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# COMPARISON OF DIFFERENT URBAN TRAFFIC REPRESENTATIONS FOR ROAD TRAFFIC NOISE INDICATORS ESTIMATION

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## ABSTRACT

This study designs a comparison of the estimation of road traffic noise from different urban traffic representations between their corresponding modelling chains. Based on a microscopic traffic dataset in Stockholm, three kinds of urban traffic representations (Microscopic traffic representations, Aggregated traffic representations, and Hybrid traffic representations) and their corresponding traffic noise estimation models are introduced from distinct perspectives. The distribution result of $L_{\mathrm{Aeq},1h}$ highlights that all models follow similar distribution patterns in noise exposure despite different traffic representations, while still slight differences in peak noise intervals remain. Two proposed hybrid traffic representation methods expand acoustic indicator sights from aggregated traffic representations by introducing dynamics and stochasticity, which can yield comparable noise estimates at high percentile indicators. The noise maps highlight that a general but uneven underestimation exists in all other modes compared to microscopic traffic representations. Desired improvements of hybrid traffic representation methods are discussed, aiming to bring acoustic evaluation enrichment in urban traffic environments.

**Keywords:** *Road traffic noise, Modelling chains, Traffic representations, Hybrid representations*

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## 1. INTRODUCTION

Accurate noise estimation is critical for understanding the environmental impact of traffic systems. In recent years, various traffic output data from traffic simulation models have been widely utilized in estimating traffic noise. Stressed in different urban conditions and spatial scales, corresponding model chains provide unique analytical perspectives in traffic noise estimation [1–3]. Macroscopic traffic models provide aggregated link-based traffic speed and flow rate [4], while micro-simulation traffic models provide granular outputs (such as float point trajectories) as a basis for noise modelling. In addition, hybrid representations allow the gap between trajectories and aggregated representations to be bridged [5, 6]. This article aims to describe the state of the art of the various couplings and implementations currently available, and to propose a comparative analysis of their advantages and limitations, including implementation specificities, and resulting acoustic level accuracy.

These different traffic representation datasets are derived from the same micro-simulation scenario in an urban area in Stockholm. Noise levels are estimated for each dataset using established acoustic models in the latest version of CNOSSOS-EU [7, 8], and compared to the reference micro-simulation based estimation. This research provides insights into the influence of different traffic representation outputs from a microscopic traffic representation scenario on noise estimation, which could be referred to by practitioners in selecting traffic outputs for urban noise assessments.

## 2. METHODS

### 2.1 Traffic representations

The study is based on microscopic traffic data, typically representative of higher density traffic on the island of Södermalm in Stockholm, Sweden. In order to assess the impact of different traffic representations on noise estimations, three kinds of traffic representations are introduced from distinct perspectives in this part.

#### *2.1.1 Microscopic traffic representations*

SUMO Mode
The original traffic simulation is based on SUMO (Simulation of Urban Mobility) [9], which is an open-source, highly flexible microscopic traffic simulator widely used for modelling urban traffic dynamics. SUMO provides detailed vehicle-level movement data, including individual vehicle trajectories, acceleration, deceleration, lane-changing behavior, and interactions with traffic control mechanisms such as traffic lights and stop signs.

In this case study, the simulation is configured to simulate typically high traffic volumes and frequent stop-and-go movements.

#### *2.1.2 Aggregated traffic representations*

Computational efficiency and usability of microscopic traffic data in large-scale studies are usually limited. Aggregated traffic representations represent the classic approach commonly used in noise mapping [10], as it relies on available urban traffic counting loops or similar detection methods. Based on SUMO Mode, three distinct aggregated scenarios are analyzed: Flow Sensor Mode, Time Mean Speed Mode, and Space Mean Speed Mode. Each mode provides a unique perspective on link attributes including traffic flow rate and mean speed.

Flow Sensor Mode
In this mode, traffic speed is estimated using randomly placed flow sensors along each link. The methodology follows these steps:

- A single sensor point is randomly assigned to each road link.
- The sensor has a detection range of 10 meters, to avoid duplicate records, recording vehicle positions and passing time on the nearest link to the vehicles.
- As recorded vehicles pass through the sensor's detection area, their speeds are calculated.
- The link mean speed is then computed as the average speed of all vehicles detected by the sensor.

This approach mimics real-world traffic monitoring via stationary sensors but is limited by the fact that only a small portion of each road segment is observed, potentially leading to biases in speed estimation.

