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MASTER CSMI

A demonstration of noise metamodelling for the case study of the Rhine Avenue in Strasbourg

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1 Introduction

1.1 Context and Motivation

In modern cities, sound is an ever-present feature of daily life — from the hum of traffic to the buzz of human activity. Yet when noise exceeds certain thresholds, it becomes more than a nuisance: it turns into a public health concern. Prolonged exposure to levels above 55 dB has been linked to sleep disturbances, cardiovascular issues, and a reduced quality of life [1], [2], [3]. As urban areas grow denser and mobility demands increase, managing environmental noise is becoming a crucial responsibility for city planners and public health institutions.

Against this backdrop, the Eurométropole de Strasbourg (EMS) launched a project focused on the Rhine Avenue — a key urban axis that blends residential life, major infrastructure, and intense traffic. The objective: to develop clear, accessible, and scientifically grounded tools that help both policymakers and the public better understand environmental noise exposure in this area.

1.2 Internship Objectives

This report presents the outcomes of an internship conducted within this project framework, focusing on the development of two complementary tools:

- An **experimental data mining tool** that provides an intuitive and interactive interface to explore acoustic and traffic data collected via external application programming interfaces (APIs) and physical sensors. This tool allows users to visualize noise levels, traffic patterns, and their relationships over time and space.
- A **metamodeling tool** that improves upon the speed of production of noise maps by using machine learning techniques to predict noise levels based on road traffic and environmental variables. Such a metamodel would allow for rapid scenario analysis and urban planning, enabling decision-makers to assess the impact of different interventions without the need for extensive simulations.

The internship was hosted by the UMRAE research group and supervised jointly by CEREMA and EMS. It combined theoretical research on environmental acoustics with practical software development and data science.

1.3 Structure of the report

The report begins by presenting the **territorial and institutional context**, outlining the stakeholders involved and their respective roles in the project. This is followed by a review of **existing tools and noise monitoring platforms**, which situates the developed tools within the broader technological landscape. The report then describes the **data architecture**, with particular attention to the APIs employed, the preprocessing workflow, and the challenges of managing real-time environmental data. Next, the **visualization tool** is introduced, highlighting its main features, design principles, and usage scenarios. The **metamodeling tool** is then discussed in depth, with a focus on its mathematical foundations, modeling choices, and performance evaluation. Finally, the report reflects on the **implications of the work**, its current limitations, and potential directions for future development. The overarching goal is not only to document the outcomes of the internship but also to provide a foundation for future contributors to the EMS noise monitoring initiative and to shed light on the broader challenges and opportunities of environmental noise management in urban contexts.

2 Territorial & Institutional Context

2.1 Strasbourg

Strasbourg is a major city in northeastern France, situated on the eastern bank of the Rhine river, along the border with Germany. The city has a population of around 300,000 residents and is known for its rich history, cultural heritage, and as a hub for European institutions.

2.2 The Rhine Avenue

The Rhine Avenue (Avenue du Rhin) is one of the main urban arteries of Strasbourg. Connecting the Europe Bridge on the french-german border with the heart of the city (see Figure 1), it forms a strategic east-west axis that supports heavy daily traffic. With approximately 41,500 vehicles per day in 2023, [4]. Its role is vital for logistics, daily commuting, and cross-border transport, but it also cuts through residential zones, creating tension between mobility needs and environmental quality.



Figure 1: Map of the Rhine Avenue in Strasbourg, showing its location and surrounding areas.
source: *OpenStreetMap*

Because of its dual function as both a transit and residential corridor, the Rhine Avenue has long been associated with significant levels of air and noise pollution.

Recognizing these challenges, the City of Strasbourg and the Eurométropole have initiated a multi-year effort to “calm” the avenue and improve the quality of life for local residents. This project —central to the current administration’s ecological transition strategy— aims to reduce both air and noise pollution, improve safety for pedestrians and cyclists, and rebalance space in favor of sustainable mobility modes.

The Rhine Avenue serves as a vital corridor for sanitary transport to the Rhéna Clinic near the German border, contributing to the high noise levels through frequent usage of sirens by emergency vehicles. The avenue also borders the Autonomous Port of Strasbourg, resulting in regular freight traffic involving heavy-duty vehicles accessing loading and unloading zones. Additionally, the presence of the Solange Fernex primary school directly along the avenue raises serious concerns regarding children’s exposure to pollution and road hazards during daily commutes. These overlapping demands make the transformation of the Rhine Avenue technically complex.

In 2023, extensive studies were conducted to better understand traffic patterns on the avenue. These efforts led to improved crossings for active mobility (pedestrians and cyclists) and the creation of new links across the road. Early results are encouraging: between 2022 and 2024, **traffic decreased by 7,000 vehicles per day, a 15.5% reduction. Air quality improved,**

carpooling rates increased from 12% to 20%, and public transport use grew by 2,500 passengers per day (+11%). [4]

3 Project actors

3.1 The EMS

The Eurométropole de Strasbourg (EMS) the intercommunal authority that encompasses the city of Strasbourg and 32 surrounding municipalities. With a combined population of approximately 517,000 inhabitants in 2023, of which nearly 300,000 live in Strasbourg proper, the EMS manages key public services such as transportation, urban planning, waste management, and environmental protection [5].

In recent years, the EMS has significantly increased its focus on environmental issues, most notably air pollution. Through a number of initiatives including the implementation of a low-emission zone and major infrastructure changes, the Eurométropole has made air quality a central policy concern.

While noise pollution has long been recognized as a public health issue, it has received less attention compared to air quality. However, the EMS is now actively working to address this gap by developing tools and strategies to monitor and mitigate noise pollution in urban areas, particularly along major traffic corridors like the Rhine Avenue.

3.2 CEREMA

The Center for Studies and Expertise on Risks, Environment, Mobility, and Urban Planning (CEREMA) is a public institution that provides technical expertise to local authorities in France. It operates across various domains including environmental protection, urban planning, mobility, and risk management [6]. CEREMA's mission is to support public decision-making through research, data analysis, and the development of innovative solutions.

3.3 UMRAE

The Environmental Acoustics Mixed Research Unit (UMRAE) is a division within CEREMA that specializes in environmental acoustics. UMRAE's expertise includes evaluation of noise sources, the propagation of sound and its effects on the environment, human health, and wildlife [7]. The unit conducts research, develops modelling and measurement techniques.

4 Background on Environmental Acoustics

4.1 Introduction to Acoustics

Acoustics is the branch of physics concerned with the production, transmission, and effects of sound. This report is a work around **environmental acoustics**, which studies sound in outdoor and urban contexts. It is particularly relevant for public health and urban planning, as noise pollution, from various sources such as traffic, construction, and industrial activity, can significantly affect human well-being and ecological balance [1], [8].

4.2 Acoustic Fundamentals

4.2.1 Sound pressure levels and decibels

The sound pressure level is commonly measured in decibels (dB), a logarithmic unit. Most acoustic indicator measurements use dB(A), a scale that weights frequencies according to human hearing sensitivity. Other dB scales exist, as shown in figure Figure 2, but dB(A) is the most

widely used in environmental acoustics. It accounts for the fact that human hearing is less sensitive to very low and very high frequencies.

