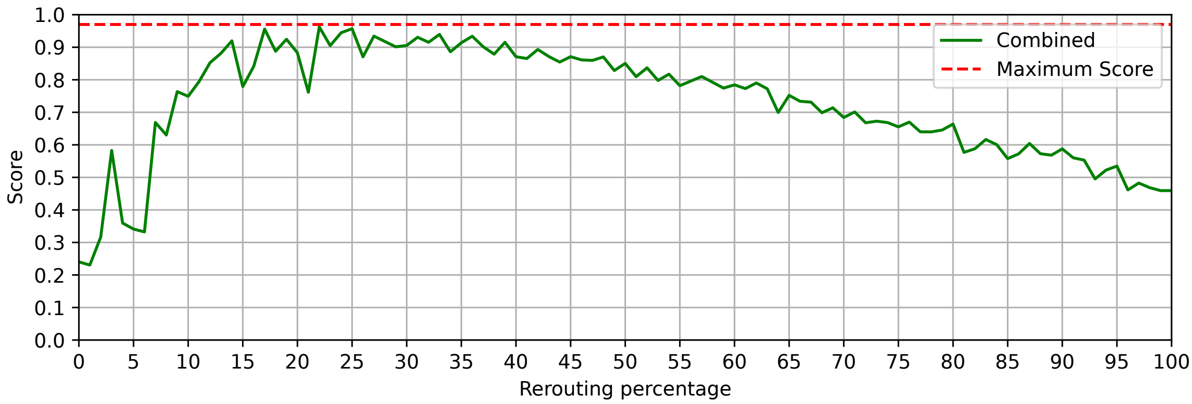


Figure 8. *Score of bicycle and vehicle traces combined in a normalized score.*

counts to the simulation turn counts, resulting in 86 comparisons. To generate the turn counts in the simulation, we utilized SUMO's Multi-Entry-Exit Detectors[11] at the specific crossings to count the selected traces. The comparison between simulated and expected traces for vehicles is illustrated in Figure 9, while Figure 10 depicts the comparison for bicycles

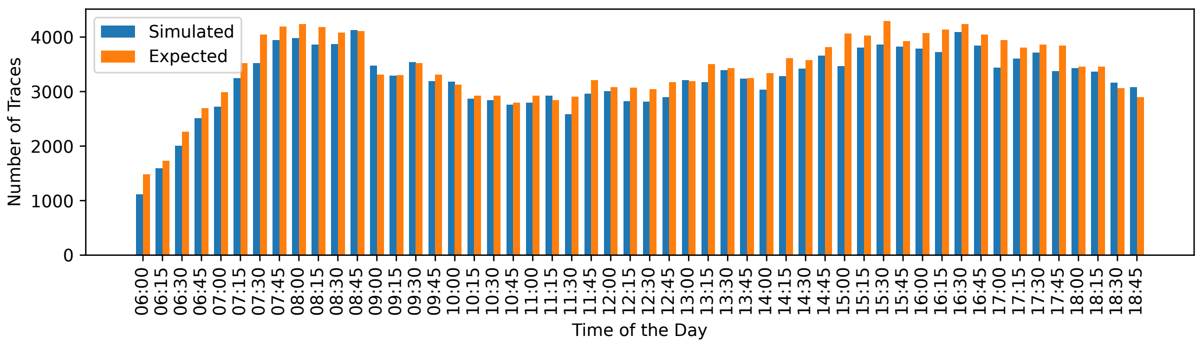


Figure 9. *Comparison between real and simulated traces of vehicles.*

The validation results for vehicles in Figure 9 indicate that the simulated traces closely match the expected distribution from the traffic count, with some notable differences. At the start of the scenario at 6 AM, there is a significant difference between the expected and simulated traces, primarily because the scenario has to build up from zero vehicles first, and the vehicles start at the fringes of the road network, leading to a high vehicle density at the fringes in the beginning. As a result, it is challenging for the vehicles to reach the measurement points in time, leading to discrepancies in the counts. Such a settling time is unavoidable in simulations. However, after the initial startup period, the differences in counts begin to decrease. Therefore, to ensure valuable simulation results, the scenario should be initiated at 6:15 AM (900 seconds in simulation time).

Another notable observation is that, particularly during peak traffic situations, the increase in simulated traces does not exactly match the increase observed in the traffic count traces. This can be attributed to congestion at the scenario fringes, as well as the interaction between vehicles and bicycles, which is not accounted for by the `routeSampler`. As a result, some vehicles arrive at the measurement points later than planned, leading to their inclusion in the subsequent time slot for counting.

[11] https://sumo.dlr.de/docs/Simulation/Output/Multi-Entry-Exit_Detectors_(E3).html

Furthermore, the simulation consistently generates a lower number of traces compared to the expected counts from the traffic data. This discrepancy is primarily attributed to rerouting, which can cause vehicles to bypass certain measurement points due to traffic jams, resulting in an underestimation of the simulated traces compared to the actual traffic count.

