Assessing the Potential for CO_2 and Pollutant Emission Reduction via Redistribution of Port-Induced Road Traffic: A Case Study of the Port of Rotterdam

Giovanni De Nunzio[1*], Suzanne Bussod[1], Celeste Muilwijk[2], Miklós Doma[2]

[1] *IFP Energies nouvelles, Rond-point de l'échangeur de Solaize, BP 3, 69360 Solaize, France*
[2] *Port of Rotterdam, Rotterdam, Netherlands*
Corresponding author's email address: giovanni.de-nunzio@ifpen.fr

Abstract – Public authorities face the challenge of air quality management in complex territories and need tools to disentangle the contributions of heterogeneous sources of emissions. Transportation is a major source of nitrogen oxides and accounts for about 30% of global carbon emissions. This becomes even more relevant in territories where transportation significantly serves other purposes than just people mobility. Port cities are among these territories where transportation is key to ensure goods displacement, and more complexity arises when goods transport interacts with people mobility. This paper aims to model and analyse port-induced road traffic emissions, and to explore reduction strategies by optimizing the temporal distribution of traffic induced by freight transport. A mesoscopic emission model incorporating road characteristics, traffic flow, and vehicle fleet data, was used to estimate the contribution of each emitter on each road segment of the studied area. Real traffic count data from the Port of Rotterdam were used to compare a reference scenario (current traffic patterns) with a scenario shifting container-shipment traffic to off-peak hours. Results indicate that while annual CO_2 emission reduction is modest (~1%), this approach noticeably reduces (~30%) peak-time pollutant peaks and traffic congestion, improving air quality and operational efficiency during the busiest hours.

Keywords – Port logistics, emission modelling, road traffic regulation, emission reduction measures

Introduction

Air pollution remains one of the foremost environmental and public health challenges of the 21st century. Global assessments attribute millions of premature deaths annually to ambient and household air pollution, with fine particulate matter ($PM_{2.5}$) and nitrogen oxides (NOx) identified as major drivers of respiratory and cardiovascular disease (WHO, 2024). The societal burden is substantial: World Bank estimates place annual health damages in the multi-trillion-dollar range, equivalent to several percent of global GDP (World Bank, 2022). Beyond direct health impacts, air pollution reduces ecosystem services and crop yields, and—because many pollutants share sources with greenhouse gases—it also exacerbates climate mitigation challenges.

Within this context, transport is a central contributor. In Europe, transport ranks among the largest sources of greenhouse-gas emissions and remains the dominant urban NOx source (EEA, 2023; CITEPA, 2024). While exhaust emissions have declined due to technological improvements, non-exhaust sources (brake, tyre and road wear) now represent a growing share of urban particulate emissions (EEA, 2024). Decarbonising transport remains technically and institutionally challenging, with uneven progress in electrification and low-carbon fuels.

Port cities exemplify the complexity of the urban-transport-air quality nexus. Maritime activity, harbour operations and the associated hinterland freight flows concentrate multiple emission sources – oceangoing vessels, auxiliary engines, cargo handling equipment, heavy-duty trucks and access traffic – within coastal metropolitan areas, generating spatially heterogeneous pollution patterns and localized hotspots of NO_x, Sulfur dioxide (SO_2) and PM (Tokaya, 2024). This co-location of freight and passenger mobility complicates both exposure attribution and mitigation design, as interventions in one sector (e.g., shore power) may have little effect on roadside concentrations if truck movements persist (Acciaro, 2025).

