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Stochastic Air Quality Dispersion Model for Defining Queuing Ships Seaport Location

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Abstract: This work develops a stochastic air quality dispersion to predict the pollution concentration originating from ships queuing in a seaport. The Gaussian dispersion model for five ships operating in the Black Sea queuing in the front of the port of Varna as sources of gas emission of NO\textsubscript{x}, SO\textsubscript{x} and PM\textsubscript{10} is used to define the air pollution concentration at receptors (crowded areas of the port and other reference points) and consequently the distance to the seaport queuing location. Uncertainties, which are inherent in the input data and mathematical model, are accounted for to estimate the propagating uncertainties of the emission concentration at the receptors accounting for the wind speed, horizontal and vertical dispersion parameters as a function of the geographical location of the emission sources (ships), effective emission height and weather conditions. The estimated uncertainties of the air quality prediction are of significant importance for the decision-making on the regulatory purposes, and the probability of exceeding the threshold limits needs to be quantified. The most expected value and the probability of exceeding the acceptable limits of pollution concentration are defined by employing the first-order reliability method. The target reliability level is defined as the failure cause and mode used for identifying the safety calibration factors that may be employed for defining the most suitable location of the ship queuing seaport. Several conclusions about the applicability of the developed stochastic model and its use for regulatory purposes are also provided.

Keywords: air quality; maritime transport; port impact; particulate matter; gaseous pollutants; shipping emissions; dispersion model

1. Introduction

Ports are one of the most important parts of the hinterland links and short sea shipping since international trade is mostly transported using ships [1]. Sea cargo transportation is constantly expanding resulting in constant growth in the emissions of nitrogen oxides NO\textsubscript{x}, sulfur oxides SO\textsubscript{x}, particulate matter PM and others originating from the diesel combustion in ocean-going vessels [2,3], and their control becomes dominant in keeping the green environmental conditions [4]. The EU Thematic Strategy on Air Pollution was identified in [5] and confirmed in [6] the importance for the health and environment the reduction of sulfur dioxide SO\textsubscript{2}, NO\textsubscript{x} and PM from ships.

The predominant fuel oil in shipping [7] is high-sulfur fuel oil (HSFO) and it is still used in many low-to-medium speed engines [8]. HSFO was the dominant fuel in international shipping about 79% of the total fuel consumption by energy content in 2018 [9]. The share of bunker sales reached 90% in the first quarter of 2019 in Singapore, which is the world’s largest bunkering hub [10]. After the quick adjustment to the global sulfur cap (from 1 January 2020), the share of HSFO declined to about 17% in the first quarter of 2020 in Singapore. The decline later stopped and the steady rise in scrubber-fitted ships has supported the demand for HSFO (23% in the first quarter of 2021 in Singapore) and this seems to remain until new solutions and future fuels are widely introduced.
Before selecting the most promising alternatives for reducing gas emissions generated by maritime transport, it is important to highlight that the exhaust gases from propulsion and auxiliary systems are not the only pollutants generated by vessels, there are other wastes with equally harmful effects like waste oil, ballast water, wastewater, greywater, solid waste, and painting of ships. The concern nowadays is that gas emissions cause adverse effects on human health related to lung cancer, heart attacks, breathing issues and premature deaths, asthma, and heart disease [11,12].

Some alternatives can be applied to existing ships in reducing gas emissions [13] while others can only be applied to the design of new ships.

The HSFO contains about 3.5% sulfur, leading to an option either buy expensive low sulfur fuel or install SO$_2$ scrubbers in reducing the gas emission. Since 1 January 2020 after the start of the global sulfur cap for 15 months the number of scrubber-fitted ships has almost doubled—from 2011 to 3935 (https://splash247.com/number-of-installed-scrubbers-has-doubled-since-last-years-global-sulphur-cap-introduction/, accessed on 13 January 2022). The number of ships for different types varies from 11.4% for dry bulk carriers to 24.5% for all crude oil tankers. However, the way the diesel engines make a 95% reduction in NO$_x$ is to install selective catalytic reduction (SCR) units [14]. The scrubbers and selective catalytic reduction units increase the capital and operational expenditure and require additional costs for maintenance.

