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Patrice Megange, Pierre Ngae, Amir-Ali Feiz, Thien-Phu Le. Dynamic site-dependent Life Cycle Assessment for assessing impact of human toxicity of a double glazed PVC window. *Procedia CIRP*, 2020, 27th CIRP Life Cycle Engineering Conference (LCE2020) Advancing Life Cycle Engineering: from technological eco-efficiency to technology that supports a world that meets the development goals and the absolute sustainability, 90, pp.316-321. 10.1016/j.procir.2020.02.056 . hal-02915108

HAL Id: hal-02915108

<https://hal.science/hal-02915108>

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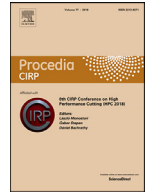
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27th CIRP Life Cycle Engineering (LCE) Conference

Dynamic site-dependent Life Cycle Assessment for assessing impact of human toxicity of a double glazed PVC window[☆]

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ARTICLE INFO

Keywords:

human toxicity by inhalation
 traditional Life Cycle Assessment
 spatial-temporal specificities
 dynamic LCA
 coupling

ABSTRACT

Current level of morbidity generated by industrial air pollution requires effective tools combining pollutant rates and their risks on human health. Traditional Life Cycle Assessment (LCA) appears to be the most appropriate method for assessing impact of human toxicity by inhalation. However, its interest is limited due to lack of spatial-temporal specificities of emissions. To solve this problem, this research work shows the feasibility of a site-dependent dynamic LCA, obtained by a coupling between a traditional LCA, a method of temporal and spatial disaggregation of pollution rates and a model of numerical dispersion.

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Introduction

Air pollution is considered to be greatest health risk related to environment (World Health Organization Report 2019). In order to control threshold of stigmatized particulates (PM10 and PM2.5) and gases (sulfur dioxide (SO₂) and nitrogen oxides (NO_x)), many countries adopt major regulations and use efficient and sophisticated technologies to measure their rates (Crunaire and Spinelle, 2018). In view of health emergency, communication of these collected data must be all part of health impact study (Merlin, 2015). Therefore, priority of manufacturers is to use effective systems for preventing and evaluating impact of human toxicity produced by air pollutants. Various environmental impact assessment tools are effective such as Carbon Footprint or traditional Life Cycle Assessment (LCA). The latter benefits from its skill to assess global issues (resource consumption) and numerous impacts (greenhouse effect, eutrophication, ozone depletion, etc.). Nevertheless, its high degree of abstraction (Marchand et al., 2013) and its static approach make it inappropriate to accurately assess local impacts such as human toxicity (Potting et al., 1999, Causse et al., 2016). A way to resolve this problem is the dynamic LCA with its ability to integrate temporal dimension of processes and physical phenomena (Negishi et al., 2018, Shimako et al., 2017, Beloin-Saint-Pierre et al., 2014). Moreover, the need to get data on many sites and

the importance of local specificities in pollutant emissions can't be neglected (Aissani, 2008). Indeed, some characteristics such as emission height, topography, meteorology, architecture of buildings modify progression of these pollutants in atmosphere and so their impact on environment. Thus, numerical modeling proves very interesting as the chemical equations and atmospheric dispersion of pollutants are solved in the entire domain (Michelot et al., March 2015). Duration of emission and its latency which modify nature of the toxic effects (Querini and Rousseaux, 2012) are also important information to reduce uncertainties and increase accuracy of assessment of human health effects (Couillet, 2002). In this paper, the proposed method provides a much more robust device in order to assess the impact of human toxicity by inhalation of air pollutants. Its principle is based on the coupling of interesting tools:

- The dynamic LCA with the Enhanced Structural Path Analysis (ESPA) method (Beloin-Saint-Pierre et al., 2014)
- The numerical modeling of the dispersion of pollutants with a Gaussian model
- The contextualized computational philosophy of the USEtox model (Rosenbaum et al., 2011).

State of the art of Life Cycle Assessment

LCA is one of the most used techniques to identify and quantify effects of emissions of toxic substances on environment. It is associated with all stages of a product (from raw material extraction to end of life, recycling or reuse) and is governed by ISO (International Organization for Standardization) 14040-14044, illustrated in Fig. 1, which describes its principles and framework.