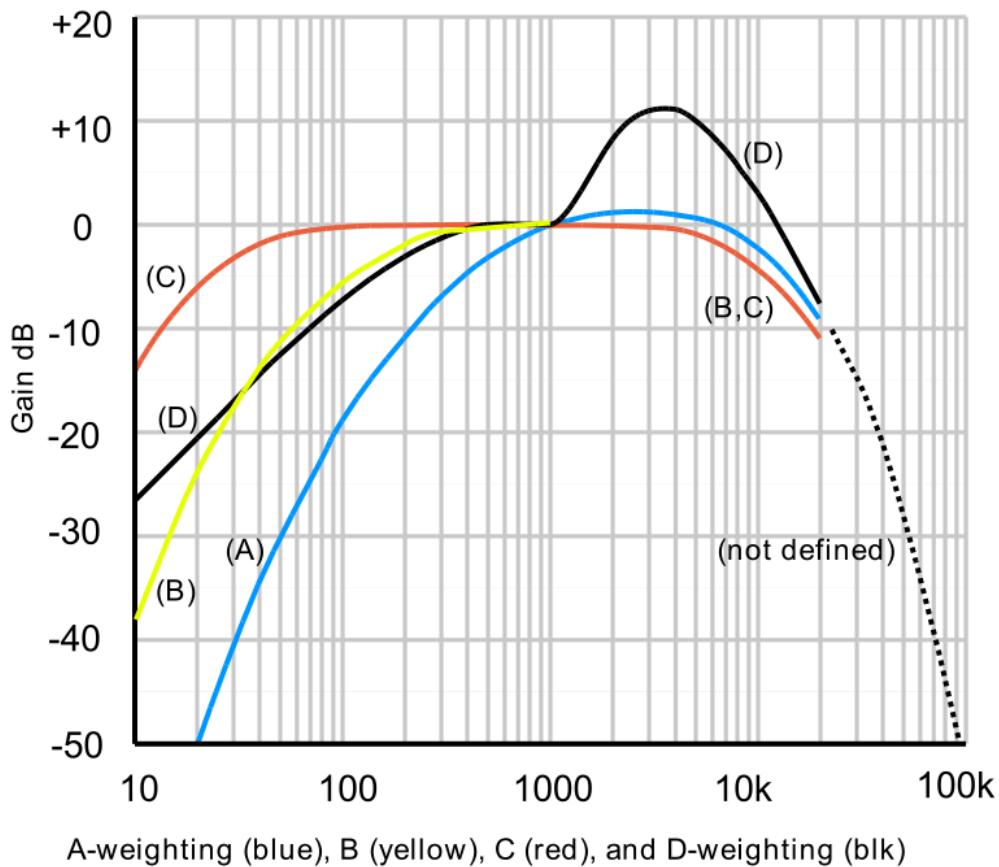


Figure 2: Corrections applied to dB levels to account for human hearing sensitivity.

When considering the modelling of noise propagation in the environment, two important quantities are the sound power level L_w and the sound pressure level L_p :

- L_w is the **sound power level**, representing the total acoustic energy emitted by a source.
- L_p is the **sound pressure level**, which is what a microphone or a sensor measures at a given location.

The relationship between them is given by:

$$L_p = L_w + 10 \log_{10} \left(\frac{S}{S_0} \right) \quad 1$$

where:

- S is the surface area over which the sound spreads (e.g., a sphere),
- S_0 is a reference surface, typically $1m^2$.

This formula expresses how sound becomes less intense with distance, as the same energy is distributed over a larger surface. In open environments, sound generally spreads spherically, so $S = 4\pi r^2$ for distance r from the source. This leads to a **6 dB loss per doubling of distance** in free field conditions [9].

4.2.2 Equivalent sound level

The **equivalent continuous sound level** L_{den} standing for day-evening-night level, is a metric that averages sound levels over a period of 24 hours, weighting the periods according to how long they are, as to reflect the average exposure over the day. It is defined as:

$$L_{den} = 10 \log \left(\frac{12 \cdot 10^{\frac{L_{day}}{10}} + 4 \cdot 10^{\frac{L_{evening}+5}{10}} + 8 \cdot 10^{\frac{L_{night}+10}{10}}}{24} \right) \quad 2$$

Where L_{day} is the average sound level from 6 am to 6 pm, $L_{evening}$ from 6 pm to 10 pm, and L_{night} from 10 pm to 6 am. The evening and night periods are penalized by +5 dB and +10 dB respectively to account for increased sensitivity to noise during these times. The formula demonstrates how the logarithmic nature of decibels requires converting back to linear scale for averaging, then converting back to dB, meaning higher noise levels have a disproportionately large impact on the equivalent level [9].

4.2.3 Propagation of Sound Waves

Sound propagates through air as pressure fluctuations—**longitudinal waves**—that radiate outward from a source. As these waves travel, their intensity naturally decreases with distance, following the inverse-square law in open environments: every doubling of distance results in a 6 dB reduction in sound pressure level.

However, in urban environments, this simple rule is complicated by physical features such as buildings, vehicles, and terrain. These elements modify how sound travels through a process influenced by three main factors, as can be seen in figure Figure 3:

- **Reflection:** Sound waves bounce off hard surfaces like walls, roads, or glass, potentially amplifying or redirecting the noise.
- **Diffraction:** When sound waves encounter an obstacle, they bend around it, allowing noise to reach areas not in direct line-of-sight from the source.
- **Refraction:** Sound waves move through different media, be it air layers with different temperatures or humidity levels, causing them to bend. This bending can lead to unexpected sound propagation patterns, such as noise traveling farther than anticipated, or redirecting sound towards quieter areas under certain atmospheric conditions.

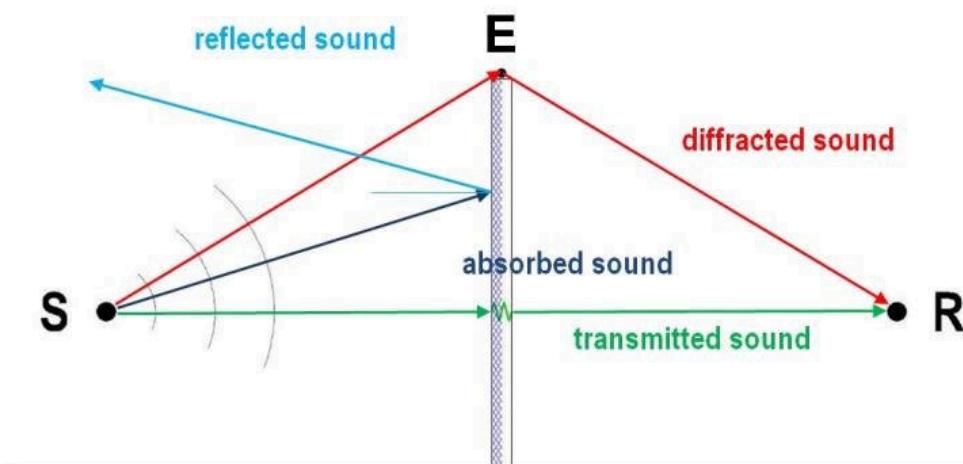


Figure 3: Schematic representation of sound propagation with reflection and diffraction in an urban environment.

For instance, temperature inversions can cause sound to travel farther than expected, increasing exposure in areas that would otherwise be quieter.

In complex environments like outdoors areas studied in environmental acoustics combine to create **highly variable noise profiles**, making measurement and prediction a challenging yet necessary task for urban planners and environmental health assessments.

4.2.3.1 Favorable vs Non-Favorable Conditions

One crucial aspect of sound propagation is favorable versus non-favorable conditions. Depending on the weather, mostly wind speed and direction, but also temperature and humidity, sound can either be diverted into high altitude, or actually refracted back at the ground and thus travel farther than expected. This is why noise maps are often produced for average conditions, where an occurrence rose of average weather condition indicates how likely favorable conditions are to occur in given cardinal directions. This creates a discrepancy between the levels that would be simulated for actual conditions and for average conditions.