An alternative to traditional heavy fuel oils is liquefied natural gas as a marine fuel with no sulfur and about 25% lower CO$_2$ emissions, while NO$_x$ emissions are 90% lower (https://www.elengy.com/en/lng/lng-an-energy-of-the-future.html, accessed on 13 January 2022). However, there are other possible alternatives, which still need some more time to be implemented in the case of long voyages.

Estimating the ship’s gas emissions, the ship’s operational activities are normally split into cruise—sailing at service speed; reduced speed zone (RSZ)—sailing at a speed less than cruise and greater than maneuvering speed; maneuvering and hotelling [15,16]. The queuing is the ship’s time when it is anchored, waiting for the next voyage or cargo loading and unloading operation in the port terminals. This operation is considered in emission inventory models [17] and is relevant to the traffic congestions in front of large container terminals at the end of 2021. The total ship gas emissions are the sum of the emissions related to all operational activities during one voyage. Special attention in the present study is paid to ship queuing as a source of pollution, the consequences of the gas emission pollutions, and the best distance to the port identified as a receptor to guarantee safe environmental conditions [18].

An important objective in this study is also to analyze the uncertainties incorporated in the Gaussian dispersion model and for this purpose, local and global uncertainties analyses are performed. The second-order approach is employed to estimate the model variance, where the uncertainty refers to the variance in the input data and the modeled output. It is important to quantify the model uncertainties and their propagation [19] and the probabilistic estimate for any location in the modeling domain of the dispersion model.

The air quality estimates and their dispersion are affected by various uncertainties and are directly associated with the decision-making processes [20]. The development of an effective stochastic approach that can explicitly incorporate uncertainty into the pollution estimates is needed for providing robust support for air quality decision management. Recently different approaches based on fuzzy, stochastic, and mathematical programming were employed for determining the least-cost strategy of reducing emissions in which the uncertainties in the source-receptor transfer coefficients were incorporated [21,22].

Recently the fuzzy logic methodology has been widely used demonstrating efficiency in analyzing complex issues. The fuzzy logic presents non-linear complex control solutions and in the case of air pollutants in a continuous value between 0 and 1 demonstrating a satisfactory solution, where for assessing air quality environmental level index has been introduced [23–25]. Most of the studies do not analyze statistically the impact of sampling deviations.
The artificial neural networks methodologies have been also applied recently in analyzing the impact of environmental pollution [26], associative memories [27], and factor analysis [28] among others.

The study here uses the Gaussian dispersion model in defining the pollution concentration at receptor locations (crowded port areas and other reference points). Uncertainties of the emission concentration at the receptors account for the wind speed, horizontal and vertical dispersion parameters as a function of the geographical location of the emission sources (ships), effective emission height, and weather conditions. A target level is defined related to failure cause and mode is used for identifying safety calibration factors in defining the most suitable location and distance from the receptors (terminal port) and the source of pollution represented by the ships queuing at the seaport.

2. Pollutant Emissions Abatement Control

The abatement cost for pollutant emissions is established based on the Gaussian dispersion model and it is associated with the applied technology for removing the air pollutants. For each pollutant, the total cost, conditional on the abatement targets is estimated using the semi-infinite programming model based on the unabated emissions and the unit cost of the cleaning technology.

The relationship between the concentrations emission rate accounting for meteorological conditions can be defined by the vertical and the crosswind Gaussian dispersion model [29–31], estimating the air pollution concentration for one specific period:

\[
C_m(x, y, z) = \frac{Q_m}{\pi \sigma_{m,y} \sigma_{m,z} u_m} \exp \left( -\frac{1}{2} \left( \frac{y}{\sigma_{m,y}} \right)^2 \right) \exp \left( -\frac{1}{2} \left( \frac{H}{\sigma_{m,z}} \right)^2 \right)
\]

(1)

where \(Q_m\) is the emission rate, \(\sigma_{m,y}, \sigma_{m,z}\) are the dispersion coefficients in crosswind and vertical directions, \(x\) and \(y\) are the longitudinal and transverse distance from the source, \(u_m\) is the wind speed, and \(H\) is the effective stack height, showing that the concentration in each point of the space is proportional to the emission rate \(Q_m\) and inversely proportional to the wind speed \(u_m\) (see Figure 1). The dispersion coefficients \(\sigma_{m,y}, \sigma_{m,z}\) are related to a specific receptor position and weather conditions.