[☆] Peer-review under responsibility of the scientific committee of the 27th CIRP Life Cycle Engineering (LCE) Conference.

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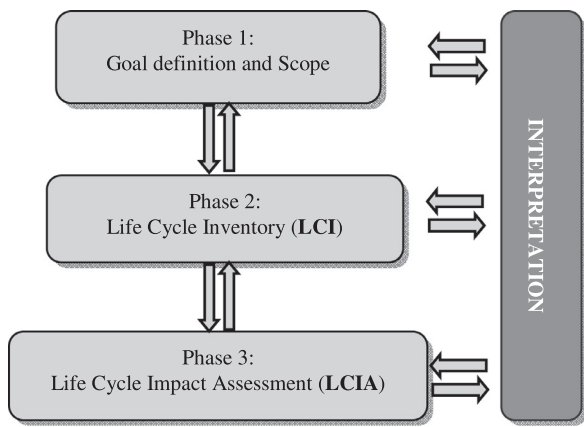


Fig. 1. Synoptic view of ISO 14040-14044

Nevertheless, in order to simplify calculation, traditional LCA does not take into account singularities of sites. It leads to loss of information concerning territorial specificities for system modeling and assessment of local impacts such as human toxicity (Aissani, 2008, Boize et al., 2008). Therefore, to improve its results traditional LCA uses a consensual model: USEtox (Rosenbaum et al., 2011). Its effectiveness lies in the fact that USEtox offers many types of scenarios depending on the compartment (air, water, soil, etc.) and the affected area (urban, continental, global) while taking into account complexities related to dispersion of atmospheric pollutants (advection, diffusion, etc.). However, coupled with traditional LCA, USEtox remains a static model while relevance of dynamic approach is suggested in many studies [(Negishi et al., 2018, Shimako et al., 2017), and (Beloin-Saint-Pierre et al., 2014)].

Dynamic LCA is defined as introduction of time parameter in traditional LCA (Collinge et al., 2013). In this way, aggregation of flows which are emitted separately is avoided (Aissani, 2008) and a more realistic analysis of generated impacts is obtained (Collinge et al., 2013). Temporal dimension can be introduced during Life Cycle Inventory (LCI) phase [(Shimako et al., 2017, Beloin-Saint-Pierre et al., 2014, Aissani, 2008), and (Beloin-Saint-Pierre, 2012)] as well as during the Life Cycle Impact Assessment (LCIA) phase [(Negishi et al., 2018, Shimako et al., 2017, Levasseur et al., 2011), and (Kirkinen et al., 2010)]. Unfortunately, most of these dynamic LCAs seem too often specific for one type of indicator and lack conceptualization (Negishi et al., 2018). Nevertheless, two approaches stand out:

- Dynamic process of LCA (DyPLCA) (Negishi et al., 2018, Beloin-Saint-Pierre, 2012). Its main goal is to develop a methodology and tools to address time dependency in LCA, with a focus on developing an integrated modeling solution for both Life Cycle Inventory (LCI), in foreground and background, and for Life Cycle Impact Assessment (LCIA). Although it is a turnkey tool, according to us, it minimizes the role played by fate factor (FF) (Shimako et al., 2017): a crucial factor to consider spatial specificities while calculating impact of human to
- Enhanced Structural Path Analysis (ESPA) method. This implementation of a dynamic LCI development methodology identifies technological fields and proposes a two-axis approach: spatial and temporal. This approach guided our choice for this method.

Methodology of Dynamic LCA site-dependent

When determining human toxicity, resulting from the inhalation of toxic substances, it is necessary to evaluate for each type of substance the dose inhaled per day, for an individual or for a population, according to the source near or far from the place of ex-

posure. The presented methodology in this paper makes it possible to compute the distribution in time and space of the polluting substances emitted using ESPA method. The transport and diffusion of these substances to the populations' exposure sites is carried out using a Gaussian solution of the transport-diffusion equation. The daily dose inhaled by the populations (USEtox, etc.) is then determined by spatial-temporal integration.

By coupling the ESPA method, the Gaussian atmospheric dispersion model and the USEtox model, human toxicity is thus estimated.

