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Interest of the Statistical Modeling in the Dynamic LCA- Fire Methodology to Assess Industrial Fire Effects

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Abstract: Life Cycle Impact Assessment, LCIA, is one of the four phases of Life Cycle Assessment (LCA) described in ISO 14042; its purpose is to assess a product system's life cycle inventory analysis (LCI) in order to better understand its environmental significance. However, LCIA typically excludes spatial, temporal, threshold and dose-response information and combines emissions or activities over space and/or time. This may reduce the environmental relevance of the indicator result. The methodology of Dynamic LCA -Fire proposed in this paper is to complete the International Standard ISO 14042 in the fire field by combining the LCA - Fire method with the Numerical Dispersion Model. It is based on the use of the plume model used to assess pollutants concentrations and thermal effects from fire accident scenarios and to cope with the presence of uncertainties in the input data we propose an uncertainty analysis enables to avoid as much as possible bad decisions that may have a large impact in domain such as safety. In this study, The Dynamic LCA - Fire methodology is applied for a case study of petrol production process management and we are interested in the uncertainty propagation related to NO_2 atmospheric dispersion resulting from a crude oil tank fire. Uncertainties were defined a priori in each of the following input parameters: wind speed, NO_2 initial concentration and its diffusivity coefficient. For that purpose, a Monte Carlo approach has been used.

Key words: Life Cycle Impact Assessment · Fire-LCA · Numerical Dispersion Model · Statistical modeling · Fire modeling · Monte Carlo

INTRODUCTION

The "Dynamic LCA -Fire" is a proposed approach that combines two tools: LCA-Fire and Numerical Dispersion Model (NDM) within the inclusion of spatial and temporal aspects in LCIA in order to give information post-process such as the residence time or the concentration of the pollutant resultant from the fire; One important purpose of such tools is to provide relevant and structured information in decision-making processes. Due to the complex nature of fire, mathematical prediction models used in fire safety engineering are often simplified and based on a number of assumptions. The first problem that has been partly overlooked is accuracy of results from mathematical models is often complicated by the presence of uncertainties in their inputs data. Uncertainty analysis investigates the effects of lack of knowledge and other potential sources of error in the model [1]. When carried out, uncertainty analysis allows model users to be more informed about the confidence that can be placed in model results and hence becomes a quality insurance factor. That is what; we study the uncertainty propagation of input parameters of NO_2 atmospheric dispersion model on the variation of its output (NO_2 concentration). The uncertainty propagation has been conducted using the Monte Carlo sampling. All the results are presented in terms of mean values and confidence interval (lower and upper) bounds.

Statistical Fire Model: Statistical models provide a useful resource that can help us to understand the causes and consequences of fires. They are used to identify and quantify the effects of the most significant fire-related factors and environmental factors.

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Fire statistical model is presented in this work by two components: Fire statistics and the uncertainty analysis in the Numerical Dispersion Model (NDM) that is used to correct the uncertainty propagation of input parameters of NO_2 atmospheric dispersion model on the variation of its output (NO_2 concentration). This goal has been achieve by the use of the statistic fire which constitute a parameters for the adjustment of the model and the analysis of uncertainty in the Numerical Dispersion Model using the Monte Carlo method.

LCA Method with Fire Considerations: The Life Cycle Assessment methodology also needs continuous improvements to incorporate new aspects and processes. An LCA typically describes a process during normal operation and abnormal conditions such as accidents are left out of the analysis, usually due to lack of a consistent methodology or relevant data [2, 3]. For example, LCA data for power production usually assume normal conditions without any accidents.

Provisions for certain accidents in the analysis of the lifecycle could be included provided these could be specified in sufficient detail and occurred with sufficient regularity to make their inclusion relevant. The Fire-LCA model is essentially equivalent to a traditional LCA approach with the inclusion of emissions [4].