4.2.4 Noise Pollution and Its Impacts

Urban noise mainly originates from road traffic, construction, and industry. Chronic exposure can lead to hearing loss, cardiovascular issues, sleep disruption, and reduced cognitive performance, especially in children. Wildlife may also experience disrupted behaviors. [1], [3]

4.3 Measurement vs Simulation

While an overwhelming majority of noise maps are generated through simulations, actual measurements remain rare and valuable. Class 1 sound level meters, like those used in this study, offer highly accurate continuous data collection and are compliant with international standards. As of 2025, recordings above 80 dB(A) also trigger a 10-second audio clip, aiding source identification.

4.4 Legal Framework

4.4.1 French and European Regulations

French law limits average daily levels to 68 dB(A) during the day and 62 dB(A) at night (10 PM-6 AM). These thresholds guide planning and environmental assessments. In Europe, the production of strategic noise maps is mandated for urban areas with over 100,000 inhabitants since 2016, and for road and rail networks since 2008. These maps help identify high-exposure zones and inform mitigation strategies.

4.4.2 WHO Recommendations

The World Health Organization advises stricter limits: 53 dB(A) by day and 45 dB(A) by night, based on health outcomes. These more conservative thresholds reflect growing awareness of chronic noise exposure risks. [1]

4.5 Acoustic Data Collection at EMS

In 2023, EMS commissioned Acoem to deploy four class 1 sound meters along the Rhine Avenue [10], [11]. These stations record continuous, second-by-second data to a high degree of accuracy, forming the basis of the acoustic survey. The data is accessible via the Cadence API, which provides real-time and historical sound level information.

5 Existing Tools & Projects

Noise monitoring and modelling tools have been developed worldwide to address urban noise pollution. This section reviews several notable projects and platforms that have informed the design and features of the EMS visualization and simulation tools.

5.1 Observatories

We distinguish two main categories of tools in the field of noise monitoring:

- **Measurement-based observatories**, which collect and visualize data from sound level meters.
- **Simulation-based platforms**, which estimate noise exposure based on modeled data such as traffic flow, urban geometry, and weather.

5.1.1 ORHANE

The **Observatoire Rhône-Alpe** (ORHANE) [12] is a regional initiative dedicated to monitoring the acoustic environment in urban areas. It collects long-term noise data and provides dashboards, including maps and temporal analyses, for public and institutional users. ORHANE was a key inspiration for EMS's visual monitoring interface, especially regarding transparency and public accessibility.

5.1.2 Bruitparif

Bruitparif is the noise observatory for the Île-de-France region [13], [14]. It operates a dense network of class 1 sound level meters and maintains an extensive public database of measurements. The organization regularly publishes technical reports, conducts epidemiological research, and works to raise public awareness about urban noise.

5.1.3 Rumeur

Rumeur is Bruitparif's public-facing platform that displays real-time noise levels through an interactive map. It allows users to access historical data, identify noise peaks, and monitor trends.

5.2 Simulation Tools

Simulation tools enable the prediction of environmental noise levels based on physical models. These tools are essential when direct measurement is impractical or incomplete. In the context of the Rhine Avenue study, they serve as a counterpart to sensor data and help extrapolate results to unmonitored areas.

5.2.1 NoiseModelling

Developed by colleagues at CEREMA and the Gustave Eiffel university, **NoiseModelling** [15] is an open-source software for simulating environmental noise. It uses GIS inputs such as road traffic, building footprints, and vegetation, and implements physics-based algorithms for sound propagation. Though it does not use sensor data directly, it is often validated against real-world measurements. This makes it particularly relevant for the EMS study, which combines both simulation and measurement data.

5.2.2 CadnaA & Mithra-SIG

Both CadnaA and Mithra-SIG are commercial software solutions widely used in the field of environmental acoustics. They provide advanced modeling capabilities for simulating noise propagation based on various input parameters such as traffic flow, building geometry, and meteorological conditions [16], [17].

6 Data mining tool

6.1 Motivation and Framing

At the start of the internship, its objectives were quite unclear, and the exact goals of the project were still left to be defined as to what kind of tool was needed. The details of the tool were decided upon during the subsequent monthly meetings with the EMS representatives, who provided feedback and suggestions on the features and functionalities that would be most useful for their work. So the first goal became the production of a user-friendly tool that allows the EMS to efficiently visualize and interpret the measured noise data.

6.2 Noise data API (Cadence)

Acoem is a private company that specializes in environmental monitoring and developing noise control solutions [11]. In 2023, the EMS commissioned Acoem to install and maintain four sound level meters along the Rhine Avenue. These sensors provide continuous measurements of the noise environment, which form the basis of the acoustic survey of the avenue. Acoem also provides an API to access the collected sound level data. Prior to this internship, the noise level data was annually downloaded by CEREMA and provided to the EMS in the form of annual reports [18].

Acoem provides access to data from the four class 1 noise sensors installed along the Rhine Avenue through the Cadence API [10]. This interface enables authenticated users to retrieve both real-time and historical acoustic measurements, including sound pressure levels, timestamps, and sensor metadata such as sensor identifiers and locations. Designed to be scalable and flexible, the API supports various data formats and query parameters.

However, several limitations were encountered during the development of the visualization tool. The API lacked formal documentation, relying instead on a basic tutorial without concrete usage examples. As a result, extensive trial-and-error testing was required to understand how to authenticate requests and parse the returned data. Additional difficulties included frequent downtimes, ambiguous error messages, data inconsistencies, and an absence of diagnostic feedback. All of which made it challenging to retrieve data reliably and integrate it into the tool.

Preprocessing steps involved cleaning the raw data, aligning timestamps, and aggregating sound level values—recorded at one-second intervals—into relevant time windows (e.g., hourly, daily) to facilitate meaningful analysis.

Following discussions with Acoem, it was agreed that improvements to the API would be addressed on their side, and that no further API-related development would be pursued by CEREMA or during the internship period. As a result, the development of such a visualization tool was temporarily suspended.

6.3 Avatar API

CEREMA provides access to road traffic data provided by a large number of road managers (state, metropolitan areas, municipalities, etc) and simulation outputs through the Avatar platform [6]. This platform includes both a web interface for general users and an API (Application programming interface) intended for technical users. The API enables queries related to vehicle counts, traffic speeds, and congestion levels. The available data combines real-time measurements with simulated values to ensure continuity and coverage.

Designed with usability in mind, the Avatar API is supported by comprehensive documentation, which greatly facilitated its integration into external tools and applications.

6.4 Project overview

6.4.1 Technologies Used

The visualization tool was developed using Python 3.8 [19], leveraging several key libraries:

- `streamlit` for building the web application interface,
- `requests` for making API calls to both Cadence and Avatar,
- `pandas` and `geopandas` for data handling and manipulation,
- `leaflet` for creating interactive maps,
- `plotly` for generating graphs and charts.

The tool is designed to be modular and extensible, allowing for future enhancements and additional features as needed.

6.4.2 Features Implemented

The visualization tool enables users to select a geographic area of interest using either square or free-polygon selection methods. After defining the area, users can choose a time range for data visualization. Upon selection, the tool displays two interactive graphs:

- Noise Levels: This graph shows the average, minimum, and maximum sound levels in decibels (dB(A)) over the selected area and period.
- Traffic Flow: This graph presents the average and interquartile range of vehicle flow (in vehicles per hour) for the same spatial and temporal scope.

The accompanying map displays the positions of both noise sensors and traffic counters, offering spatial context to the data.