![Gaussian dispersion model](image)

Figure 1. Gaussian dispersion model.

The Gaussian dispersion model is developed based on the general transport-diffusion equation considering the stationary process, representing no changing in time, homogeneous and flat spatial domain, wind speed \(u_m\) direction only along \(x\) with a zero speed along other axes, negligible dispersion without any chemical reaction.

The average concentration over a long period can be estimated by assuming that the period is composed of a sum of a series of stationary conditions, not accounting for the possible correlation between the sequence conditions, where assuming that the
concentration $C_m$ is estimated for the meteorological condition $m$ in one specific period, which may occur with a probability $p_m$ of occurrence, where the average concentration is defined as:

$$C(x, y, z) = \sum_m C_m(x, y, z)p_m + C_b$$

(2)

where $C_b$ is the background concentration.

If the emission rate of the source $Q_m$ is a constant for a relatively long period, and the probability of occurrence of any possible weather condition is known $p_m$, the average pollution at the receptor can be estimated as:

$$C(x, y, z) = Q \sum_m a_m p_m + C_b$$

(3)

where $a_m$ is constant depending only on the weather condition for a distance from the receptor to the source.

In general, the air pollution is dispersed in a three-dimensional space $\Omega$ generated from $n$ sources (ships), where at each of the $m$ point receptor locations $x_i, y_i, z_i$ the concentration on the contaminant is:

$$C_i(x_i, y_i, z_i) = \sum_{j=1}^n C_j(x_{ij}, y_{ij}, z_{ij}), \quad i \in [1, m]$$

(4)

where $C_j(x_{ij}, y_{ij}, z_{ij})$ is the concentration provided by the $j$th source and $i$th receptor and based on the meteorological and geographic conditions and the geographical distance between the resources and receptors $x_{ij}, y_{ij}, z_{ij}$ are calculated as:

$$x_{ij} = (x_{S,j} - x_{R,j}) \sin \theta + (y_{R,j} - y_{S,j}) \cos \theta$$

$$y_{ij} = (x_{S,j} - x_{R,j}) \cos \theta + (y_{R,j} - y_{S,j}) \sin \theta$$

(5)

where $\theta$ represents the angle of the wind direction, $x_{S,j}, y_{S,j}$ are the coordinates of the point source and $x_{R,j}, y_{R,j}$ are the coordinates of the receptor.

If $w_j$ is the reduction factor of the air contamination from the $j$th source, when $j = 1 \ldots n$, and $w = (w_1, \ldots, w_n) \in [0,1]^n$ and assuming that the total cost $G(w)$ is a linear function of $w_j$ defined as:

$$G(w) = \sum_{j=1}^n a_j w_j$$

(6)

the problem of minimizing the air pollution control costs into the space $\Omega$ can be defined by satisfying the following conditions:

$$\min_{w=(w_1, \ldots, w_n)} G(w) = \sum_{j=1}^n a_j w_j, \quad w \in R^n$$

(7)

which is constrained to

$$C_i(x_i, y_i, z_i) \leq C_{MAC,i}(x_i, y_i, z_i), \quad \forall (x_i, y_i, z_i) \in \Omega$$

(8)

where $C_{MAC,i}$ is the maximum allowable concentration at the $i$th receptor location.

The result of minimizing the air pollution cost will be the maximum emission rate that the sources (ships) may have without crossing the threshold of the intolerable average air pollution concentration at the location of receptors (ports).

In general, it can consider the existence of finite sources (ships), and an infinite number of constraints, as many as the number of receptors leading to a semi-infinite programming problem. This problem allows the compliance of the constraints observed at each receptor point. The optimal values of the $w_j$ indicate the contamination reduction of each source at the least cost [32].
Some discussions about the cost associated with the air pollutants at the source can be found in [33]. In the case of cyclones, momentum separators, filters, scrubbers, electrostatic precipitators, the cost is about 0.71 Euro per kg removed particulates. For scrubber, catalytic conversion the cost is about 0.55 Euro per kg removed SO₂. For scrubber, catalytic conversion the cost is about 0.55 Euro per kg removed NOₓ.