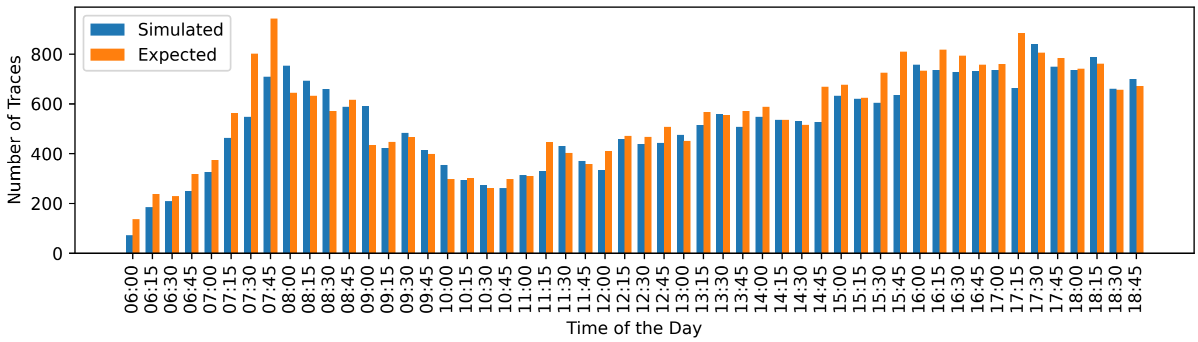


Figure 10. *Comparison between real and simulated traces of bicycles.*

Similar to the vehicles, the validation results for bicycles in Figure 10 also exhibit a comparable pattern. In the initial time slot, there is a significant discrepancy between the simulated and expected traces for bicycles. However, after the settling period, these differences decrease. Nevertheless, it is noticeable that during peak time slots, such as 5:15 PM, the simulation exhibits a delay in representing the high volume of bicycle traces. This delay can be attributed to congestion at the edges of the scenario and the functioning of the `routeSampler` as explained for the vehicles. Interestingly, the delay for bicycles is slightly more pronounced than for vehicles. This can be explained by the higher relative increase in bicycle traffic from pre-rush hour to rush hour compared to vehicles. As a result, there are numerous bicycle insertions occurring within a short timeframe. Most of these insertions take place at the fringes of the scenarios, leading to an increase in traffic density in those areas. Consequently, this results in smaller jams, which in turn contributes to the observed delays. While a similar pattern is evident for vehicles, the smaller slope in their traffic increase results in a comparatively reduced delay effect.

Figure 11 illustrates the relative deviations between simulated and expected traces for both vehicles and bicycles, confirming the previously discovered results and providing further insights. The highest difference is observed at the first time slot, and for most time slots, there are slightly fewer simulated traces than expected, as previously explained. The highest absolute difference observed for bicycles, excluding the settling time, occurs at 9 AM, reaching 36%. In comparison, the highest absolute difference for vehicles is 14%, noted at 3 PM. When examining the absolute median differences, bicycles show a median difference of 6.6%, while vehicles exhibit a slightly lower median difference of 5.2%. The representation for vehicles is generally slightly better than for bicycles, which could be attributed to the `routeSampler` primarily being developed for vehicles and not bicycles. Additionally, the interaction between vehicles and bicycles is not accounted for, as the routes are generated independently of each other.

Another factor impacting the simulation accuracy is that real-world road participants do not always perfectly adhere to traffic rules, especially bicycles, which may cross roads while leaving the bicycle lane or proceed through a red traffic light. In contrast, the simulation assumes near-perfect adherence to traffic regulations. This is only slightly influenced by the `tau` parameter of the car-following model, which governs the behavior of road users in terms of their following distance and response to traffic condi-

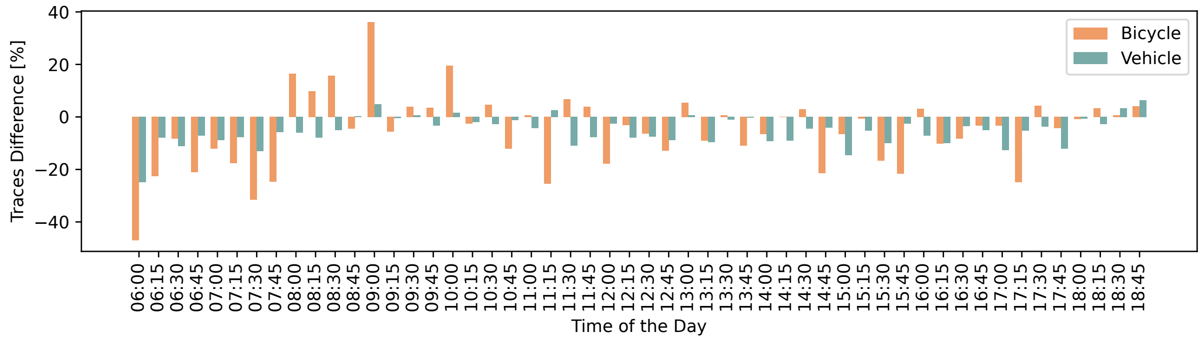
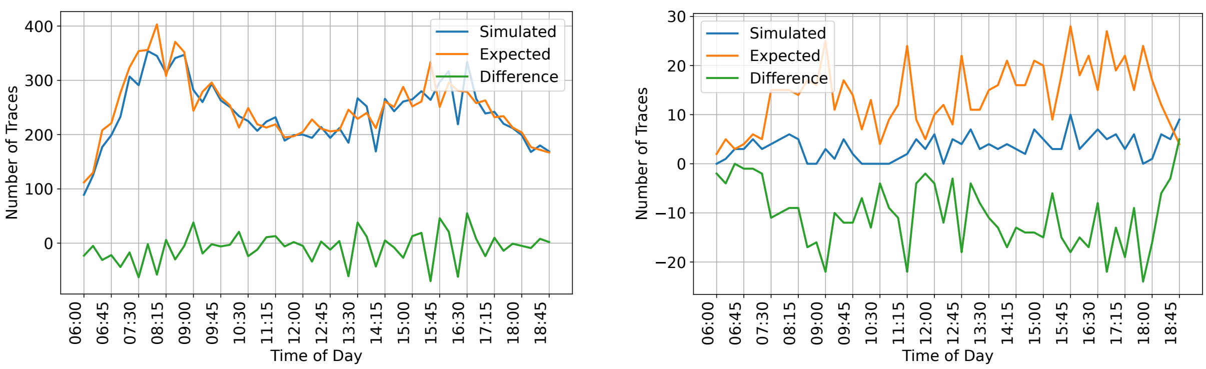