Time Mean Speed (TMS) Mode
The Time Mean Speed (TMS) [11] mode refines speed measurement from Flow Sensor Mode by considering all the appearances of vehicles on the same link. The process involves:

- Identifying vehicles that appear on the same nearest link at least twice within a given time window, capturing travel distance and time between vehicle positions.
- Calculating the speed of each detected vehicle along the nearest link.
- Computing the average speed of all identified vehicles on the link.

Space Mean Speed (SMS) Mode
The Space Mean Speed (SMS) [11] mode focuses on speed accuracy by incorporating the total travel time and travel distances regardless of the identification of single vehicles. This method follows a similar counting mechanism to the TMS mode but differs in speed computation:

- Vehicles are counted if they appear on the same nearest link at least twice.
- The total travel time and travel distance of all the vehicles along the link are recorded.
- The space mean speed is then computed as the ratio of the total travel distance to the total travel time for all vehicles on the link.

#### *2.1.3 Hybrid traffic representations*

In addition to the three traffic aggregation methods discussed earlier, this study explores two hybrid traffic representation methods. These methods aim to reconstruct individual vehicle movements along road links using link-aggregated traffic data, specifically traffic flow rates and average traffic speeds. By leveraging these hybrid techniques, we can generate a more detailed microscopic representation of traffic while preserving the macroscopic traffic characteristics derived from aggregated datasets, such as the traffic output from macroscopic and agent-based simulation models.

Two proposed methods introduce stochastic variations to generate more dynamic vehicle trajectories: Density-Based Vehicle Movement Reconstruction [12] and Poisson-Based Vehicle Trajectory Reconstruction [13]. Each method uses different statistical modelling techniques to introduce variability in vehicle movements while maintaining consistency with the underlying link-aggregated data, giving an output similar to a microscopic traffic simulation with individual vehicle position and speed on 1-second time resolution. Time Mean Speed (TMS) Mode was selected as the base dataset. This choice ensures that vehicle movements are reconstructed based on a more refined speed estimation approach.

Density-Based Vehicle Movement Reconstruction Mode
This approach reconstructs individual vehicle movements at each predefined position based on the estimated road traffic density along each link. Traffic density is a key parameter in traffic flow theory, representing the number of vehicles per unit length of a roadway. The computed density determines the probability of vehicle occurrence at different positions along each road. Individual vehicle movements are then reconstructed through iterative probabilistic processes.

Poisson-Based Vehicle Trajectory Reconstruction Mode
The second method reconstructs vehicle trajectories using a Poisson process, which is commonly used to model the random arrival of vehicles in traffic flow theory. Unlike the density-based method, this approach does not rely on estimating the occurrence probabilities of all the possible positions along each road, but on distributing vehicles' trajectories under a Poisson random arrival model.

### 2.2 Modelling chains

All the noise simulation modelling chains in this article consist of two parts: the traffic model output representations and the noise calculation model. For aggregated scenarios, the noise levels emitted by road traffic are estimated based on the average flow rates and speeds of vehicle flows per road section. Alternatively, the noise source levels are estimated from the trajectory points along the roads for dynamic traffic scenarios including SUMO Mode, Density-Based Mode, and Poisson-Based Mode.

### 2.3 NoiseModelling

NoiseModelling [14] serves as the core computational framework for the noise calculation model, which is an open-source library capable of producing noise maps. This research employs the CNOSSOS-EU standard methodology to estimate noise emissions and propagation effects, utilizing its emission model, path-finding algorithm, and attenuation model to simulate noise transmission from traffic sources to receiver points. However, for the acceleration correction component, the IMAGINE method is applied over CNOSSOS-EU here. While CNOSSOS-EU includes a distance-based acceleration correction in relation to intersections, the choice made to use the IMAGINE method [15] offers a more precise approach to capture acceleration-induced noise variations by directly considering the actual accelerations.

### 2.4 Case Study and Parameters

This study is based on the traffic conditions in the Södermalm district, a central island in Stockholm, covering approximately 10 km² of urban traffic activity. Södermalm is a densely populated area with a well-developed road network, making it an ideal location for evaluating different traffic representation methods. (See Figure 1)

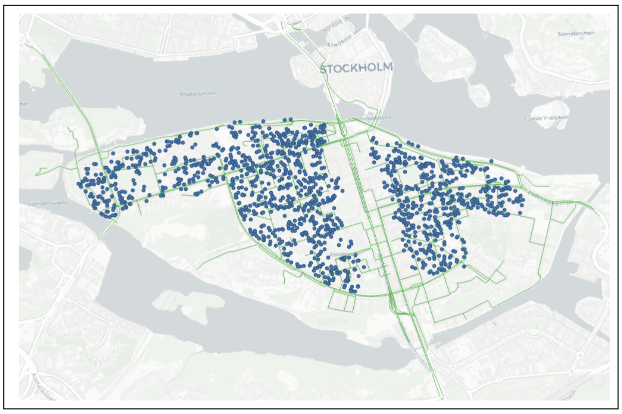


**Figure 1**. Network and position of noise receivers.

Most of the major roads within the study area are included in the simulation, with microscopic traffic data suitable to capture a representative snapshot of urban mobility and one of the most significant noise sources throughout the day.