The variation of the pollution concentration at any distance from the source depends on the variation of the input parameters and the sensitivity of the output estimate on the sensitivities of the input.

A study about the requirements and cargo transportation demand in the Black Sea as part of a multimodal transportation frame was performed, estimating the potential need for a shipping fleet of multipurpose ships [34,35]. Five of these ships, transporting cargoes and queuing very closely in the front of the port of Varna are considered as a one-point source of pollution, n = 1.

The emission rate generated by the source of pollution is 4347 NOₓ kg/day, 2344 SOₓ kg/day and 276 PM₁₀ kg/day located at x = 0.00 m, y = 0.00 m, y = 0.00 m, m = 1, Cₒ = 0, as indicated in Equation (1). The ocean sea is assumed as a flat surface, and the effective stack height is 12 m. The wind speed is 2 m/s, oriented from the source to the receptors [36]. The environmental stability parameters are based on night-cloudiness used for calculating the horizontal and vertical dispersion parameters, 𝜎ₒ and 𝜎ₓ.

The original pollution concentration generated by the queuing ships cross the acceptable limit and the receptor locations and cleaning devices were employed to reduce it, as shown in Figure 2. The Maximum Allowable Concentrations, 𝐶𝑀𝐴𝐶, are considered here are: 𝐶𝑀𝐴𝐶,NOₓ = 30 μg/m³, 𝐶𝑀𝐴𝐶,SOₓ = 20 μg/m³, 𝐶𝑀𝐴𝐶,PM₁₀ = 20 μg/m³ more information can be seen in [37].

![Figure 2. Pre, post abatement and allowable concentration, NOₓ.](image)

The problem analyzed here can be extended to define what is the maximum emission rate that may guarantee a tolerable air pollution concentration with a given probability in a determined period, what is the minimum abatement cost in the presence of several air pollution sources (ships) that may guarantee a tolerable air pollution concentration at receptors located at the port. It can also be solved an inverse engineering problem related to how large are the pollution emissions at given locations that determine the existing concentration at a specific source location sharing and to find the optimal abatement rates for several ships to guarantee a tolerable air pollution concentration at a series of receptors. Finally, is to find the best position of a seaport for queuing ships with emission rates at a distance from a port for cargo operation, which is analyzed in the next sessions.
3. Sensitivity and Uncertainty Analysis

Two types of sensitivity analysis are usually distinguished: local and global sensitivity. The local sensitivity analysis focuses on the local impact of the factors on the model outputs, and it is carried out by computing partial derivatives of the output concerning the input factors. With this kind of approach, the factors are allowed to vary within small intervals around the nominal values. These intervals are not related to the uncertainty in the factor values.

The global sensitivity analysis can be used to identify the importance of any individual factor concerning the uncertainty in the output. The global sensitivity analysis involves the distributions of the input factors and computes the output variation. The computation involves the sensitivity index for each input variable. These indices are estimated to vary the factors over their whole uncertainty ranges. The global sensitivity analysis allows identifying the variables that need an accurate measure or estimation.

First, a local sensitivity analysis is performed to evaluate the Gaussian dispersion model output sensitivities caused by the variation of the input parameters identifying the most significant ones. The specified important parameters will require the greatest accuracy and precision in their quantification in reducing the uncertainty in model predictions.

The local sensitivity of the governing variables is calculated by:

$$\alpha_{xi} = \frac{1}{\sqrt{\sum_{i=1}^{n} \left( \frac{\partial C(x)}{\partial x_i} \right)^2}} \frac{\partial C(x)}{\partial x_i}$$  \hspace{1cm} (9)

where \(x = \{Q, u, \sigma_y, \sigma_z, H\}\). The local sensitivities estimates are shown in Figure 3, conditional to \(y = z = 0\). In defining the air pollution concentration, the most sensitive parameters vary with the distance between the source of pollution (ships) and the receptor (port), where the most sensitive factors are, \(u, \sigma_z, H, \sigma_y, Q\) and as can be seen from Figure 3.