Fire Statistics: The fire statistics that are used to develop the fire model must be detailed. It must be able to determine the number of primary and secondary fires each year. In addition it must be able to estimate the size of these fires, i.e. the number of fires that grow to involve the rest of the room and/or the rest of the building. Fire statistics tend only to include fires that are large enough for the fire brigade to be summoned. In many cases small fires are extinguished by people nearby and the fire brigade is not called. These fires are, however, often reported to insurance companies as part of an insurance claim. Therefore statistics from insurance companies should also be included in construction of the fire model. Also, The quantitative output of the statistical analysis of a scenario constitute parameters for the adjustment model, resulting in an equation that can be used to make conservative adjustments of model predictions, by the modelling of the uncertain parameters of the model by means of random variables and then construct explicitly the probabilistic model of these random variables using the available information [5].

Uncertainty Analysis in the NDM: The Numerical Dispersion Model allows to follow-up of the plume by determining the quantities of the NO_2 at each position and at every moment along the life cycle of the plume, which will make it to determine the residence time of the pollutant. That shows the importance of modelling as tool for decision making aid, especially to the experience feedback.

The plume is described in terms of unsteady state convective transport by a uniform ambient wind of heated gas and particulates matter introduced into a stably stratified atmosphere by a continuously burning fire. The mathematical model of a smoke plume consists of the conservation equations of mass, momentum and energy which govern the temperature T, pressure P, density and velocity (u,v) in the direction (x,y), in connection with the k-ε turbulence model [6]. The induced flow, mass fraction and temperature field can be described by a set of equations derived from the conservation laws for mean flow quantities. A more detailed description can be found in Chettout *et al*. (2013).

Mathematical models are necessarily simplified representations of the phenomena being studied and a key aspect of the modeling process is the judicious choice of model assumptions [7]. That is why; fire management is subject to manifold sources of uncertainty.

Uncertainty analysis is the most appropriate and most effective way to take into account the uncertainties in the model parameters when the probability theory can be used.

Uncertainty analysis may be achieved by means of different approaches depending on the level of uncertainty associated to the considered parameters. Monte Carlo sampling, fuzzy sets based-approach, intervals analysis are among these approaches [8].

Monte Carlo sampling method is being used in various disciplines [9], it has become the industry standard for propagating uncertainties [10].

The general scheme of that method is depicted in Figure 1. We give hereafter, in connection with the Numerical Dispersion Model, the main steps of Monte Carlo approach.

The Place of Statistical Model in the Dynamic LCA-fire: The Dynamic LCA - Fire model is essentially equivalent to a traditional LCA approach with the inclusion of emissions from fires and the dispersion of the emitted pollutants in the atmosphere. During the lifetime of the products to be analysed, some products will be involved

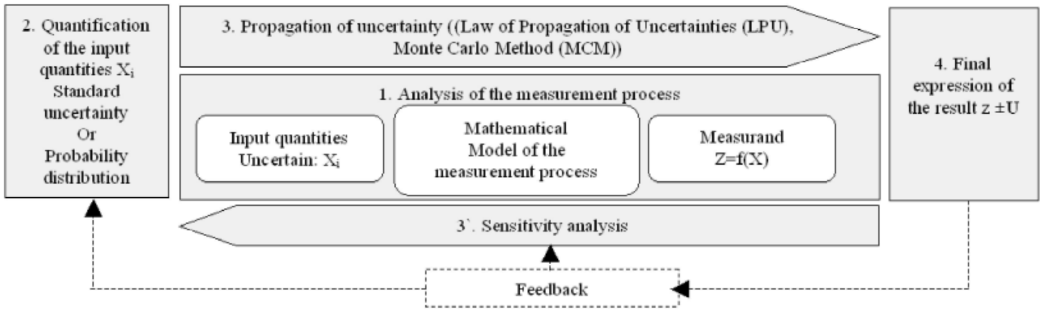

Fig. 1: Uncertainty propagation framework

in different types of fires. The Dynamic Fire-LCA model is composed of the following modules: LCA method with fire considerations, Statistical fire model and Dispersion numerical model, Figure 1. LCA model will therefore include modules to describe the fire behaviour for the different types of fires. Fire statistics are used to quantify the amount of material involved in the different types of fire [11]. In addition, the model also includes modules for evaluating the pollution produced from the fire that are needed due to the shortening of lifetime that the fires have caused [12].