Since this research primarily investigates traffic representation methods, vehicle composition is intentionally simplified. To reduce complexity and maintain consistency in the analysis, only light vehicles are simulated, while heavy vehicles, buses, and motorized two-wheelers are excluded. These vehicle types introduce additional variability in both traffic dynamics and acoustic noise emissions, which may lead to increased uncertainty in hybrid traffic representation methods.

To assess the impact of traffic on noise levels, a total of 1,389 receiver points are strategically placed around buildings and along traffic corridors. The following noise level indicators are considered in the analysis: $L_{\text{Aeq},1h}$ (A-weighted equivalent continuous sound level per hour per point) is computed for all traffic scenarios. $L_{A10,1h}$, and $L_{A1,1h}$ are evaluated specifically for dynamic traffic representation scenarios (SUMO Mode, Density-Based Mode, and Poisson-Based Mode), where more detailed vehicle movement patterns are simulated.

Table 1 provides a summary of the key parameters used in the acoustic calculations for this study.

**Table 1**. Parameter values for sound propagation

| Parameters | Configuration |
|---|---|
| Maximal order of reflection | 1 |
| Maximal order of diffraction | 1 |
| Maximal distance source-receiver | 250m |
| Maximum source-reflection distance | 50m |
| Receivers height | 1.5m |
| Ground absorption coefficient | G=0 |
| Spatial resolution | D=20m |

## 3. RESULTS

### 3.1 Statistical results

Figure 2, 3, and 4 present the Kernel Density Estimation (KDE) curves of the road traffic noise indicators chosen $L_{\text{Aeq},1h}$, $L_{A10,1h}$, and $L_{A1,1h}$ across various modelling chains. These figures allow for a direct comparison of noise level distributions under the different traffic simulation approaches introduced in 2.1, including the initial SUMO microscopic mode, the density-based mode, and the Poisson-based mode.

As shown in Figure 2, the KDE curves of $L_{\text{Aeq},1h}$ illustrate the overall equivalent noise levels across different scenarios. Despite minor variations, all modes exhibit a similar bimodal distribution, indicating that the general noise exposure trends remain consistent regardless of the underlying traffic modelling approach. However, the SUMO mode (blue curve) shows slightly higher noise levels in the first and the second peaks, and gains more density in the highest noise interval (60 - 70 dB), which may be explained by a more detailed representation of vehicle flow dynamics.

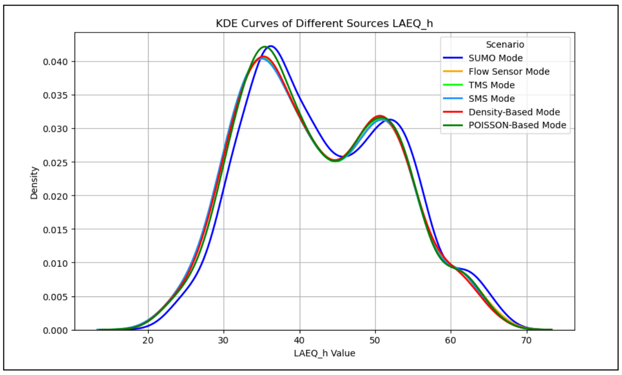


**Figure 2**. KDE Curves of Different $L_{\text{Aeq},1h}$ .

Figure 3 presents the KDE curves for $L_{A10,1h}$. Unlike $L_{\text{Aeq},1h}$, which can be estimated from any aggregated traffic scenario, $L_{A10,1h}$ requires dynamic approaches to capture variations in noise over time. Therefore, only the SUMO microscopic mode, the Density-based mode, and the Poisson-based mode are represented in this figure. The Density-Based mode (red curve) and the Poisson-Based mode (green curve) align closely with the SUMO mode, particularly at lower noise levels. However, minor deviations appear in the tail of the distribution, indicating that high-intensity noise events may be influenced by traffic flow representation differences.