The tool includes functionality to export the generated graphs in HTML format. This allows users to incorporate the visualizations into presentations, reports, or spreadsheet software, facilitating further analysis and communication.



Figure 4: Screenshot of the visualization tool interface, showing the map with acoustic sensor locations

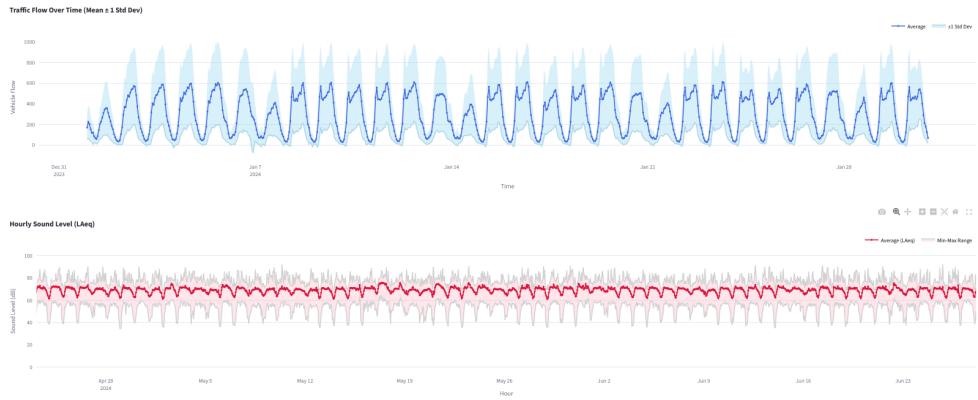


Figure 5: Screenshot of the visualization tool displaying noise and traffic graphs

6.4.3 Known Limitations and Improvements

While the tool serves as a functional proof of concept demonstrating the potential of integrating real-time acoustic and traffic data, several limitations remain:

- API Constraints: Integration of real-time sound data is currently hindered by technical limitations of the Acoem API. These include insufficient documentation, inconsistent availability, and limited error reporting. A robust deployment would require significant improvements to this interface.
- Scalability and Deployment: Full deployment would necessitate resources beyond the scope of this internship. This includes hosting infrastructure (e.g., a dedicated server), data storage solutions, and a long-term maintenance team.
- Frontend Limitations: To support a fully web-based experience, significant reengineering would be needed, including reimplementing parts of the data-processing pipeline in JavaScript to ensure browser compatibility and interactivity.

Future iterations could also explore more advanced features such as live updates, multi-variable filtering, and integration with weather data for example.

7 Metamodelling Tool

7.1 Motivation and Framing

Following discussions with the project coordinators at the Eurométropole de Strasbourg and considering external constraints on front-end development, the visualization component of the project was put aside for the time being. The focus of this internship shifted instead to a higher-impact deliverable: accelerating the generation of strategic noise maps.

Producing such maps using NoiseModelling –or any detailed, validated acoustic simulation tool— is computationally very expensive, since it requires acoustic ray computations. A single simulation run on an area of a few square kilometers in a densely built area can take several minutes or even hours depending on how accurate the input data is, and what settings of said model are used. To support scenario analysis and urban planning, a faster approach is required.

Thus, the new objective is to create a **metamodel**: a machine learning surrogate model, trained on the outputs of NoiseModelling. This surrogate approximates the simulation’s behavior and allows for near-instantaneous predictions of noise levels under new environmental or traffic conditions.

7.2 NoiseModelling: Emission and Propagation Tool

NoiseModelling is a free, open-source software designed to compute environmental noise maps across large urban areas with high spatial resolution. It is available both as a Java library and through a user-friendly web interface. The software implements the CNOSSOS-EU standard for road traffic noise emission and propagation [20] and integrates seamlessly with spatial databases such as H2GIS and PostGIS for managing large-scale geospatial datasets.



Figure 6: Noise propagation for a single receiver

As illustrated in Figure Figure 6, even simulating noise propagation at a single receiver point is computationally demanding. This is because reflections, diffractions, and atmospheric effects must all be considered. While NoiseModelling performs many calculations in parallel, generating detailed noise maps for large cities with thousands of receiver points remains resource-intensive –particularly since the software does not yet leverage GPU acceleration.

Traditional light-based ray-tracing approaches are not directly applicable. Unlike light, sound propagation is non-linear and subject to distance-dependent attenuation. Furthermore, sound

travels not only through air but also through the ground, buildings, and other kinds of obstacles. This complexity demands more advanced acoustic models than those used in conventional ray tracing.

Thanks to multi threading and efficient algorithms, NoiseModelling can handle large urban areas with thousands of receiver points in a reasonable time frame. While it does run in java and is not optimized for GPU acceleration, it remains a powerful tool for generating detailed noise maps.

Its modular design supports:

- Standard static noise maps,
- Dynamic maps coupled with traffic simulations (e.g. MATSim, SUMO),
- Probabilistic noise assessments and sensitivity analysis,
- Veteran use in research, education, and urban planning (e.g. Nature4Cities project)

For our metamodel project, NoiseModelling serves as the ground truth, meaning that all predictions made by the surrogate model are systematically compared against its outputs. The decision to use NoiseModelling over other noise simulation tools is motivated by several factors. First, it provides high-fidelity estimates of LAeq levels across the receiver mesh under controlled input conditions. Second, the use of a structured and consistent receiver mesh across simulations enables straightforward comparison between predicted and reference values. In addition, being open source and well-documented, NoiseModelling supports a fully reproducible workflow and integrates seamlessly with code interfaces such as Python, which was the main environment for this internship. Finally, since the development team behind NoiseModelling are colleagues at UMRAE, the tool benefits from in-house expertise, facilitating a deep understanding of its strengths and limitations while ensuring direct feedback and support.

7.2.1 Architecture and Input Requirements

NoiseModelling relies on multiple geographic and traffic-related datasets, including:

- Building geometries (footprint and height),
- Road geometries with traffic attributes (flow, vehicle type, speed),
- Ground surfaces and topography (soil type, vegetation, elevation),
- Receiver locations (fixed measurement points across the study area).

These inputs can be prepared and loaded using WPS Builder, a graphical workflow editor integrated with GeoServer. This allows users to configure and run noise simulations without writing code. However, for the purposes of this internship, the NoiseModelling library was accessed directly from Python scripts, bypassing GUI tools and executing simulations via command-line calls.

The input tables required for NoiseModelling simulations were sourced from the Geoclimate spatial database. Geoclimate provides standardized GIS layers for building footprints, road networks, land cover, and other spatial features [21].

7.2.2 Computational Modules

NoiseModelling can be viewed as a modular system with several key components:

- **Emission:** computes sound power levels using CNOSSOS-EU formulas.
- **Pathfinder:** identifies all potential sound paths between sources and receivers (direct, reflected, diffracted),
- **Propagation:** applies attenuation and diffraction effects along each path,
- **JDBC:** handles database management and communication with GIS layers.

For refined spatial distribution, it subdivides the study area into **sub-domains** with buffer zones extending to the maximum propagation radius. This serves to ensure anything within the studied area actually has accurate noise levels calculated even when sources are outside the area of interest. Ray-tracing from receivers back to sources allows for efficient computation of noise levels, as it avoids the need to simulate every possible path in a brute-force manner. Still, this computation is resource-intensive, especially in urban environments with complex geometries and high source density.

7.2.3 Output Format

The outputs of Noisemodelling can vary between types of noise maps. To remain compatible with the metamodelling framework the raw noise levels on the receiver mesh were used, which are stored in a **GeoJSON** format, or inside a **geopandas** dataframe. This format preserves the spatial structure of the data, allowing for easy integration with other geospatial tools and libraries.