Model Application:

Fire - LCA Results: The obtaining is the environmental impact measure of the choice of a given fire safety level. Implicitly, this model is the fact that, to obtain a high level of fire safety measures to improve fire performance should be taken; these could be for example the addition of Flame Retardants (FR) or a fire extinguishing system or to change the design of the product. The case chosen for this application represent an industrial fire illustrated by the refinery products (petrol and gasoil) [11]. For the determination of the pollutant quantity emitted from the fire and also we could take into account the heat flux generated from the fire and represented by the temperature elevation. The data of this part could be acquired from the database of fires occurred in the refineries. For this, we could reference to a fire which took place in the refinery of Skikda (city in Algeria). The fire started on the crude oil storage tank terminal S106, later on the fire extended to the tank S105. The "Boilover" happened would reject the entire contents of the tank. The S106 tank was being filled at 70 % since 21 h 40 the night before. The specification of a maximum RVP (Reid vapor pressure) is of 0.75 kg/cm^2 for a floating roof tank. The RVP corresponding to the atmospheric conditions of 11-th October and the 13-th October

Table 1: The incorporation of fire statistics in the LCA model of Petrol and Gasoil.

	Fire	% of 448 fires
Only tank fireInvolved several tank	143	31.9
	139	30

(7 and 9 days after discontinuation) were respectively 0.91 and 0.94 kg/cm^2 and the estimated content of LPG (Liquefied petroleum gas) was 3 % (mole) to 0.75 kg/cm^2 and 5 mole % to 0.95 kg/cm^2. For a tank, this equates to a mass of 75 t evaporated, the volume occupied by the gas at a concentration of 100 % is then 60 000 m^3 [13]. This investigation is carried out by a team of experts, showed also that smoke contains gaseous pollutants in particular NO_x (Oxides of Nitrogen) and VOCs (Volatile Organic Compounds).

Fire Statistics: Using the complete database of the 448 fire incidents from 1960 to 2005 where it is possible to obtain almost full information about the fire size, the number of fires that are confined to the original tank fire (only tank fire) and those that fire spread beyond the original tank to other tanks in area (involved several tanks: domino effects). The statistics concerning distribution of the size of fire, describe the number of tanks which are destroyed only and those involved in the original tank fire [14]. It is assumed that the same percentage (30%) of 448 tank fires is in the "only tank fire" and "domino effects", Table 1.

$$\frac{\partial \Phi}{\partial t}+\frac{\partial U\Phi}{\partial x}+\frac{\partial V\Phi}{\partial y}=\Gamma\left(\frac{\partial^2\Phi}{\partial x^2}+\frac{\partial^2\Phi}{\partial y^2}\right)+S \tag{1}$$

The fire occurred in the refinery of Skikda (2005), represent serious accident that involved two tanks and have a considerable human and material damage [15]. These values are used as input in the model, Table 2.

Table 2: Number of identified tank fire incidents in Skikda from 2003 to 2013

	Fire	% of 35 fires
Only tank fireInvolved several tank	7	20%
	2	6 %

Uncertainty in the Numerical Dispersion Model: Uncertainty analysis investigates the effects of lack of knowledge or potential errors on the model (in our case, the uncertainty associated with parameter values).

