ADVANCED METHODOLOGIES AND DATA COLLECTION TECHNIQUES IN URBAN TRAFFIC DYNAMIC NOISE MODELING

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Abstract

Following the adoption of European Directive 2002/49/EC (END) on environmental noise, the comparability of results has improved substantially through the introduction of the common CNOSSOS-EU method and its subsequent updates. Nevertheless, the transition from "strategic" to "dynamic" noise maps does not depend primarily on computational capacity but rather on the quality, temporal resolution, and consistency of input data. This contribution reports recent results (2020–2026) addressing three complementary categories of action capable of enhancing the accuracy of dynamic noise maps and, consequently, of reducing the impact of road traffic noise: (i) a "Good Practices" approach to the construction and validation of databases and associated uncertainty management, acknowledging both limitations and advantages as outlined in operational guidance documents for noise mapping; (ii) the recognition and classification of vehicles in accordance with CNOSSOS-EU using sensor systems equipped with artificial intelligence, including novel AI algorithms with blurring functions for acoustic cameras, which show considerable promise in eliminating visual compression artefacts and minimizing sound source localization errors; (iii) the monitoring of road surface condition through in-tyre sensors and other pattern recognition methods, complemented by the Urban Statistical Pass-By (U-SPB) protocol, a highly effective unattended in-situ measurement approach for assessing low-noise pavements in urban contexts and predicting long-term equivalent noise levels. Furthermore, the integration of microscopic traffic simulators, such as SUMO, into noise mapping software enables dynamic, high-resolution evaluations of noise exposure, overcoming the limitations of the static modelling framework defined by the END Directive, and supports the development of real-time Intelligent Transportation Systems (ITS) capable of modulating traffic flows and mitigating urban noise exposure. What we provide is an integrated vision in which noise reduction is understood not merely as the implementation of barriers, revised limit values, and sound-absorbing asphalt following physical measurements, but as a systematic effort to enhance the reliability of observations and the quality of data feeding the models that ultimately shape priorities and policy decisions.

Keywords: noise mapping, traffic management, modelling uncertainty, artificial intelligence

1 Introduction

Road traffic noise remains one of the most pervasive environmental stressors in urban areas, with negative effects on human health, sleep quality, and cognitive performance [1-5]. The Directive 2002/49/EC (END) [6] established the obligation for Member States to produce strategic noise maps and action plans for major agglomerations, roads, railways, and airports, also providing a common basis for assessing and managing environmental noise exposure.

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CNOSSOS-EU framework defines baseline data for evaluating exposure to road traffic noise [7], moreover near-real-time noise mapping represents a quality improvement in environmental noise exposure assessment [8, 9]. Such approach is strongly sensitive to how vehicle flows, speeds, fleet composition, and road surface conditions are characterized. Recent advances in sensor technology, artificial intelligence, and microscopic traffic simulation open new opportunities for improving the entire *data-to-decision* pipeline to reduce noise exposure in urban areas.
This paper aims to present some recent results and approaches concerning traffic data collection, dynamic noise simulation, and innovative *in-situ* measurement techniques by analyzing data collection methods, traffic simulation approaches for dynamic noise mapping.

2 Data collection methods for traffic noise modeling

The introduction of the CNOSSOS-EU model in 2015 represented a significant step forward in the standardization of noise calculations but it does not eliminate the primary source of variability/errors: the quality and representativeness of the collected input data [10]. Dynamic maps can tolerate lower approximations in comparison with END mapping (static) procedure requiring data of greater granularity in both time and space instead of operating on long term data averages.

Table 1 Estimated light vehicles [7]

Road, Country	light vehicles - day			light vehicles - evening			light vehicles - night		
	TC	CAM	API	TC	CAM	API	TC	CAM	API
Regional, IT	332	310	350	207	236	369	38	41	348
	296	324	320	131	162	357	37	52	323
Residential, RO	114	116	169	86	107	201	18	22	136
	281	338	285	223	232	188	38	39	121
Boulevard, RO	459	614	603	449	542	558	131	108	183
	442*	704	704	290*	506	601	177*	217	360

Data from one of the lanes was doubled to account for the technical issues (modified data are marked with "*")

As regards traffic data in [7] three collection methods (microwave radar traffic counters (TC), artificial intelligence-based cameras (CAM), and Google API-derived flows (API)) have been compared showing very different performance (table 1 and figure 1). Preliminary results obtained across test sites in Italy and Romania highlighted that CAM is the most stable and reliable method across different traffic regimes and time periods [7]. While TC performs reasonably well under moderate traffic, it tends to systematically underestimate flows when traffic intensity decreases or when complex vehicular conditions cause detection failures [7]. Conversely, API-derived flows proved reliable only when traffic volumes exceeded approximately 150 vehicles per hour and heavily depended on the proper calibration of the traffic model parameters for specific time periods [7].