7.2.4 Why Use NoiseModelling for Metamodelling

For our metamodel project, NoiseModelling serves as the **ground truth**, meaning that all predictions made by the surrogate model are compared against its outputs. The choice of NoiseModelling over other noise simulation tools is motivated by several factors:

- It provides high-fidelity outputs of LAeq levels across the receiver mesh under controlled input conditions.
- The structured mesh is consistent across all simulations, allowing for direct comparison of predictions.
- NoiseModelling is open source and well-documented, it supports a reproducible workflow and integration with code interfaces like python, which was used for this internship.
- The people working on NoiseModelling are colleagues at UMRAE, which facilitates understanding the tool and its limitations, and allows for direct feedback and support.

7.3 Mathematical Modeling

7.3.1 Input Variables and Output Targets

We aim to predict the LAeq levels at a set of predetermined receiver points -provided by NoiseModellings own Delaunay mesh generator- based on a set of environmental and traffic variables. The goal is to create a surrogate model that can quickly estimate noise levels under varying conditions, without the need for time-consuming simulations.

7.3.2 Problem Definition

We want to learn a surrogate model for mapping environmental variables to noise levels at a large number of receiver points. Formally, we seek a function $f : \mathbb{R}^4 \rightarrow \mathbb{R}^d$ where:

The metamodel takes as input a vector $x \in \mathbb{R}^4$:

- Temperature T [°C]
- Humidity H [%]
- Wind speed v [m/s] *
- Wind direction φ [°]

* Both wind speed and direction are encompassed by the occurrence rose in NoiseModelling, which dictates how likely favorable conditions are in a particular direction.

$y = (y_1, y_2, \dots, y_d) \in \mathbb{R}^d$ is the vector of LAeq values at $d = 26502$ receiver points.

Our dataset is :

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N, N = 250$$

with y_i obtained from NoiseModelling simulations.

7.3.3 Latin hypercube Sampling

To efficiently explore the input space, Latin hypercube sampling (LHS) is employed. Unlike pure random sampling, which often produces clusters and gaps, LHS ensures more uniform coverage across all dimensions, leading to a more diverse and representative training dataset – a critical requirement for building robust surrogate models. This is particularly valuable in high-dimensional settings, where a regular grid becomes computationally infeasible; for example, sampling just four points per axis in a 7-dimensional space would require $4^7 = 16,384$ simulations. LHS overcomes this limitation by ensuring each dimension is uniformly sampled without the need for exhaustive combinations [22], see Figure 7.

The procedure begins by selecting a sample size $n \in \mathbb{N}$. For a d -dimensional input space, d independent random permutations of the integers $[1, 2, \dots, n]$ are generated randomly. These are assembled into a matrix $X \in \mathbb{R}^{n \times d}$, where each row corresponds to a permutation of the sample indices for each dimension.

To get a LHS sampling of input space \mathcal{I} with $\dim(\mathcal{I}) = d$, it is divided into n^d hypercubes. Using the columns of X , uniformly distributed hypercube coordinates along each axis are obtained. The final LHS sample is obtained by uniformly selecting one point from each hypercube in the permutation π ensuring that the points are well distributed across the entire input space. This is done for the i -th hypercube like this:

$$x_i^j = \mathcal{U}\left(\frac{\pi_{j(i)} - 1}{n}, \frac{\pi_{j(i)}}{n}\right) \in \mathbb{R}^d \quad 4$$

where x_{ij} is the j -th coordinate of the i -th point, sampled uniformly from the j -th dimension of the hypercube, guaranteeing uniform marginal coverage across all dimensions.

Comparison of Sampling Techniques

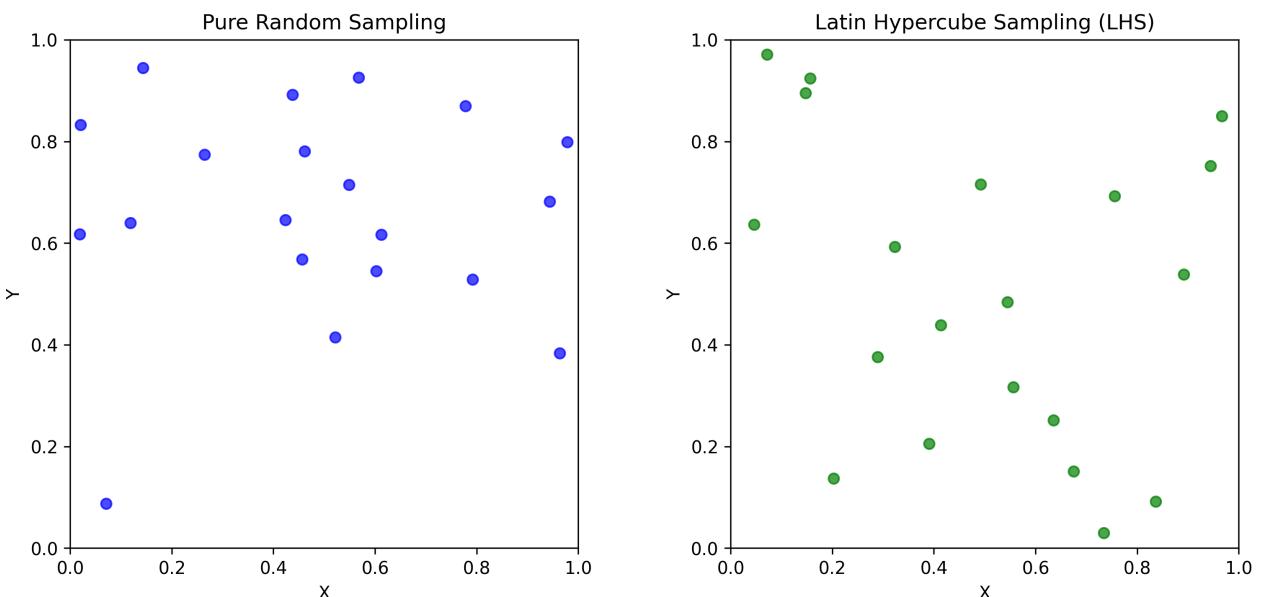


Figure 7: Comparison of pure random and LHS sampling for 20 points in a 2D $[0, 1]^2$

As shown in Figure 7, pure random sampling tends to leave some regions of the domain sparsely covered – especially when projected onto individual axes and with small samples. LHS avoids this by systematically filling the space, making it better suited for metamodel training.

7.4 Data Preparation

7.4.1 Receiver Coordinates

Receiver locations are fixed for a given urban zone and simulation grid. Their spatial layout is stored once and reused throughout training and evaluation. Predictions are later saved in GeoJSON format to preserve this structure.

The receivers mesh is generated by NoiseModelling using Delaunay triangulation, which ensures that the points are well distributed across the area of interest. For example densely built areas tend to be more densely covered with receiver since the gradient of noise levels is expected to be higher there.

7.4.2 Dimensionality Reduction through PCA

Since $y \in \mathbb{R}^d$ and d is large (≈ 26000), learning a model directly in that space is impractical.

Instead, **Principal Component Analysis (PCA)** is applied to project y into a lower-dimensional latent space:

First, the data is centered :

$$Y = Y_{computed} - \bar{Y} \quad 5$$

Where $Y \in \mathbb{R}^{N \times d}$

then we compute the covariance matrix:

$$\Sigma = \frac{1}{N} Y^T \cdot Y \in \mathbb{R}^{d \times d} \quad 6$$

Eigen decomposition of Σ gives us the principal vectors to form the PCA basis ψ :

$$\Sigma \nu_j = \lambda_j \nu_j \quad 7$$

where λ_j are the eigenvalues and ν_j the corresponding eigenvectors, with $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d$.