Consequently, robust policy design requires source-aware, high-resolution tools that connect activity data, traffic dynamics and emission processes (Rodriguez-Rey, 2021). Traditional inventory models (e.g., COPERT and related EMEP/EEA procedures) provide consistent long-term national and regional emission estimates but typically operate at coarse spatial or temporal resolution and therefore may not resolve the intra-urban, road-segment-level contributions needed for targeted interventions (Ntziachristos, 2009). Receptor-based approaches and dense monitoring networks can recover source fingerprints where available, yet they are costly and do not always translate readily into activity-based policy levers. In this methodological gap, mesoscopic emission models – which combine traffic flow representations, road-segment attributes and fleet composition to estimate emissions at finer spatial and temporal granularity – have shown promise as a computationally tractable compromise between macroscopic inventories and fully microscopic simulations (Dib, Balac and Sciarretta, 2025). Integrated with measured traffic counts and sectoral activity models, such mesoscopic frameworks enable source apportionment at the road-link level and support scenario testing of operational strategies.

Building on these motivations, this study develops and applies a mesoscopic emission modelling framework to quantify the contribution of port-induced road traffic to local NO_x and CO_2 emissions, and to evaluate the air-quality and congestion impacts of temporal redistribution policies for goods movements. Using real traffic counts from the Port of Rotterdam as a case study, we compare a reference scenario that reproduces current daily traffic patterns with an alternative in which a share of container-shipment truck trips is shifted to off-peak hours. The approach combines link-level traffic flows, fleet and emission factors, and scenario-based adjustments to departure time distributions; it is designed to be operationally transparent and readily adoptable by municipal and port authorities for decision support.

Methodology

To accurately simulate the temporal shift of port-related road operations, it is essential to rely on a modelling framework capable of representing both the current and prospective state of the transport system. Such a framework must capture three interrelated dimensions: the temporal and spatial distribution of traffic volumes, the resulting emissions produced along each road segment, and the composition of the vehicle fleet that conditions emission intensities.

Estimation of hourly traffic flow per road segment

Accurate estimation of road traffic volumes at a fine spatial and temporal resolution is a prerequisite for reliable emission modelling. In this study, we applied a data-driven flow estimation approach developed at IFPEN, which enables hourly traffic predictions on any road-link of a given network, even when direct measurements are unavailable.

Let $\boldsymbol{\mathcal{L}}$ denote the set of road links (segments). For each link $l \in \boldsymbol{\mathcal{L}}$, we ingest:

(i) X_l^{static}: *static* features from Geographic Information System (GIS) layers, including geometry and length L_l, functional class, number of lanes, curvature, slope ∇l, signage and junction types, and posted speed limit.

(ii) X_l^{dyn}: *dynamic* features such as historical speed patterns, real-time probe speeds (FCD), counting stations (where present), and temporal descriptors (hour-of-day, day-type, season).

All features are harmonised to an hourly time base $h \in \{1, \dots, 24\}$ for the target day.

For each road link *l* and hour *h*, a supervised deep learning model $\boldsymbol{F}_\theta(X_l^{static}, X_l^{dyn})$ predicts the total flow $Q_{l,h}$ (veh/h) from static and dynamic features, following a spatio-temporal approach for network-wide flow profile estimation (Laraki, 2022; Hammoumi, 2025). The reference dataset of traffic flow measurements used for training the supervised model contains traffic counts from French major urban and peri-urban areas. The vehicle flow is aggregated across all vehicle classes.

The model produces hourly flows on all links, with uncertainty estimates derived from validation residuals.

To ensure network-wide consistency, a correction model enforces flow continuity across nodes. This is formulated as an optimization problem solved with an interior-point method, with constraints on connectivity and congestion states. Measurement-equipped links are given higher weights in the objective function, so that available counts anchor the estimation. The final output is a temporally resolved traffic flow estimate for each link, at an hourly resolution, consistent both with local data and with global network continuity.

The traffic flow prediction model, grounded in an artificial intelligence framework, offers both flexibility and computational efficiency, enabling rapid calibration against real-world measurements when such data are available. As demonstrated in the results section, the model can be fine-tuned to align closely with observed traffic counts in the study area, thereby improving the accuracy and contextual relevance of the predictions.