The main stages of uncertainty analysis are summarised as follows:

- Construct a probability density function (*pdf*) for each input parameter (*pdf* reflects state of knowledge about the value of the parameter). In our case, the *pdfs* related to the previously mentioned uncertain parameters are defined in Table 3.
- Generate one set of input parameters by using random numbers (uniformly distributed between 0 and 1) according to pdfs assigned to those parameters.
- Quantify the output function (NO_2 concentration) using the above set of random values and according to the developed NDM. The obtained values are a realization of a random variable (X).
- Repeat steps 2 to 3 N times (until a sufficient number, e.g. 1000) producing N independent output values. These N output values represent a random sample from the probability distribution (empirical distribution) of the output function.
- Generate statistics from the obtained sample for the output result: Mean, standard deviation, confidence interval (percentiles), etc [16].

The precision in the generated statistics is improved by increasing the number of iterations. It is therefore important to run enough iteration so that the statistics are stable. We note that sensitivity analysis, i.e. the study of how a model's response can be apportioned to changes in model inputs [17], is out the scope of this paper.

The induced flow, mass fraction and temperature field can be described by a set of equations derived from the conservation laws for mean flow quantities, the model used in this paper is simplified and described in [12].

The solution of the partial differential equation described by the general Eq(1), using the finite volumes method which has been implemented on a FORTRAN environment, led to the establishment of curves depicted on Figure 2. This figure presents the NO_2 atmospheric dispersion (plume) at time t = 1200 s from the beginning of the tank fire, NO_2 concentration profile for cloud height y = 100 m and y = 200 m against the Downwind distance (x) and NO_2 concentration profile for a fixed Downwind distances x = 500 m and x = 1.5 Km against the cloud height (y). For each figure, the Lower bound, Mean and Upper bound are reported. The achieved iterations number is 1000. The output of each iteration is stored in a matrix which gives the NO_2 concentration for all coordinates (x, y): c_{xy}. On the basis of the resulted matrixes (1000 in total), one can compute the mean matrix (c_{xy}^{Mean}), the lower bound matrix (c_{xy}^{Lower}) and the upper bound matrix (c_{xy}^{Upper}) as follows:

$$c_{xy}^{Mean} = \frac{\sum_N c_{xy}}{N};$$

$$c_{xy}^{Lower} = c_{xy}^{Mean} - E \cdot \frac{\sqrt{\sum_N (c_{xy}^{Mean} - c_{xy})^2 / N}}{\sqrt{N}};$$

$$c_{xy}^{Upper} = c_{xy}^{Mean} + E \cdot \frac{\sqrt{\sum_N (c_{xy}^{Mean} - c_{xy})^2 / N}}{\sqrt{N}}.$$

To investigate the NO_2 impact on the local population, Figure 2 has been drawn. In fact, NO_2 is a very toxic gas which leads through inhalation to pulmonary oedema because of its low solubility in water. Some NO_2 concentration threshold values are given in Table 4 [18].

According to Table and for 1,200 s; (20 min) of release duration, the reference threshold values are taken equal to 55 ppm (for irreversible effects) and 90 ppm (for 1 % lethality).

Figure 2 (a and b) shows that the obtained concentrations (lower (2823 ppm), mean (3751 ppm) and upper bounds (4677 ppm)) at the fixed downwind distance (x = 0.5 km) are by far very high compared to threshold values. For the second position, the Lower bound concentration (80.4 ppm) is lower than the threshold values related to 1% lethality (90 ppm), while the Mean and Upper bound still greater than the fixed threshold values. Therefore, the obtained values are unacceptable. This means that in case of a similar accident, all the population would be exposed to an intolerable NO_2 concentration. Hence, the population must be relocated to a safe area. For this purpose, concentration profiles using upper bounds to be pessimistic indicate that the threshold concentrations of 55 and 90 ppm remain exceeded even for the downwind distance of 2 km.