Σ is symmetric and positive semi-definite, so it has real, nonnegative eigenvalues and orthogonal eigenvectors.

Take any direction $\|\nu\| \in \mathbb{R}^d$, $\|\nu\| = 1$, projecting the data onto ν gives :

$$z = Y \nu \quad 8$$

With variance

$$var(z) = \nu^T \Sigma \nu \quad 9$$

So finding the maximum variance direction is equivalent to solving the eigenvalue problem above. The first principal component ν_1 corresponds to the largest eigenvalue λ_1 , and so on, which allows us to rank components by explained variance.

By selecting k principal components with $k \ll d$, we form a latent space $z \in \mathbb{R}^k$ that captures most of the variance in the original data:

$$z_i = \Psi^T (y_i - \mu), \Psi = [\nu_1, \nu_2, \dots, \nu_k] \in \mathbb{R}^{d \times k} \quad 10$$

Thus each high-dimensional output y_i is approximated by a low-dimensional representation z_i . The original output can be reconstructed as:

$$\hat{y}_i = \mu + \Psi z_i \quad 11$$

PCA reduces the output dimensionality from d to k , making it feasible to learn separate models for each component z_i . The choice of k balances model complexity and reconstruction accuracy.

7.5 Modelling Techniques

7.5.1 Linear Regression

This model assumes a linear relationship between input features and output targets. The model is trained to minimize the mean squared error (MSE) between predicted and actual values. Each component is modeled independently as:

$$\hat{z}_i = \sum_{j=1}^p w_{ij} x_j + b_i \quad 12$$

where w_{ij} are the learned weights, x_j are the input features, and b_i is the bias term for component i . This model is simple and interpretable, but may struggle with complex relationships, and has no spatial awareness.

While this model isn't expected to perform well, it gives us a baseline for what is achievable, and to assess the added value of more complex approaches.

7.5.2 Principal Components Analysis and Gaussian processes

This method combines **Principal Component Analysis (PCA)** for output compression with **Gaussian Process Regression (GPR)** for flexible nonlinear prediction. While the former was explained in detail at section Section 7.4.2, the latter treats the latent coordinates z , modelling them independently as Gaussian processes over the input space.

Each component $z_{i(x)}$ is treated as a random function drawn from a Gaussian process:

$$z_{i(x)} \sim \mathcal{GP}(0, K(x, x')) \quad 13$$

This distributional assumption means that any finite set of function evaluations $[z_{i(x_1)}, \dots, z_{i(x_n)}]$ is jointly Gaussian, with mean zero and covariance determined by a kernel K . Predictions are made by conditioning this distribution on the observed training values.

7.5.3 Kernel function : Matérn

We use the **Matérn kernel**, a widely used covariance function in geostatistics and machine learning. It is particularly suited for data that has high variability, which is exactly the kind of behavior to be expected from environmental noise data. The Matérn kernel is defined as:

$$K(x, x') = \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu} \cdot \|x - x'\|}{\lambda} \right)^\nu k_\nu \left(\frac{\sqrt{2\nu} \cdot \|x - x'\|}{\lambda} \right) \quad 14$$

where :

- ν controls the smoothness of the function, low values (e.g., $\nu = 0.5$) lead to rougher basis functions, while higher values (e.g., $\nu = 2.5$) yield smoother basis functions
- $\lambda \in \mathbb{R}^d$ is a vector of length scales, allowing the kernel to adapt to different input dimensions and capture varying degrees of correlation

- k_ν is the modified Bessel function of the second kind, which ensures that the kernel is positive definite and can be used in Gaussian processes

This kernel has two main advantages:

- It models **locality**, meaning it captures how close inputs x and x' are in a meaningful way.
- It is flexible: by tuning ν and λ , the model can adapt to varying degrees of smoothness, anisotropy, and correlation in the data.

7.5.4 White Noise

To account for measurement noise and model uncertainty, a white noise term is added to the covariance function of the Gaussian process. This modifies the kernel as:

$$K(x, x') = K_{signal}(x, x') + \sigma^2 I \quad 15$$

where $K_{signal}(x, x')$ represents the covariance structure of the underlying smooth function to be learned, σ^2 is the noise variance, and I is the identity. The addition of $\sigma^2 I$ has several important implications.

First, it explicitly acknowledges that the observed data may contain random fluctuations due to measurement error, numerical artifacts from NoiseModelling simulations, or other sources of variability not captured by the deterministic part of the model. By doing so, the Gaussian process avoids treating every observation as perfectly exact.

Second, the noise term ensures numerical stability during model training. Without it, the covariance matrix could become nearly singular if two training points are close together, leading to unstable matrix inversions. The noise guarantees well-posed computations.

Finally, this adjustment provides a regularization effect. By allowing small deviations between the predicted latent function and the actual data points, the model avoids overfitting, leading to smoother predictions that generalize better to unseen inputs.

7.5.5 Implementation

The PCA-Kriging model is implemented using the `scikit-learn` library in Python. The pipeline consists of the following steps:

1. **Data Preprocessing:** Input features are standardized, and PCA is applied to reduce the output dimensionality.
2. **Model Training:** For each PCA component, a Gaussian process regressor is trained using the Matérn kernel.
3. **Prediction:** For new input data, the model predicts the latent vector z , which is then transformed back to the original output space using the PCA basis.

7.5.6 Training

Given training data (X, z_j) with $z_j \in \mathbb{R}^N$, the Gaussian process model is trained by maximizing the log-marginal likelihood:

$$\log p(z_j | X, \theta) = -\frac{1}{2} z_j^T K_\theta^{-1} z_j - \frac{1}{2} \log|K_\theta| - \frac{N}{2} \log 2\pi \quad 16$$

where K_θ is the covariance matrix computed using the kernel with hyperparameters $\theta = \{\lambda, \nu, \sigma^2\}$. The hyperparameters are optimized using gradient-based methods provided by `scikit-learn`.

7.5.7 prediction

For a new input x_* , the predictive distribution for the latent variable $z_{j(x_*)}$ is Gaussian with mean and variance given by:

$$\hat{z}_{j(x_*)} = k(x_*, X)K_\theta^{-1}z_j \quad 17$$

with $k(x_*, X) = [K(x_*, x_1), \dots, K(x_*, x_N)]$, the covariance vector between the new point and training points.

Combining both PCA and GPR, the final prediction in the original output space is:

$$\hat{y}(x_*) = \mu + \Psi\hat{z}(x_*) \quad 18$$

where $\hat{z}(x_*) = [\hat{z}_1(x_*), \dots, \hat{z}_k(x_*)]^T$.

This serves as our surrogate model for estimating noise levels at all receivers given new environmental conditions. PCA compresses the high-dimensional output, while GPR captures complex nonlinear relationships in the input space. Inverse PCA reconstructs the full noise map from the predicted latent representation.

7.6 Results and Validation

7.6.1 Experimental Setup

The model was trained on a dataset of 250 NoiseModelling outputs, each corresponding to a different configuration of environmental conditions. The inputs variables were sampled using LHS sampling, ensuring a diverse and representative coverage of the input space. The outputs were the sound levels at exactly 26.502 receiver points along the Rhine Avenue.

7.6.2 Model Performance

The PCA-Kriging model demonstrated strong generalization, achieving RMSE scores as low as **8e-3 dB** on held-out test sets. It consistently outperformed linear and MLP-based baselines.