![Figure 3. Sensitivity factors, NO_2, Sy = σ_y, Sz = σ_z.](image)

The global Gaussian dispersion model uncertainties are evaluated using the standard deviation around the mean value of the output air pollution concentration employing the Taylor series expansion. Several assumptions are made where the estimations of the parameters included in Equation (1) are uncertain including the wind speed, \(u\), horizontal dispersion parameter, \(\sigma_y\), vertical dispersion parameter, \(\sigma_z\), emission rate, \(Q\), and effective emission height, \(H\). The error related to \(u, \sigma_y, \sigma_z, Q\) and \(H\) are random, uncorrelated, and are normally distributed with mean values of \(E_u, E_{\sigma_y}, E_{\sigma_z}, E_H, E_Q\) and standard deviation equal to \(S_u, S_{\sigma_y}, S_{\sigma_z}, S_H, S_Q\), respectively.
The second-order approximation of the variance based on the Taylor series expansion is used to describe the uncertainty in the modeled dispersion. A non-linear relationship between the input variables and the output estimate exists. It has to be pointed out that the dispersion parameters, \( \sigma_y(x), \sigma_z(x) \) are calculated as functions of downwind distance \( x \) and \( y = z = 0 \) for discrete stability classes as defined by Pasquill (1961).

The uncertainty related to \( C(x, 0, 0) \) when the input parameters are in a non-linear relationship to the output, the higher-order terms of the Taylor series equation are included, and the second-order approximation of variance is given as:

\[
E[C] = C[E(Q), E(u), E(\sigma_y), E(\sigma_z), E(H)] + \frac{1}{2} \sum_{i=1}^{5} \left( \frac{\partial C}{\partial x_i} \right)^2 S_{x_i}^2
\]

\[
S_C^2 = \sum_{i=1}^{5} \left( \frac{\partial C}{\partial x_i} \right)^2 S_{x_i}^2 + \frac{1}{2} \sum_{i=1}^{5} \left( \frac{\partial^2 C}{\partial x_i^2} \right)^2 S_{x_i}^4
\]

where \( \frac{\partial C}{\partial x_i} \) and \( \frac{\partial^2 C}{\partial x_i^2} \) are the first and second-order sensitivities of the input parameters.

Here for the concentration rate, an uncertainty of 10 percent is assumed. The wind speed and direction are measured at a 10 m height with the wind vanes and anemometers within a tolerance of 0.25 m/s, 15 percent uncertainty is assumed.

The original data on which the Pasquill [30] dispersion curves are based, it is difficult to estimate the measurement uncertainties for \( \sigma_y, \sigma_z \). For the base case uncertainties, a conservative value of 20 percent is used to represent the measurement portion of the total uncertainty.

The effective emission height, \( H \) (height of plume above ground), depends on the release height and plume rise, expressed as a function of wind speed, ambient and stack gas temperatures, and exit velocity. For simplicity, \( H \) is treated as a measured variable and assigned a base case uncertainty to 15 percent of its value. The stochastic model of the basic variables considered in this study is presented in Table 1.

| \( x_i \) | Distribution | Mean Value | COV |
|------|--------------|------------|-----|
| \( Q \) | Normal | \( E_Q \) | 0.10 |
| \( u \) | Normal | \( E_u \) | 0.15 |
| \( \sigma_y \) | Normal | \( E_{\sigma_y} \) | 0.20 |
| \( \sigma_z \) | Normal | \( E_{\sigma_z} \) | 0.20 |
| \( H \) | Normal | \( E_H \) | 0.15 |

A Normal distributed random variable \( B_{x_i} \) is introduced to take into account the model uncertainty on \( Q, u, \sigma_y, \sigma_z, H \). The uncertainty calculations can be performed using the total uncertainty on any individual variable estimate and model uncertainty represented by the random variable with a mean value of \( B_{x_i} = 1 \) and coefficient of variation \( COV_{B_{x_j}} = 0.05 \) for \( B_Q, B_u, B_{\sigma_y}, B_{\sigma_z} \) and \( B_H \) are determined as:

\[
E(x) = B_x E_x
\]

\[
COV(x) = \sqrt{(1 + COV_{B_x}^2)(1 + COV_{E_x}^2) - 1}
\]