Estimation of traffic emissions per road segment

Once traffic flows are estimated, emissions are computed using an enhanced mesoscopic model. Traditional macroscopic approaches (e.g., COPERT, HBEFA) rely solely on average speed and tend to underrepresent the effects of congestion, slope, and road characteristics. In contrast, the proposed model incorporates additional input dimensions: infrastructure type (e.g., urban arterial, motorway), slope classes, posted speed limits, and average speed. These descriptors are linked to emission factors derived from a large microscopic emissions database.

The calibration database is based on trajectories from the *Geco air* platform, which aggregates over 100 million km of real driving data collected at 1 Hz resolution from GPS-enabled smartphones. Each trajectory includes detailed speed, acceleration, and altitude profiles, which are then coupled with vehicle-specific models to estimate emissions of CO_2, NOx, hydrocarbons, CO, particulate matter, and noise. Emission factors are not limited to median driving styles: the model also provides 25th and 75th percentile values, reflecting gentle and aggressive driving conditions, respectively.

To reduce computational complexity, the calibration dataset was binned by infrastructure type, slope, average speed,

and speed limit. Within each bin, representative trajectories corresponding to the median and extreme quartiles were retained, producing a compact yet representative training set. A supervised learning model (random forest, neural network, or multivariate regression depending on pollutant and vehicle type) was then fitted to link the input variables to emission factors (De Nunzio, 2021; Bussod, 2024).
For each vehicle category and pollutant, the mesoscopic model thus predicts average emission factors and their variability for any road segment. Combined with hourly traffic flows, this yields temporally and spatially resolved emission inventories. Crucially, the approach captures the sensitivity of emissions to congestion and road attributes, providing results that are both computationally tractable and closer to real-world dynamics than factor-based averages.

Model of the vehicle fleet composition
Finally, realistic emission estimates require a representation of the circulating vehicle fleet. Fleet composition is specified at the level of four broad categories: light vehicles (LV), light commercial vehicles (LCV), heavy-duty vehicles (HDV), and two-wheelers (2WD). For each category, the distribution across fuel types (diesel, gasoline, electric, hybrid) and Euro standards is derived from national statistics (CITEPA, SDES) and International Energy Agency (IEA) scenarios. Importantly, road fleet shares are corrected to reflect actual usage, since vehicles differ in mileage intensity. For instance, while motorcycles are numerous in stock, heavy-duty vehicles dominate road presence in terms of vehicle-kilometres travelled. This correction ensures that the computed emission shares reflect real exposure conditions rather than ownership statistics (Sabiron, 2025).

Results

We applied the proposed road traffic emission modelling framework to the area of the Port of Rotterdam to assess both its sensitivity and its extrapolation capability to territories outside the training domain. This application provides a stringent test of the model's generalisation performance.

Port of Rotterdam measurement data
The Port of Rotterdam dataset comprises 409,571 traffic measurements collected from 40 sensors distributed across the port area. Sensor coverage is heterogeneous: blue sensors record aggregate vehicle counts, cyan sensors provide counts disaggregated into three vehicle classes, and green sensors differentiate up to five classes. These data were systematically processed to extract hourly vehicle counts, average speeds, and, where possible, vehicle category information, which served as inputs for calibration and validation of the modelling approach.

Figure 1 – Location of the sensors providing the measurement data. Blue sensors record aggregated vehicle counts, cyan sensors provide counts disaggregated into three vehicle classes, and green sensors differentiate up to five classes.