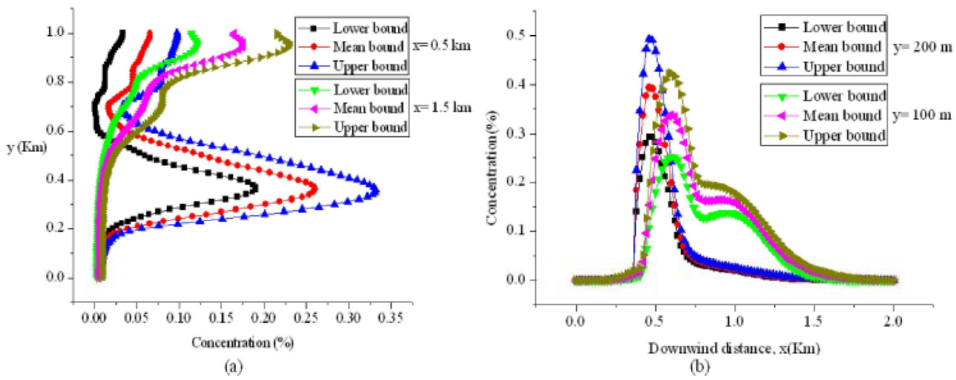

Fig. 2: NO_2 plume dispersion at t = 1200 s for: (a) fixed x (b) for fixed y.

Table 3: Probability distribution functions

		Parameters range		
Inputs parameters	Type of distribution	Min	Mod	Max
Wind speed (m.s-1)	Triangular	2	4.5	7
NO_2 initial concentration (% in the smoke)	Continuous uniform	0.1		0.8
NO_2 diffusivity coefficient characterized via the Prandtl number	Continuous uniform	0.7		1

Table 4: NO_2 concentration for the considered positions

	NO_2 concentration		
Positions	Lower bound: C^{Lower}	Mean: C^{Mean}	Upper bound: C^{Upper}
y= 100 m; *x*= 0.5 Km	0.2823% (2823 ppm*)	0.3751 % (3751 ppm)	0.4677 % (4677 ppm)
y= 200 m; *x*= 1.5 Km	0.00804 % (80.4 ppm)	0.01626 % (162.6 ppm)	0.02445 % (244.5 ppm)

*C(ppm)= C(%).10^6/100.

CONCLUSION

There is no easy way to collect detailed information about tank fires, in the Fire – LCA analysis, especially to complete LCI, very little fire emission data is reported in the literature and also data at industrial sites is confidential. One of the objectives of this work is to propose an easy methodology approach to collect all information of the site sinister before and after accident, this help to elaborate a database of statistics and the different fire effects.

There are two alternatives for combating a tank fire, either to let it burn out and thereby self-extinguish or, alternatively to actively extinguish the fire using firefighting foams. As the burn out procedure will result in a fire that is likely to persist several days, complete loss of stored product, environmental problem, large cooling operation to protect fire spread to adjacent tanks. In another case, when the amount of fuel in fire is important, the heat generated can destroy the tank and we have then to replace it.

While the Fire-LCA tool provides a good starting point for a holistic interpretation of a realistic life – cycle of a product including information concerning the probability that the product may be involved in a fire it does not provide information concerning, for example, the effect of the toxicity of chemicals used in the product or the fate of pollutants emitted during the fire in the atmosphere. The Numerical Dispersion Model responds to this limit by determining the residence time of the pollutant in atmosphere and other parameters like temperature. The dynamic fire-LCA is an organized approach to be used as an aid decision-making tool and experience feedback.

In this study, we also have studied the relative influence of uncertainty in input parameters of an Numerical Dispersion Model (wind speed, NO_2 initial concentration and NO_2 diffusivity coefficient) on the variation of the outputs.

Knowing the uncertainty of a prediction is critical for the decision making process. While the uncertainties in various elements of the modeling process are being determined, it is also important to investigate how those uncertainties interact with each other and contribute to the uncertainty in the final result (e.g. NO_2 concentration predictions). Therefore, decision-makers should not base their judgment solely on the mean values, but they should, in particular, consider the upper bound plume concentration. In further work, we will include all parameters and also consider the parametric sensitivity analysis of the numerical dispersion model.

Conflict of Interests: The authors declare that there is no conflict of interests regarding the publication of this paper.

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