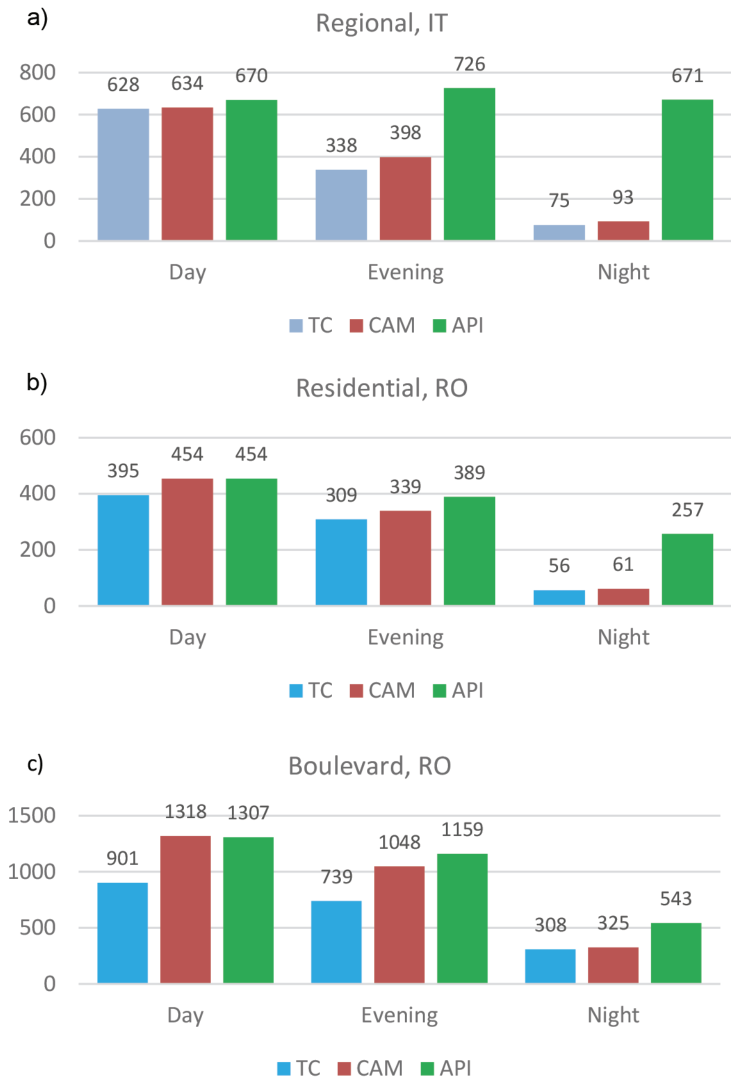

Figure 1 Comparing different vehicle counting methods in three different scenarios using the data in table 1: a) Regional, IT; b) Residential, RO; c) Boulevard, RO

These discrepancies in input data can influence noise simulations results: CAM inputs resulted in the closest agreement with measured in-situ noise levels, whereas API produced unreliable nocturnal estimations unless continuous high traffic guaranteed stable travel time smoothing [7]. Furthermore, a primary benefit of AI cameras is their advanced vehicle recognition capability, which accurately classifies vehicles to meet categories required by the CNOSSOS-EU framework, that is an added value when integrated with microscopic traffic simulation tools reducing preprocessing time. On the other hand, where CAM data is not available additional information for traffic on secondary and tertiary roads, for example by using travel times from Google APIs (where applicable), and congestion data as feedback to improve the traffic model estimate can be used.

The integration between data quality check, information recovery, data processing and near-real-time noise maps calculations can be modeled in a simple workflow as in figure 2 [11]. The workflow is integrated into an automated process that enables the calculation of granular noise exposure in urban scenarios and supports the selection of alternative routes to minimize it.