Traffic flow calibration
Traffic flow estimations were first compared against available ground-truth measurements, and the model was subsequently calibrated to improve accuracy for this specific use case. In the baseline modelling approach, historical traffic speed information from HERE Maps is used to estimate traffic flows, which are subsequently converted into emission estimates. In the case of the Port of Rotterdam, however, traffic count measurements were available, allowing for a two-step calibration procedure. First, whenever a sensor provided speed data, the corresponding HERE speed on the associated road segment was replaced with the observed sensor speed. Second, for links equipped with traffic

counters, sensor-based vehicle counts were incorporated to fine-tune the AI-based flow estimation model.
To reduce the risk of overfitting, the calibration did not attempt to exactly reproduce the measured flows at each sensor location. Instead, fitting errors were smoothed across the network, ensuring that adjustments improved global consistency rather than producing local biases. A summary of the calibration results is provided in Figure 2. Calibration is particularly important in this scenario due to the specific traffic characteristics of the A15 highway, which crosses the southern part of the Port of Rotterdam. On regular working days, this corridor is predominantly used by port employees and heavy-duty vehicles, resulting in atypical traffic dynamics. Consequently, despite being a two- to three-lane highway, the measured traffic volumes remain relatively low compared to similar road infrastructures. This fine-tuning strategy proved effective in enhancing the accuracy of the model while preserving its generalisation capacity. The procedure is transferable and can be replicated in other port or urban areas where traffic sensors provide flow and speed data.

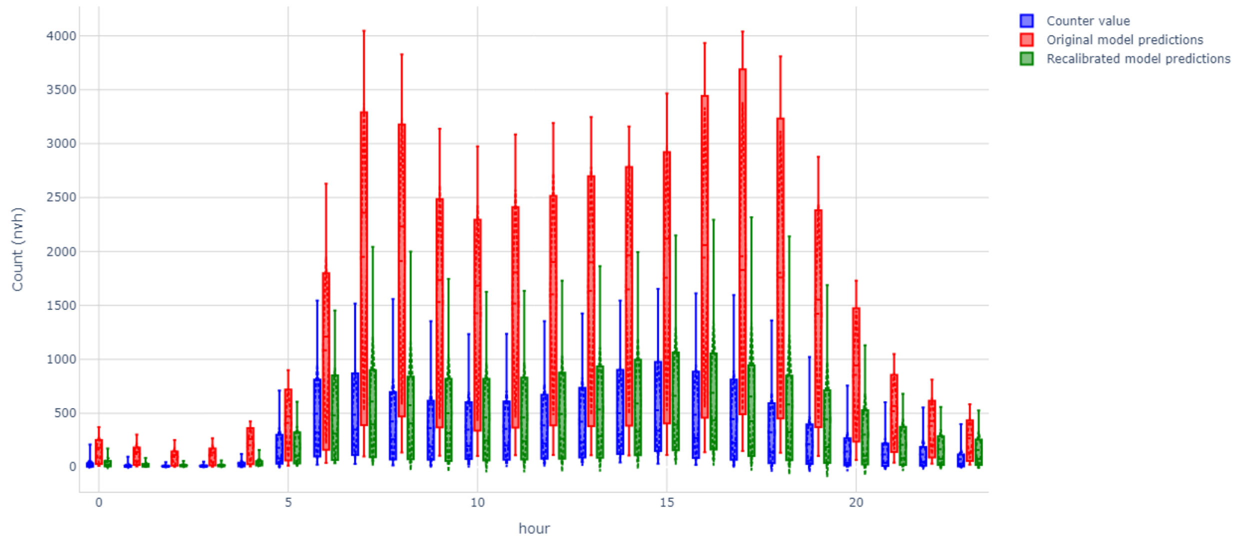

Figure 2 – Average hourly traffic flow at sensor locations as a function of the hour of the day. The blue boxplots indicate the measured data. The red boxplots indicate the model estimation before calibration. The green boxplots indicate the model estimation after calibration.