Model	RMSE	prediction time
guess the mean of training data	1e-1 dB(A)	25 ms
per-point linear regression	7e-2 dB(A)	60 ms
PCA -regression model	8e-3 dB(A)	170 ms
NoiseModelling	0 dB	1h25 min

Here, the error is given with respect to the reference results, which in this case is the NoiseModelling output. Execution times are given for a single prediction on a standard laptop (Intel i7-10750H, 16GB RAM). The NoiseModelling time is for a single simulation run on a high-performance computer cluster.

7.6.3 Error Analysis

Residuals were spatially analyzed via predicted GeoJSON maps. Most prediction errors clustered near hard-to-model acoustic zones such as building corners or street canyons. Future work could integrate local geometric descriptors to mitigate this.

In environmental noise modelling, errors on the magnitude of 1-2 dB(A) are generally considered acceptable, given the inherent variability in acoustic environments and measurement uncertainties. The PCA-Kriging model's RMSE of **8e-3 dB(A)** is exceptionally low, indicating

that it captures the underlying patterns in the data with high fidelity. The maximum observed error over all test wasses was a datapoint with a 1.201 dB(A) error, which is still within acceptable limits for practical applications.

Training on 250 samples proved ot be way to much for the model to learn the underlying patterns, as quick testing showed performance plateaued beyond 90 samples. This suggests that the model effectively captures the relationships in the data without overfitting, and that additional training data would likely yield diminishing returns. However this also indicates that additional variables, such as traffic density or heavyweight vehicle percentage, could be included to further improve usability of the model.

7.6.4 Output formatting

While both NoiseModelling and the metamodel output GeoJSON files, the code written during this internship includes a custom script to build interpolated heatmaps on the 26502 values produced by the models. This script reads the GeoJSON files and convert them into a format suitable for visualization. It then applies a spatial interpolation method to create smooth heatmaps that are outputted as html files that can be easily embedded in web applications or viewed in a browser. The data is then treated from a heatmap to a contour map, going from 30 to 90 dB(A) in 5 dB(A) intervals, which is the standard for noise maps. This allows for easy visualization and interpretation of the noise levels across the study area.



Figure 8: Example of a heatmap generated from the metamodel predictions

As can be seen in Figure 8, the underlying data is a grayscale map with labels provided by OpenStreetMap, which was chosen as to not interfer with the colors of the heatmap. The map is interactive, allowing users to zoom in and out.

8 Conclusion

8.1 Deliverables

- Fully functional Python pipeline for training and testing surrogate models on NoiseModelling outputs.
- GeoJSON-compatible prediction outputs for easy visualization and GIS integration.

8.2 Added Value for EMS

From the outset, the Eurométropole de Strasbourg (EMS) sought a decision-support tool for exploring environmental noise scenarios. While NoiseModelling provides validated, high-resolution simulations, its computational cost prevents real-time use in planning workflows.

The metamodel developed in this project addresses that limitation. By combining Principal Component Analysis (PCA) for dimensionality reduction with Gaussian Process Regression (GPR) for nonlinear prediction, it produces near-instant forecasts of noise levels under varying meteorological conditions. Once trained, the model can generate spatial predictions over the Rhine Avenue mesh in seconds, enabling rapid assessment of interventions such as traffic regulation, construction scheduling, or climate impacts — without rerunning costly simulations.

This speed-up transforms environmental acoustics from an offline process into an interactive tool, providing EMS planners with the capacity to prototype and compare interventions in real time.

8.3 Deployment

To make the metamodel usable beyond research, deployment was explored. The Shiny framework was chosen given CEREMA's existing server infrastructure, enabling fast prototyping of a web application. The prototype allows non-technical users to specify environmental conditions and instantly obtain standard 5 dB(A) contour maps over the Rhine Avenue mesh.

Scaling this into a production tool, however, would require the development of a secure and scalable prediction API, together with proper authentication and logging mechanisms to ensure controlled access. Input validation and data integrity checks would be essential for reliability, while a more intuitive, user-centered interface would improve accessibility for non-technical stakeholders. Finally, automated retraining pipelines, fed with new NoiseModelling data, would ensure that the model remains accurate and up to date. Together, these elements form the roadmap toward a robust and sustainable operational product.

8.4 Long-Term Vision

This project lays the groundwork for what could evolve into a broader system for noise monitoring and urban acoustic forecasting. Several promising extensions and future directions can already be identified:

- **Dynamic Forecasting input data:** In a future version, the metamodel could ingest real-time data from sources like the Cadence API, adjusting predictions dynamically as weather or traffic conditions evolve. Although current limitations in data availability and resolution restrict this possibility, it remains a long-term goal for this project.
- **Expanded Feature Space:** Future iterations of the model could incorporate additional covariates, such as street-level traffic flow statistics, infrastructure layout (e.g., road type, elevation), seasonal variations, or socio-economic indicators (e.g., residential density, income levels).

- **Retrospective Policy Evaluation:** As more data becomes available over time, the metamodel could serve as a historical comparator. It would allow policy makers to assess how prior decisions have impacted acoustic conditions, thereby closing the feedback loop between planning and impact evaluation.

8.5 Case Outlook: The Rhine Avenue

The Rhine Avenue serves as a concrete example of how such a tool can interface with real-world policy. In 2025, EMS is launching a new wave of interventions designed to reduce vehicle noise and improve the public realm along this corridor. These include:

- In the **western section (M352)**: installation of a smart traffic signal at the entrance of the Étoile tunnel to alleviate congestion, coupled with resurfacing of a high-traffic lane connecting France and Germany.
- In the **central area near Solange Fernex school**: enhancement of pedestrian safety through brightly colored crosswalks, new vegetation to act as sound buffers, and installation of an **experimental noise-awareness radar** — a first in the region.
- In the **eastern section (post-Vauban bridge)**: improvements to cyclist and pedestrian crossings and adjustments to traffic patterns to minimize bottlenecks.

8.6 Summary of Contributions

This internship delivered two complementary tools aligned with the strategic goals of the Eurométropole de Strasbourg:

1. **A Metamodel for Environmental Noise Prediction:** A robust machine learning surrogate trained on detailed acoustic simulations. The model leverages PCA and Kriging to reduce the problem's complexity and enable fast, accurate prediction of sound levels under varying meteorological inputs. While not a replacement for NoiseModelling — which remains necessary for fully general spatial predictions — the metamodel dramatically accelerates scenario analysis over fixed receiver meshes.
2. **A Visualization Tool for Real-Time Exploration:** A lightweight dashboard prototype that integrates weather and traffic data, offering an intuitive spatial representation of acoustic conditions along the Rhine Avenue. While the visualization module was ultimately deprioritized, its development informed data formatting and laid the groundwork for future deployment.

Together, these components provide a solid methodological and technical foundation for future work in environmental noise modelling, urban planning, and public health forecasting. The project demonstrates that machine learning can meaningfully assist municipal authorities in making data-informed, timely decisions that benefit residents' quality of life.

This work also opens the door to a more agile, interactive, and transparent approach to environmental governance — one in which simulations can keep pace with political ambition and civic urgency.