Figure 4 focuses on $L_{A1,1h}$, capturing the highest noise levels experienced during the simulation. Similarly to $L_{A10,1h}$, $L_{A1,1h}$ can only be derived from dynamic

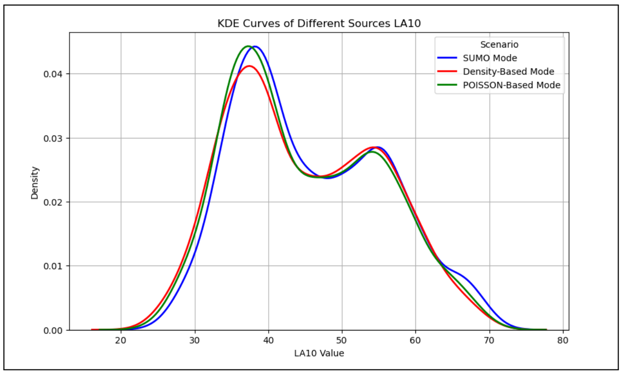


**Figure 3**. KDE Curves of Different $L_{A10,1h}$.

traffic models. The results indicate that the SUMO microscopic mode captures more pronounced peaks, reinforcing the idea that detailed vehicle-level modelling better represents transient events such as acceleration and braking. The Density-Based and Poisson-Based modes follow similar trends but exhibit smoother distributions, likely due to their simplified vehicle representation.

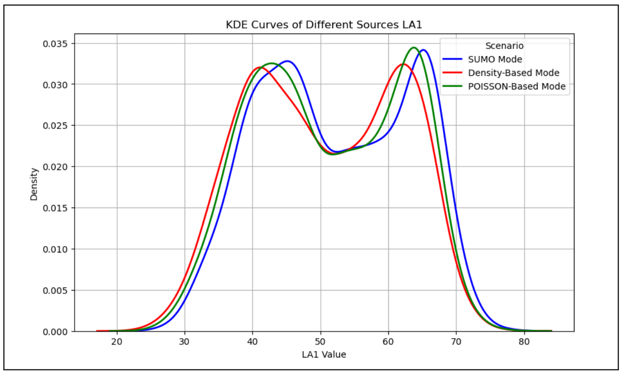


**Figure 4**. KDE Curves of Different $L_{A1,1h}$.

### 3.2 Noise mapping

Figures 5, 6, 7, 8, and 9 display the estimated $L_{\mathrm{Aeq},1h}$ difference values of various scenarios compared with the reference SUMO mode. These figures contribute to explaining the deviations from the SUMO mode (blue curve), as most of the estimated $L_{\mathrm{Aeq},1h}$ levels are underestimated while only a few of the receivers exhibit higher $L_{\mathrm{Aeq},1h}$ levels in aggregated link-based scenarios.

Noteworthy is the fact that among these figures, the portion of receivers at which levels are greatly underestimated (deep blue color dots) is much reduced for Density-Based and Poisson-Based modes when compared to the other three aggregated traffic representation scenarios. This result suggests that hybrid traffic representations have the potential to alleviate the underestimation induced by the loss of details in the description of vehicle dynamics associated with aggregated traffic representations.

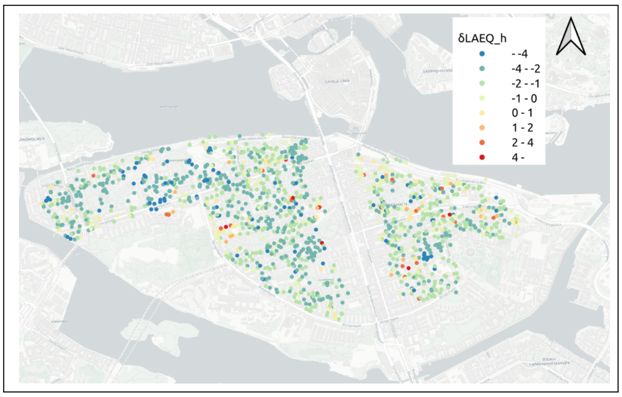


**Figure 5**. Sensor Mode acoustic indicators compared to SUMO Mode.

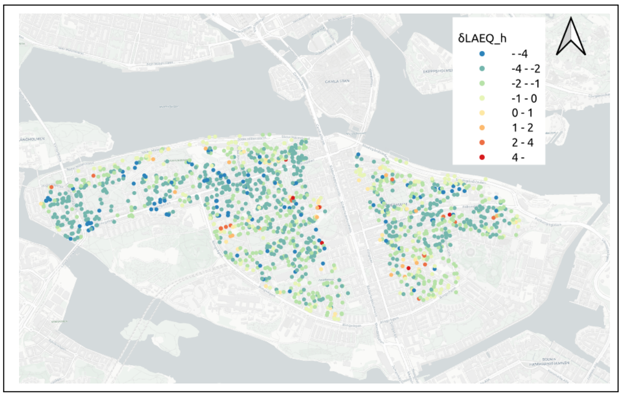


**Figure 6**. TMS Mode acoustic indicators compared to SUMO Mode.

## 4. CONCLUSIONS

This study offers a comparison of different modelling chains for estimating road traffic noise, focusing on