<u>Vehicle fleet composition calibration</u>
The traffic sensors deployed around the Port of Rotterdam provide vehicle counts with varying levels of disaggregation. Three sensor types are distinguished: (i) *blue sensors*, which record undifferentiated counts for all vehicles; (ii) *cyan sensors*, which classify vehicles into three length-based categories ($l \leq 5.60$ m; $5.60 \text{ m} < l \leq 12.20$ m; $l > 12.20$ m); and (iii) *green sensors*, which offer a finer classification into five length intervals ($1.85 \text{ m} < l \leq 2.40$ m; $2.40 \text{ m} < l \leq 5.60$ m; $5.60 \text{ m} < l \leq 11.50$ m; $11.50 \text{ m} < l \leq 12.20$ m; $l > 12.20$ m).
Data pre-processing was required to ensure consistency. Approximately 0.8% of the raw data were discarded due to sparsity, incoherence, or missing values. In addition, sensors that did not provide vehicle-type distinctions were excluded, representing 71.1% of the initial dataset. After filtering, only 17 of the 40 sensors remained, corresponding exclusively to the green category with five vehicle classes. This resulted in a curated dataset of 80,680 measurements, equivalent to 19.7% of the original records.
For compatibility with the emission modelling framework, which is based on four broad vehicle categories—heavy goods vehicles (HGV), light commercial vehicles (LCV), light vehicles (LV), and two-wheelers (2W)—the two longest sensor classes were merged and treated as HGV. This mapping is consistent with empirical evidence showing a strong correlation between vehicle length, gross vehicle weight, and typical usage (e.g. long-haul trucks and articulated lorries fall within the longest length categories, whereas shorter segments capture vans and passenger cars). As a result, the aggregated fleet composition derived from the sensor data is 40.2% HGV, 6.5% LCV, 53.0% LV, and 0.3% 2W. This adjusted distribution provides a realistic representation of the active road fleet in the port area, while ensuring methodological consistency with the emission models.

<u>Analysis of the container-shipment traffic volume shifting scenario</u>
As part of a policy aimed at reducing peak-time emissions, we simulate a traffic volume-shifting scenario. In this scenario, we assume that the average hourly traffic flow in the port area can be regulated by redistributing heavy-duty-vehicles missions throughout the day in such a way that it remains uniform throughout the daytime period (06:00–18:00) and accounts for 60% of the total daily flow, while the off-peak flow is also uniform and represents the

remaining 40% of daily traffic.
This traffic redistribution results in modest but measurable impacts on annual emissions, yielding a 1% reduction in CO_2 and a 1.1% reduction in NO_x compared to the nominal scenario. This reduction is modest because in our simulation we do not alter the total traffic volume in the two scenarios and at the annual aggregation level only the effect of reduced congestion during most congested hours, as measured by the sensors, is visible on the total emissions. However, more interestingly, the effects on the hourly distribution of emissions reveal that a decrease in daytime traffic flow leads to a more significant reduction in emissions, whereas an increase in off-peak traffic flow produces a corresponding rise in emissions (Figure 3, road traffic emissions are indicated in dark blue).
Consequently, peak-time emissions are mitigated by about 30%, and emissions are more evenly distributed across the 24-hour period. This effect is particularly relevant for local pollutants such as NO_x, for which peak-shaving measures can have a substantial impact on air quality and public health in areas surrounding ports.