The emission rate \( E_Q = 4347 \) NO\(_x\) kg/day, \( E_{SO_2} = 2344 \) SO\(_2\) kg/day and \( E_{PM_{10}} = 276 \) PM\(_{10}\) kg/day, \( E_u = 2 \) m/s, \( E_H = 12 \) m, and \( E_{\sigma_y}, E_{\sigma_z} \) as a function of the distance and weather conditions as defined by Pasquill [30]. The propagating second-order global uncertainties are shown in Figure 4.
4. Risk-Based Decision Making

A distance analysis is performed here in defining the best location of the seaport for queuing ships, identified as a source of air pollution. The analysis involves the port for cargo operation (receptor), the seaport for queuing (source), the distance between the cargo operation and queuing ports, and the metric defined either as a distance or time between the ports for cargo operation and queuing.

The distances between the cargo operation and queuing ports can be calculated using the shortest route between the ports. The distance analysis includes the pull problem to minimize the distance between the ports, the capture problem that relates to the cost associated with the distance of the queuing ship (port services and cargo transportation), push problem that considers pollution issues that maximize the distances between the ports.

The final objective is to find a distance that minimizes the sum of the total risk and associated cost. The push and pull distance strategies will be employed to estimate the risk and associated cost as a function of the distances between the cargo-operation port and queuing-seaport. The push strategy will minimize the emission exposure by maximizing the distances between the ports such that the pollutant exposure to the cargo-operation port is less than the established threshold for air pollution. The pull strategy focuses on finding a distance, where the total cost of queuing ships losses, and cargo delivery are minimized. The pull strategy will tend to reduce the distance between the ports.

A decision about the location of the seaport for queuing ships can be made by analyzing the pollution concentration generated by the ships and resulting environmental damage in minimizing the total expected risk. The risk associated with the ecological collapse is estimated as the probability of collapse, defined as the pollution concentration crosses acceptable limits, times the consequences in a monetary term defined as:

\[
Risk_f(t_n|x, \beta) = P_f(t_n|x, \beta)G(t_n|x, \beta)
\]  

where \(P_f(t_n|x, \beta)\) is the probability of failure, \(G\) is the cost associated with the failure \(x\) is the vector of governing parameters, \(\beta\) is the Beta reliability index, and \(t_n\) is the period where the risk is estimated.

The reliability, \(R\) or the probability of failure, \(P_f = 1 - R\), analysis is incorporated into the decision-making procedure, where the statistical nature of the governing parameters and decision-making problem is defined in an objective function, and the probabilistic constraints specify the required reliability target level.
The reliability analysis performed here uses the First Order Reliability Method, FORM [39–41] that identifies a set of basic random variables that influence the failure mode or the limit-state under consideration. The failure probability, \( P_f \) concerning a single failure mode can formally be defined as:

\[
P_f = P[\gamma(x) \leq 0]
\]  

(15)

All random variables are considered non-correlated Normal distributed. The limits state function, \( \gamma(x) \) is minimized, and it is subjected to constraints, where \( x \) is the vector of the random variables.

The limit state function is defined as:

\[
\gamma(x) = C_u(x) - C_d
\]  

(16)

where

\[
C_u(x) = \frac{B_Q Q}{\pi B_a u} \exp \left(- \frac{(B_H H)^2}{2B_a^2 u} \right)
\]  

(17)

The Beta index, as a function of the distance between the source and receptor, is presented in Figure 5. The minimum Beta index is achieved at 1794 m and from the source and from that point ahead the Beta index group up since the pollution concentration reduces.

The importance of the contribution of each random variable to the limit state function \( \gamma^*(x) \) at the design point is assessed by the sensitivity factors, which are determined as:

\[
a_{xi} = \frac{1}{\sqrt{\sum_{i=1}^{n} \left( \frac{\partial \gamma^*(x)}{\partial x_i} \right)^2}} \frac{\partial \gamma^*(x)}{\partial x_i}
\]  

(18)

and are shown in Figure 6.

The uncertainties associated with the pollution and the potential ecological damage resulting from the air pollution gases, which is expressed as a probability of failure, \( P_f \) is accounted for in the risk assessment.
where $SO_\text{X}$, $NO_\text{X}$, $NO_\text{Y}$, $NO_\text{Z}$, $H_\text{X}$, $Q_\text{X}$, $B_\text{X}$, and $S_\text{X}$ are the emission rates after the abatement.