Table 2 Comparison of different traffic data collection methods

Method	Pro	Cons	Best for
Microwave Radar Traffic Counters (TC)	Easy and fast installation with simple equipment Consistent accuracy across day and night periods Does not capture sensitive or personal data	Systematically underestimates flow during congestion due to vehicle occlusion Cannot distinguish between multiple lanes traveling in the same direction Vehicle categorization (based solely on length) is prone to mismatches Cannot be controlled remotely	Moderate traffic conditions precise vehicle categorization is not critical
Artificial Intelligence-Based Cameras (CAM)	Optimal vehicle identification and precise categorization Can monitor and separate traffic flows for up to four lanes simultaneously Algorithms can be applied to standard surveillance cameras	May overestimate flows during severe traffic congestion Detection can be hindered by adverse weather (fog, rain), reduced night illumination Initial geometric setup for speed estimation may require temporary road closures	Scenarios requiring highly accurate performance across different traffic regimes and lane-by-lane analysis
Google API-Derived Flows (API)	Entirely remote data acquisition: no physical on-site instrumentation needed Capable of quickly generating large datasets over wide geographical areas Versatile for Intelligent Transportation Systems	Highly unreliable in low-flow or heavily congested conditions Requires independent knowledge of the local modal split to assign vehicle categories The API service is not free (incurs a cost per request)	Wide-area macro-estimations where traffic volumes are stable and sufficiently high

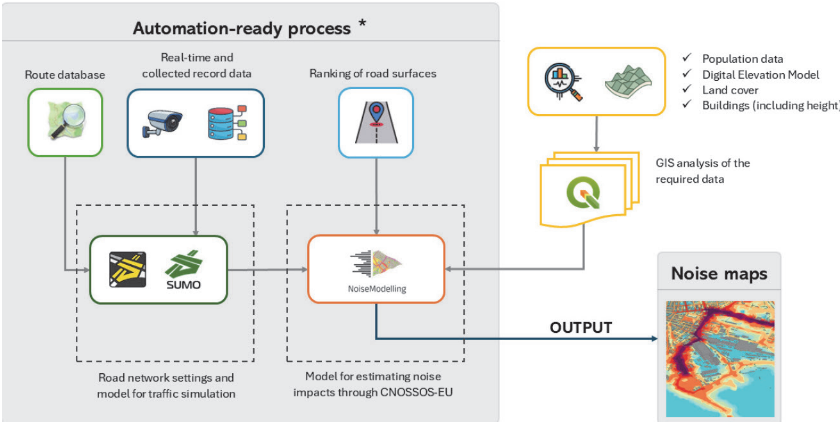

Figure 2 Flowchart of the proposed noise mapping infrastructure to produce near to real time dynamic noise maps, (*) Applications managed by automated data processing routines

3 Traffic simulation and dynamic noise mapping

Dynamic noise mapping represents a significant improvement over traditional, static environmental noise assessments by coupling microscopic traffic simulation tools with acoustic calculation software [12]. The detailed traffic data (including vehicle composition, traffic flows, speeds, and acceleration/deceleration profiles) coupled with complex variables like road gradients, digital elevation models (DEM), and attenuation matrix allow the calculation of sound power levels of each road segment and the subsequent near-real time noise immission at receivers [11, 13] with low calculation effort. By coupling the SUMO simulation tool with NoiseModelling open-source software in the city port of Piombino case study near-real time noise emissions have been dynamically assessed [11]. City model with roads and receivers (by the integration of GIS and OSM data), microscopic traffic simulation (SUMO) and emission/propagation calculation software (NoiseModelling), have been chained by Python scripts where, in such pipeline, flows and speeds averaged over intervals (e.g. 15 minutes) become the main inputs for emission calculations by calculating each road segment's noise power levels and then applying a pre-calculated attenuation matrix. First results indicated that while total traffic volumes were underestimated in certain periods, the simulation accurately captured the distribution patterns of light, medium, and heavy vehicles according to CNOSSOS-EU classification throughout the day [13]. Dynamic simulations, while subject to input uncertainties predominantly tied to vehicle speed and traffic flow fluctuations, successfully reflect how changes in vehicle distribution directly affect the noise exposure of specific urban receivers allowing redefining traffic routes in order to reduce people exposure to urban traffic noise.