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Bibliography

- [1] R. Guski, D. Schreckenberg, and R. Schuemer, “WHO Environmental Noise Guidelines for the European Region: A Systematic Review on Environmental Noise and Annoyance,” *International Journal of Environmental Research and Public Health*, vol. 14, no. 12, p. 1539, Dec. 2017, doi: 10.3390/ijerph14121539.
- [2] “Estimated percentage of inhabitants within urban areas across countries exposed to road traffic noise levels using the day-evening-night indicator (Lden), based on END threshold.” Accessed: Jul. 23, 2025. [Online]. Available: <https://www.eea.europa.eu/en/analysis/publications/environmental-noise-in-europe-2025/estimated-percentage-of-inhabitants-within-urban-areas-across-countries-exposed-to-road-traffic-noise-levels-using-the-day-evening-night-indicator-lden-based-on-end-threshold>
- [3] “Bruit, nuisances sonores et pollution sonore | Ministères Aménagement du territoire Transition écologique.” Accessed: May 21, 2025. [Online]. Available: <https://www.ecologie.gouv.fr/politiques-publiques/bruit-nuisances-sonores-pollution-sonore>
- [4] “La Ville et l’Eurométropole de Strasbourg engagées pour l’apaisement de l’avenue du Rhin à Strasbourg.” Accessed: Jul. 18, 2025. [Online]. Available: <https://www.strasbourg.eu/-/apaisement-avenue-du-rhin>
- [5] “Site de la Ville et l’Eurométropole de Strasbourg.” Accessed: May 21, 2025. [Online]. Available: <https://www.strasbourg.eu/>
- [6] “Cerema, climat et territoires de demain. Aménagement et résilience.” Accessed: May 21, 2025. [Online]. Available: <https://www.cerema.fr/fr>
- [7] “UMRAE.” Accessed: May 21, 2025. [Online]. Available: <https://www.umrae.fr/>
- [8] “Environmental noise in Europe 2025.” Accessed: Jul. 21, 2025. [Online]. Available: <https://www.eea.europa.eu/en/analysis/publications/environmental-noise-in-europe-2025>
- [9] C. Ayrault, “Le Mans Université, Master Acoustique - Acoustique urbaine : généralités.”
- [10] “Acoem Cadence.” Accessed: Apr. 16, 2025. [Online]. Available: <https://cadence.acoem.com/overview>
- [11] RACE, “ACOEM - Spécialiste de l’acoustique, vibration et pollution de l’air.” Accessed: May 21, 2025. [Online]. Available: <https://race-cluster.fr/2021/10/13/acoem/>
- [12] “ORHANE | L’Observatoire Régional des Nuisances Environnementales.” Accessed: May 21, 2025. [Online]. Available: <https://www.orhane.fr/>
- [13] “L’observatoire du bruit en Ile-de-France.” Accessed: May 21, 2025. [Online]. Available: <https://www.bruitparif.fr/index.hbs>
- [14] “CENSE.” Accessed: May 21, 2025. [Online]. Available: <https://cense.ifsttar.fr/>
- [15] P. Aumond, L. Jacquesson, and A. Can, “Probabilistic modeling framework for multisource sound mapping,” *Applied Acoustics*, vol. 139, pp. 34–43, Oct. 2018, doi: 10.1016/j.apacoust.2018.04.017.
- [16] Géomod, “Découvrez notre logiciel de cartographie du bruit en milieu extérieur.” Accessed: Jul. 22, 2025. [Online]. Available: https://www.geomod.fr/savoir_faire/propagation-des-ondes/mithrasig
- [17] D. GmbH, “CadnaA – State-of-the-art Noise Prediction Software - Datakustik GmbH.” Accessed: Jul. 22, 2025. [Online]. Available: <https://www.datakustik.com/products/cadnaa/cadnaa/>

- [18] Cerema, “Suivi acoustique et modélisation de l’Avenue du Rhin à Strasbourg - Volet 1 : Analyse des données 2023,” Feb. 2024.
- [19] “Welcome to Python.org.” Accessed: May 21, 2025. [Online]. Available: <https://www.python.org/>
- [20] Institute for Health and Consumer Protection (Joint Research Centre), F. Anfosso-Lédée, M. Paviotti, and S. Kephhalopoulos, *Common noise assessment methods in Europe (CNOSSOS-EU): to be used by the EU member states for strategic noise mapping following adoption as specified in the environmental noise directive 2002/49/EC*. Publications Office of the European Union, 2012. Accessed: Jul. 29, 2025. [Online]. Available: <https://data.europa.eu/doi/10.2788/31776>
- [21] “Geoclimate.” Accessed: May 21, 2025. [Online]. Available: <https://github.com/orbisgis/geoclimate/wiki/Home>
- [22] M. D. McKay, R. J. Beckman, and W. J. Conover, “A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code,” *Technometrics*, vol. 21, no. 2, pp. 239–245, 1979, doi: 10.2307/1268522.
- [23] “Avatar.” Accessed: May 21, 2025. [Online]. Available: <https://avatar.cerema.fr/accueil>
- [24] “Acoem Cadence.” Accessed: Apr. 16, 2025. [Online]. Available: <https://cadence.acoem.com/overview>
- [25] “Zotero \textbar Connectors.” Accessed: May 21, 2025. [Online]. Available: <https://www.zotero.org/download/connectors>
- [26] P. Aumond, L. Jacquesson, and A. Can, “Probabilistic modeling framework for multisource sound mapping,” *Applied Acoustics*, vol. 139, pp. 34–43, Oct. 2018, doi: 10.1016/j.apacoust.2018.04.017.
- [27] “L’observatoire du bruit en Ile-de-France.” Accessed: May 21, 2025. [Online]. Available: <https://www.bruitparif.fr/index.hbs>
- [28] “ORHANE \textbar L’Observatoire Régional des Nuisances Environnementales.” Accessed: May 21, 2025. [Online]. Available: <https://www.orhane.fr/>
- [29] “Avatar.” Accessed: May 21, 2025. [Online]. Available: <https://avatar.cerema.fr/accueil>
- [30] “Geoclimate.” Accessed: May 21, 2025. [Online]. Available: <https://github.com/orbisgis/geoclimate/wiki/Home>
- [31] RACE, “ACOEM - Spécialiste de l’acoustique, vibration et pollution de l’air.” Accessed: May 21, 2025. [Online]. Available: <https://race-cluster.fr/2021/10/13/acoem/>
- [32] “CENSE.” Accessed: May 21, 2025. [Online]. Available: <https://cense.ifsttar.fr/>
- [33] C. Ayraut, “Le Mans Université, Master Acoustique - Acoustique urbaine : généralités.”
- [34] Cerema, “Suivi acoustique et modélisation de l’Avenue du Rhin à Strasbourg - Volet 2 : Modélisation de référence,” Dec. 2024.
- [35] “Cerema, climat et territoires de demain. Aménagement et résilience.” Accessed: May 21, 2025. [Online]. Available: <https://www.cerema.fr/fr>
- [36] “Guidance on environmental noise.” Accessed: May 21, 2025. [Online]. Available: <https://www.who.int/tools/compendium-on-health-and-environment/environmental-noise>

- [37] P. Aumont, A. Can, V. Mallet, B. Gauvreau, and G. Guillaume, “Global sensitivity analysis for road traffic noise modelling,” *Applied Acoustics*, vol. 176, p. 107899, May 2021, doi: 10.1016/j.apacoust.2020.107899.
- [38] A. Lesieur, V. Mallet, P. Aumont, and A. Can, “Data assimilation for urban noise mapping with a meta-model,” *Applied Acoustics*, vol. 178, p. 107938, Jul. 2021, doi: 10.1016/j.apacoust.2021.107938.
- [39] “Environmental noise in Europe – 2020.” Accessed: Jul. 21, 2025. [Online]. Available: <https://www.eea.europa.eu/en/analysis/publications/environmental-noise-in-europe>