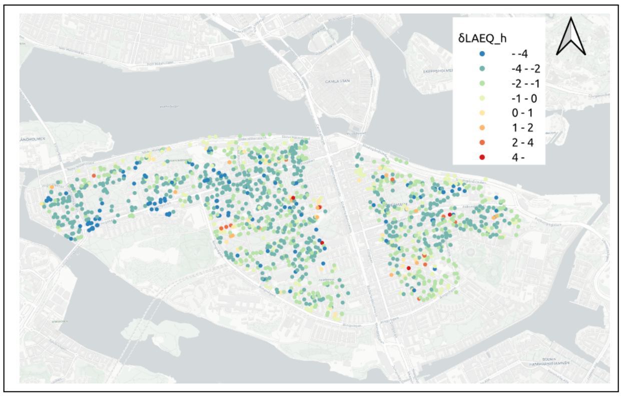


**Figure 7**. SMS Mode acoustic indicators compared to SUMO Mode.

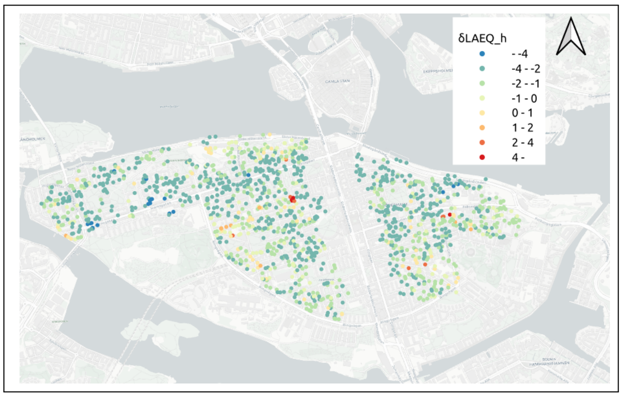


**Figure 8**. Density Mode acoustic indicators compared to SUMO Mode.

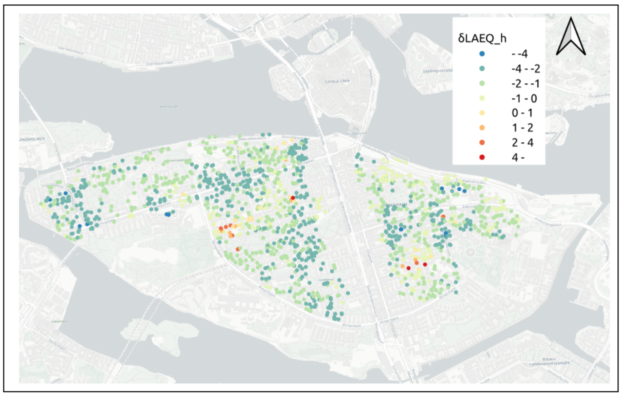


**Figure 9**. Poisson Mode acoustic indicators compared to SUMO Mode.

variations in noise distributions under distinct traffic representation approaches. By analyzing the Kernel Density Estimation curves of various noise indicators and noise indicator maps, several key observations are made.

First, despite differences in traffic representation, all models exhibit similar distribution patterns. This suggests that hybrid traffic modelling approaches, including Density-based and Poisson-based methods, can yield comparable noise estimates, especially at high percentile indicators. These indicators are limited in aggregated link-based scenarios, making hybrid methods a practical alternative when detailed microscopic data is unavailable.

However, the differences observed in the KDE curves and the distribution of noise maps indicate that while these methods effectively capture general trends, they may not fully account for noise from transient vehicle behaviors and uneven vehicle movement distributions. These factors can contribute to variations in high-noise conditions, generally leading to slightly lower noise level estimation when ignored.

Overall, this comparative analysis highlights the influence of different traffic representations on noise estimations with a range of noise indicators. While detailed microscopic simulations offer high-fidelity vehicle dynamics, Density-based and Poisson-based methods provide alternatives, particularly suited for scenarios with limited data availability. Compared to detailed microscopic simulations and static aggregated link-based scenarios, these approaches maintain a balance between broad accuracy insights and practicality. Future research could further refine these models by integrating detailed vehicle behaviors and improving their adaptability to complex urban traffic environments.

## 5. ACKNOWLEDGMENTS

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