4 Advancements in in-situ noise measurement techniques

As regards in-situ measurements, the Urban Pass-By (U-SPB) method has been validated as a highly effective procedure, unattended protocol for evaluating the acoustic performance of road surfaces in urban contexts [14]. Tested against the standard attended SPB-L method, U-SPB demonstrated the ability to operate continuously, gathering robust statistical data without requiring operator presence [14]. Validation results revealed that the Statistical Pass-By Index (SPBI) calculated via U-SPB matched standard SPB-L results with a difference of less than 1 dB(A) [14].

Furthermore, U-SPB successfully predicted long-term equivalent noise levels based strictly on traffic flow data; the estimated daytime noise level (LD) differed from the experimentally measured level by 0.2 dB(A), and the day-evening-night level (LDEN) by only 0.9 dB(A) [14]. This proved the efficacy of U-SPB for verifying the implementation of low-noise pavements and assessing local noise mitigation measures [14].
The structural characterization of pavements and precise sound source localization results as a key issue both for monitoring pavements quality and for model input parameter supply [15]. To measure the acoustic impedance and absorption of road surfaces dynamically, a mobile laboratory equipped with a p-u sensor has been developed [16]. Reducing the inaccuracies induced by vehicle movement by using a Proportional Integral Derivative (PID) controller, which successfully constrained vertical displacement to a maximum excursion of 0.021 meters at a speed of 30 km/h [16]. This stabilization significantly minimized the relative error in absorption measurements compared to non-stabilized setups. Additionally, to enhance the interpretation of visual sound maps generated by Acoustic Cameras (AC), a novel feature extraction algorithm was developed [16]. By applying a blurring function (B = 1) to eliminate image compression artifacts, the fault rate of the fitting process was drastically reduced from over 7% to approximately 1.4% [16]. This analytical approach allows to accurately quantify the distance (r) between the true source and the localized emission point, moving beyond qualitative visual inspections [16].

5 Road distress identification methods

Road conditions influence noise emission, but accurate road distress classification is labor intensive because traditionally it is done by inspecting the road surface. Covering the totality of the road network interested by a noise map is unpractical. Newer methods allow fast road distresses identification and classification using cameras [17] and evaluating the corresponding noise emission worsening with the use of CPX or Tire Cavity Noise (TCN) measurements [18]. Figure 3 shows the TCN spectra of two roads in different states of distress.

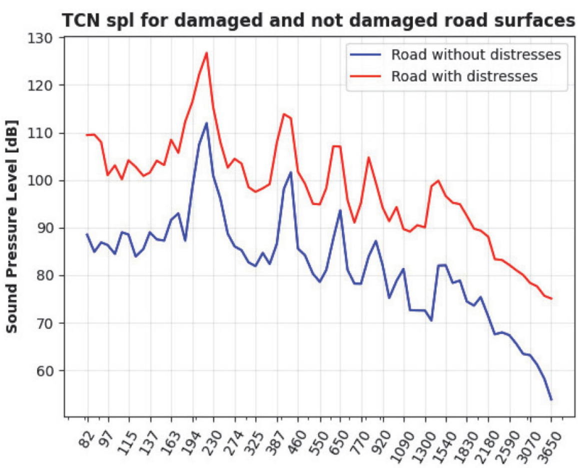

Figure 3 An example of the Tire Cavity Noise one-twelfth octave spectrum for road surfaces with distresses and without distresses

6 Conclusion

It has been shown that the transition from static noise mapping to dynamic, time resolved assessment frameworks is primarily driven by the improvement of input data quality. AI-based camera systems demonstrated the most robust and reliable performance under varying traffic and environmental conditions, offering a clear advantage over microwave radar counters and API-derived estimates [7]. When integrated into microscopic traffic simulators such as SUMO, these detailed datasets enable dynamic noise models to more accurately reproduce temporal fluctuations in traffic composition and speed profiles, thus providing a more realistic representation of noise exposure at the urban scale [11, 13].
The recent U-SPB approach has proven to be a useful unattended technique for evaluating pavement performance and estimating longterm noise indicators, achieving close agreement with standard SPBL measurements [14]. Similarly, stabilization systems for mobile p-u sensors and enhanced feature-extraction algorithms for acoustic cameras contribute to more precise pavement impedance measurements and source localization, thereby reducing uncertainties in model calibration and validation [15, 16]. The implementation of dynamic noise maps and intelligent traffic management systems allow urban planners and local stakeholders to better define and verify effective noise mitigation strategies in near-real time [14].

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