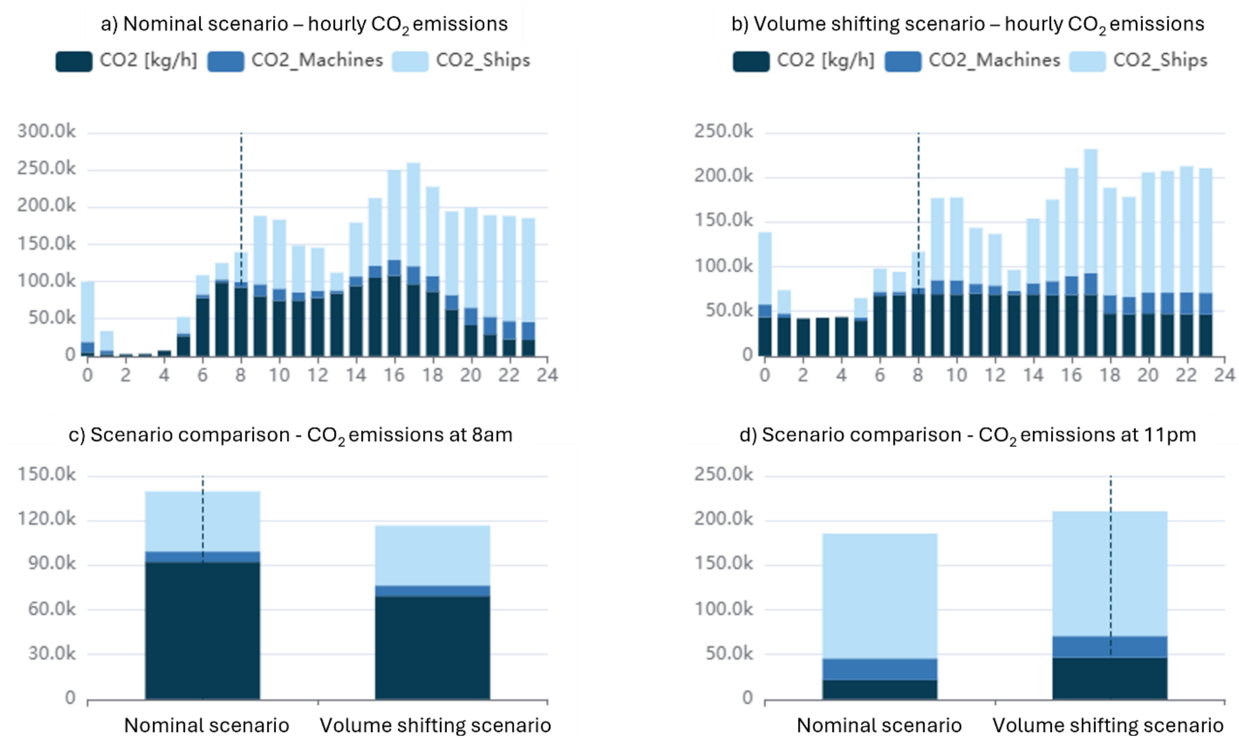

Figure 3 – Evaluation of CO2 emissions in the two analysed scenarios. The dark blue bars indicate emissions caused by road traffic, the denim blue bars indicate emissions caused by container-handling machines, the light blue bars indicate emissions caused by berthed vessels. Subfigures a) and b) show the hourly CO2 emissions for the two scenarios. Subfigures c) and d) show a zoom of the carbon emissions for a peak-time and an off-peak hour, respectively.

Conclusion

In conclusion, this study has highlighted the role traffic distribution strategies can play in reducing road-traffic emissions from port freight transport, a major source of port-induced hinterland emissions. By calibrating the base traffic and emission model with real sensor data, we compared the current traffic scenario with an alternative "optimal" configuration, in which traffic was evenly distributed between peak and off-peak hours. This analysis confirmed that the maximum achievable reduction in annual emissions through traffic spreading is about 1% for CO_2, with a similar marginal effect observed for NO_x. At hourly scale, however, peak-time emissions are mitigated by about 30%. While such a reduction demonstrates the technical feasibility of regulating traffic flows and its potential in reducing population exposure to local pollutants such as nitrogen oxides, it also underscores the limited potential of this strategy to deliver meaningful progress toward ambitious decarbonization targets.
Consequently, if the objective is to achieve substantial progress toward sustainability, greater emphasis should be placed on transformative measures, particularly replacing conventional fuels with cleaner alternatives, such as electrification or hydrogen-based propulsion. These strategies hold more promise in aligning port operations with long-term environmental goals.
This work also represents an important step within the MAGPIE project. With the transition of emission calculations

to the HESP tool, developed by the Port of Rotterdam Authority in collaboration with BigMile, future analyses will benefit from more advanced data and improved transparency in tracking transport-related emissions. This handover ensures continuity of research and paves the way for more comprehensive insights into heavy-duty vehicle emissions.

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