Figure 11. *Percentage variances between expected and simulated traces.*

tions. As a result, the simulation imposes limitations on the number of bicycles that can safely cross a junction within a given time slot. This discrepancy between real-world behavior and simulated adherence to rules contributes to the observed differences in representation between simulated and expected traces for both vehicles and bicycles.

The differences between simulated and expected traces vary between different turn counts at crossings, while some turns are represented by the traces with a very small difference, others are represented with a larger difference. In Figure 12 the best and the worst case are plotted. For the best case (Figure 12a) the difference between expected and simulated traces is very small with a median difference of 2.2%. In the worst case (Figure 12b) the difference is higher with a median difference of 76.1%. The high differences are due to rerouting and congestion.



(a) *Best Case* ***(b)*** *Worst Case*

Figure 12. *Best and worst turn count representation in Simulation.*

5. Conclusion and Discussion

This paper presented HaTS, a novel scenario for the SUMO simulator that encompasses an urban environment with high-density bicycle and vehicle traffic. HaTS covers an area of 5.5 km^2 with a total road length of 224 km, of which 175 km is dedicated to bicycle traffic. The representation of the road network in HaTS, including lanes, intersections, and traffic lights, closely mirrors the real road network of Hanover, Germany due to manual corrections of the exported OSM road network, resulting in a highly realistic simulation.

The traffic demand for vehicles and bicycles in HaTS is based on and validated on real traffic counts. They were collected at seven distinct crossings from 6 AM to 7 PM, with a resolution of 15 minutes. This data set includes detailed turn counts for all possible trajectories at the crossings, allowing a more detailed representation of the traffic demands. In order to improve traffic flow and the representation of traffic demand, a novel metric was introduced to optimize the parameterization of HaTS. For validation purposes, detectors were added to the simulation that were able to generate traffic count files at the seven intersections with real data available. The validation of HaTS showed that the representation of both bicycle and vehicle traces within the scenario is very realistic. The median difference for vehicle traces over the whole scenario is only 5.2% and for bicycles slightly higher, but still only 6.6%.

However, HaTS does also have limitations. The SUMO `routeSampler` encounters challenges in creating accurate trips for bicycles compared to vehicles. In addition, the lack of consideration for the interaction between vehicles and bicycles, as routes are generated separately, leads to deviations between expected and simulated traces. Real-world behavior that is not represented in simulations, such as bicyclists crossing streets while leaving designated lanes or disregarding red traffic lights, also contributes to these deviations.

Furthermore, the concentration of traffic counts in a limited segment of the road network restricts the validation of traffic traces in other locations. Another limitation involving the traffic counts is that they are based on video analysis. The accuracy of this method is susceptible to environmental conditions, such as weather or lighting, as well as technical factors and the specific algorithms employed. The error margin associated with the reported traffic volumes remains therefore undetermined. Furthermore, the analysis lacks dynamic traffic parameters. Real-world vehicle speed data, which could be used to characterize traffic flow and identify congestion dynamics, were not available in the data. Similarly, direct measurements of vehicle travel times between network points were not available.

However, despite these limitations, HaTS is the first scenario capable of representing realistic, high-density urban bicycle and vehicle traffic. HaTS enables the testing and analysis of new technologies, such as V2X, to improve road safety for bicycles and vehicles. Notably, HaTS[12] is open source, providing a valuable resource for the research community to further explore and improve urban traffic simulation.

Author contributions

The authors contributed to this paper in the following ways: Nico Ostendorf was responsible for the conceptualization and methodology, developed the software, conducted the analysis of the results, and prepared the original manuscript draft. Keno Garlichs and Lars Wolf contributed to the validation of the results and the reviewing and editing of the manuscript.

Competing interests

The authors declare that they have no competing interests.

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