1.1. ESPA method

This chapter explains how the ESPA method, described in (Beloin-Saint-Pierre et al., 2014) and (Shimako et al., 2017), is adjusted to obtain temporally and spatially differentiated LCI. Thus, for a given pollutant substance "x", the temporal distribution of emitted mass is obtained at different sites "k", $m_{x,k}(t)$. The inventory distribution vector (of the spatial and temporal emitted mass distribution) is given by the following equations (1) and (2):

$$v_x(t) = E_x(t) * (I + T(t) + T^2(t) + \dots + T^p(t)) * r(t) \quad (1)$$

where:

- "*" represents the matrix convolution product
- $E_x(t)$ is an $l \times n$ intervention distribution matrix of emitted pollutant flow (f_{e_i}) by each process. l is the total number of sites and n is the total number of elementary flows
- I is an $n \times n$ identity distribution matrix
- $T(t)$ is a $n \times n$ technological distribution matrix of economic flow ($f_{p_{ij}}$ is supplied to process P_i and manufactured by process P_j)
- T^p , p -times convolution distribution matrix product
- $r(t)$ is a $n \times 1$ reference distribution vector of the final process flow (f_{p_0})
- $v_x(t)$ is an $l \times 1$ inventory distribution vector

$$v_x(t) = [m_{x,1}(t) \ m_{x,2}(t) \ m_{x,3}(t) \ \dots \ m_{x,l}(t)]^T \quad (2)$$

3.2. Gaussian model of atmospheric dispersion

Gaussian plume dispersion model is used in this study for local assessment of air pollutant concentrations (Equation 3). This paper takes into account numerous hypotheses such as unidirectional wind field in space, and steady state. The last assumption is justified because it is considered that the distribution time step is large compared to the transport-diffusion time in the domain. In this study, the plume dispersion is just an alternative to the puff dispersion. Here we are only interested in the dispersion of pollutants due to atmospheric turbulence and the spatial-temporal variation of meteorological parameters.

$$C_{x,k}(x, y, z) = \frac{Q_{x,k}}{2\pi U_k \sigma_y \sigma_z} e^{\left(-\frac{(y-y_0)^2}{2\sigma_y^2}\right)} \left[e^{\left(-\frac{(z-H)^2}{2\sigma_z^2}\right)} + e^{\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)} \right] \quad (3)$$

where:

- $C_{x,k}(x,y,z)$ (kg/m^3): concentration of the substance "x" in site "k" at a coordinate point (x, y, z)
- $Q_{x,k}$ (kg/s): substance "x" flow rate emitted from the stack or the extract unit is given by equation (4):

$$Q_{x,k} = \frac{\sum m_{x,k}(t)}{nnz \times \Delta t} \quad (4)$$

where: nnz is a number of non-zero element of $m_{x,k}(t)$. Δt is the time step of $m_{x,k}(t)$

- U_k (m/s): average local wind speed

- $\sigma_y\} (m)$: standard deviations of the Gaussian distribution from σ_z their location determined by the empirical dispersion coefficients of Briggs in urban areas.

3.3. USEtox model of calculation of human toxicity impacts

USEtox is the consensus model for impact assessment of human toxicity and eco-toxicity. By integrating temporal parameter into coefficient $m_{x,k}(t)$ and taking into account spatial specificities of emission and reception zone of pollutants retained during calculation of characterization factor, an impact score of spatial-temporal human toxicity by inhalation ($IS_{hk}(t)$) is therefore determined (Equation 5):

$$IS_{hk}(t) = \sum_x CF_{x,k} \times m_{x,k}(t) \quad (5)$$

where $CF_{x,k}$ is the Characterization Factor (Comparative Toxic Unit/kg emitted) of the substance "x" determined in a site "k". $CF_{x,k}$ is given by:

$$CF_{x,k} = \overbrace{FF_{x,k} \times XF_{x,k} \times EF}^{IF_{x,k}} \quad (6)$$

where:

- $FF_{x,k}$: Fate Factor (day) of substance "x", in a site "k"
- $XF_{x,k}$: Exposure factor (day^{-1}) or mass fraction (or volume fraction) of a substance "x" absorbed (directly or indirectly) by local population per day
 $XF_{x,k}$ is determined using Equation (7), considering, for this study, only one environmental medium (outside air) and one single absorption process (inhalation):

$$XF_{x,k} = \frac{IR_{air} \times N_k}{V_k} \quad (7)$$

where:

- IR_{air} ($\text{m}^3/(\text{person}\cdot\text{day})$): Individual human consumption rate of air; by average $IR_{air} = 13\text{m}^3/(\text{person}\cdot\text{day})$
- N_k (persons): number of persons in selected area "k"
- V_k = Area of the location \times height of the urban area (240 m high according to USEtox): volume (m^3) of air in the site "k"
- EF : toxicological Effect Factor of a chemical on humans
- $IF_{x,k}$: Intake Fraction of emitted mass coming into contact by air with the local human population.
- $FF_{x,k}$ is determined by the Equation (8):

$$FF_{x,k} = \frac{M_{x,k}}{Q_{x,k}} \quad (8)$$

where:

- $M_{x,k}$ (kg): is the mass of substance "x" available in site "k", calculated using Equation (9):

$$M_{x,k} = \left(\sum_{j=1}^n C_{x,k}(x_j, y_j, z_j) \right) \times V_k \quad (9)$$

In order to carry out a site-dependent dynamic LCA, the methodology used in this study is based on two steps illustrated in Fig. 2, as a complement to phases imposed by ISO 14040-14044; both are carried out by two softwares, OpenLCA and MATLAB:

- Step 1: making a spatial and temporal disaggregation of substance emission rates during LCI phase: coupling between traditional LCA and ESPA method.
- Step 2: using a numerical model of dispersion (Gaussian model for this study) in order to introduce spatial specificities for the computation of Fate Factor (FF) and Intake Fraction (IF) during LCIA phase: coupling between USEtox model and Gaussian numerical model.

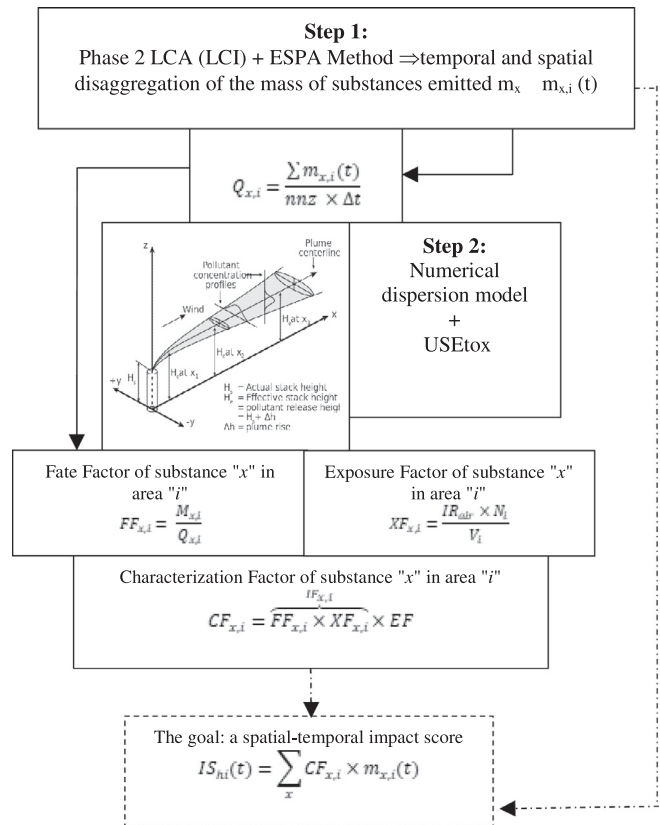


Fig. 2. Methodology of Dynamic LCA site-dependent

Results and discussions

This research work presents a method introducing the temporal dimension to perform a dynamic site-dependent LCA in the inventory phase of the traditional LCA (phase 2) of ISO 14040-14044. It helps comparing the use of a site-dependent dynamic LCA to a traditional LCA to carry out the assessment of human toxicity impact in an eco-design approach.

The product studied is a double glazed window and the functional unit, inspired by the Technical Sheet of the Environmental and Health Declaration (FDES), is defined by: to close a permanent opening of 1 m^2 in an exterior wall, while allowing the passage of light, the opening / manual closing, thermal insulation, sealing, wind resistance, air permeability and acoustic insulation, in accordance with good practice.