The optimal safety level is defined by employing a cost-benefit analysis. The goal is to establish an acceptable safety and reliability level by using the risk control option in determining the acceptable threshold of the air pollution concentration. The cost-benefit analysis is performed based on the total expected risk, $Risk_k(x)$, which is a product of the probability of failure and consequence cost \cite{35,42}:

$$Risk_k(x) = Risk_f(x) + Risk_m(x)$$  \hspace{1cm} (19)$$

where $Risk_f(x)$ is the risk associated with the environmental failure and its consequence costs and $Risk_m(x)$ is the cost of the implemented safety measures in keeping the environment safe.

A decision can be made analyzing the cost associated with the pollution abatement, ecological damage, and port service as a function of the distance where the ships are queuing in minimizing the total expected risk. The risk associated with the environmental collapse accounts for the probability of failure and the cost of consequences is defined as:

$$Risk_f(x) = P_f\{P[g(x) \leq 0]\} G_f(x)$$ \hspace{1cm} (20)$$

where $P_f\{P[g(x) \leq 0]\}$ is the probability of the air pollution concentration crossing the threshold limit and $G_f(x)$ is the impact, which defines the consequence cost of the air concentration crossing the threshold limit.

The damage of the ecosystem estimated in a monetary unit, $G_{eco}(x)$, due to the air pollution gases generated by the ships engine propulsion and auxiliary systems, once the abundant concentration is abated (using scrubbers or other cleaning systems) to satisfy the minimum allowable concentration, it is defined as:

$$G_{eco}(x) = \sum_{k=1}^{3} Q_{a,k}(x|x, 0, 0) G_{eco,k}$$ \hspace{1cm} (21)$$

where $G_{eco,k}$ denotes the damage cost of the pollutant $k$, Euro per $\mu g/m^3$ and $Q_{a,k}(x|x, 0, 0)$ is the emission rate after the abatement.

A recent study about the contribution of different pollutants to our health and economy reveals that $SO_\text{X}$, $NO_\text{X}$ and $PM_{10}$ contributes as 15%, 18%, and 50% respectively of the total annual damage per $\mu g/m^3$, assumed here as 2000 €/$\mu g/m^3$.

The cost related to the enhancement of environmental safety by taking measures is the target reliability level that depends on different factors and may vary from one industry to another, as a function of the seriousness of its consequence, or public and media sensitivity.
The target level defined here is related to failure cause and mode. Considering a reference period, \( t_r \), of one year, the Beta target reliability level, \( \beta(t_r) \), is defined as 2.71. A more detailed recommendation is provided in [43] where the Beta target reliability index is given for the service life and related not only to the consequences but also to the relative costs of safety measures [44].

The cost of the implemented safety measures in keeping the environment safe is defined as:

\[
Risk_m(x) = G_{air}(x) + G_{port}(x|x) \tag{22}
\]

where \( G_{air}(x) \) is the cost associated with the air pollutants at the source that needs to be cleaned (abated), and \( G_{port}(x|x) \) is the cost associated with the port services as a function of the distance between the port and queuing seaport where the ships are waiting to enter the port.

The weight of pollution discharge that needs to be cleaned up (abated) is defined as \( C_{MAC,k} \) and the cost, associated with that is:

\[
G_{air}(x) = \sum_{k=1}^{3} C_{MAC,k}(x)G_{air,k} \tag{23}
\]

where \( G_{air,k}(x) \) is the cost associated with the air pollutants at the source that need to be cleaned [33].

The anchoring areas where the ships are queuing and generating pollution are established by examining environmental, navigational, and economic conditions converting each designated anchoring area to a polygon, conditional to local judgment for a specific port. Depending on the distance to the port, size and services need to the ship a specific cost is generated, which is defined here as \( G_{port}(x|x) \) and may vary from port to port.

As can be seen from Figures 7–9 the optimal distance where the ship as a source of pollution needs to queue to keep the safe environment is 1794 m, with a concentration of the pollution at the receptor (port) with a location \((0, 0, 1794 \text{ m})\) 9.35 \(\mu g/\text{m}^3\) \(NO_x\) respecting a Beta index of 2.71.

![Figure 7](image_url)

**Figure 7.** Cost as a function of pollution concentration, \(NO_x\).

Figure 10 shows the total cost as a function of distance including the impact of \(SO_x\), \(NO_x\) and \(PM_{10}\).
Figure 8. Cost as a function of distance, NOₓ.

Figure 9. Cost as a function of Beta index, NOₓ.

Figure 10. Total cost function of distance and beta index, SOₓ, NOₓ, PM₁₀.
Partial safety factors are developed based on the characteristic values of the governing factors \( Q, u, \sigma_y, \sigma_z, C_d \) and \( H \) calculated at a confidence level of the original probability density function. The probabilistic design values of all parameters involved in the limit state functions are \( Q^*, u^*, \sigma_y^*, \sigma_z^*, C_d^*, H^* \). The resulting partial safety factors can be used in the decision-making for defining the Beta target index and minimum total risk (cost) by satisfying the following design criterion:

\[
\gamma_{C_d} = \frac{C_d^*}{C_d}, \quad \gamma_u = \frac{u^*}{u}, \quad \gamma_{\sigma_y} = \frac{\sigma_y^*}{\sigma_y}, \quad \gamma_{\sigma_z} = \frac{\sigma_z^*}{\sigma_z}, \quad \gamma_H = \frac{H^*}{H}, \quad \gamma_Q = \frac{Q^*}{Q}
\]  

(24)

The resulting partial safety factors can be used in the decision-making for defining the queuing (anchoring) location as the best distance from the receptor (port) conditional to the target Beta index and minimum total risk (cost) by satisfying the following design criterion:

\[
C_{w\gamma} \geq C_{u\gamma}
\]  

(26)

where

\[
C_{u\gamma} = \frac{C_u}{\gamma_{C_d}}
\]  

(27)

\[
C_{w\gamma} = \frac{\gamma_Q Q^*}{\pi \gamma_y \sigma_y^* \gamma_z \sigma_z^* \gamma_u u^*} \exp \left( -\frac{1}{2} \left( \frac{\gamma_H H^*}{\gamma_z \sigma_z^*} \right)^2 \right)
\]  

(28)

The estimated partial safety factors are: \( \gamma_Q = 1.07, \gamma_{C_d} = 1.49, \gamma_{\sigma_y} = 0.67, \gamma_{\sigma_z} = 0.84, \gamma_H = 0.95, \gamma_u = 0.85 \).

As can be seen from Figure 11 the ideal distance solution, satisfying the minimum risk and target reliability index is associated with 1794 m. Any distance greater than that will be an acceptable but somehow more expensive solution and any distance lesser than that is not acceptable. The solution of the problem can be defined as:

\[
\min_{x=(x_1, \ldots, x_n)} C_{w\gamma} - C_{u\gamma}(x), \quad x \in \mathbb{R}^n
\]  

(29)

which is constrained to the Beta target reliability level, \( \beta(r) \), defined here as 2.71.

---

**Figure 11.** Distance solution.
5. Conclusions

This study developed a stochastic model for predicting the air pollution concentration of ships queuing in a seaport. The Gaussian dispersion model was used to define the pollution concentration at receptor locations (crowded port areas and other reference points). Uncertainties related to the input data and mathematical model were accounted for to estimate the propagating uncertainties of the air pollution emission concentration at the receptors accounting for the wind speed, horizontal and vertical dispersion parameters as a function of the geographical location of the emission sources (ships), effective emission height and weather conditions. The most expected probability of exceeding the acceptable limits of pollution concentration was defined by employing the first-order reliability method. A target probability level was defined based on the failure cause and mode and was used to develop safety calibration factors. The safety partial factors together with the Gaussian dispersion model were developed to be used for defining the safety location of the queuing ships in a seaport avoiding air pollution at the receptor (port). The developed approach is flexible and demonstrated capacity to be used in defining the distance between the port and queuing seaport in preserving the environment from the air gas pollution generated by waiting ships. Different assumptions were made that are not essential for the approach but are needed for the example calculation.

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