The geographical boundary chosen is France. The resource cradle respects the processes given by the Ecoinvent 3.4 database, used for this study, and the manufacturing processes illustrated in Fig. 3. The grave of the outputs is considered depending on Ecoinvent system model Cut-Off (the point of cut-off is at the end of the activity producing the recyclable material). The substance "x" selected for this study is nitrogen oxide (NO_x).

Regarding the manufacturing phase, the window components not selected for this study are:

- The thermal insulation gas between the two panes
- Packaging elements such as plastic film, cardboard, polystyrene, and so on
- Installation elements such as fixing lugs, seals, and so on

A first prospection work made it possible to define the various manufacturing processes, presented on fig. 3, as well as their geographical site, fig. 4. Therefore, the main cities selected and impacted by pollutant emissions are Paris in Ile-de-France; Strasbourg in the Grand Est region; Lille in the Hauts de France and Lyon in

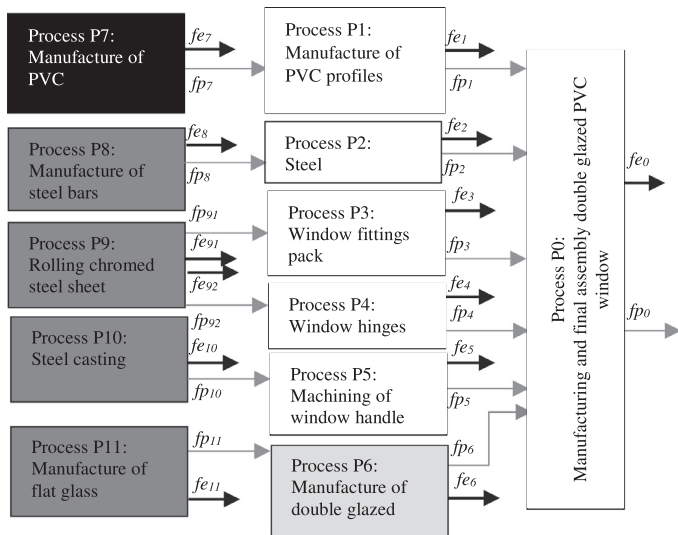


Fig. 3. Manufacturing process of a double glazed PVC window

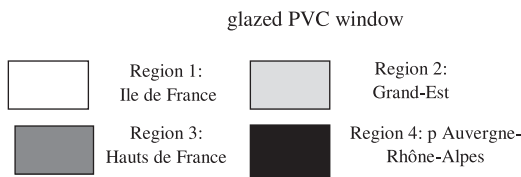


Fig. 4. Manufacturing regions of a double glazed PVC window

Table 1

Temporal distribution of the process flows

double glazed PVC window (day "0" : end of assembly)							
day	-38	...	-18	...	-4	...	0
$fp_0(t)$ (m ²)	0	...	0	...	0	...	1
$fp_{0,1}(t)$ (kg)	0	...	0	...	11.45	...	0
$fp_{0,2}(t)$ (kg)	0	...	0	...	1.32	...	0
$fp_{0,3}(t)$ (kg)	0	...	0	...	0.23	...	0
$fp_{0,4}(t)$ (kg)	0	...	0	...	0.21	...	0
$fp_{0,5}(t)$ (kg)	0	...	0	...	0.08	...	0
$fp_{0,6}(t)$ (kg)	0	...	0	...	20.24	...	0
$fp_{1,7}(t)$ (kg)	0	...	1	...	0	...	0
$fp_{2,8}(t)$ (kg)	0	...	1	...	0	...	0
$fp_{3,9a}(t)$ (kg)	0	...	1	...	0	...	0
$fp_{4,9b}(t)$ (kg)	0	...	1	...	0	...	0
$fp_{5,10}(t)$ (kg)	0	...	1	...	0	...	0
$fp_{6,11}(t)$ (kg)	0	...	1	...	0	...	0

the Auvergne-Rhône-Alpes region. The color indication used for the process is associated with that of its region.

To resolve the Step 1 (Fig. 2), Table 1 gives the values of process distribution flows, $fp_{ij}(t)$ (Fig. 3), included in $T(t)$. $T(t)$ is presented in Equation (10).

$$T(t) = \begin{bmatrix} 000000000000 \\ fp_{0,1}(t)0000000000 \\ fp_{0,2}(t)0000000000 \\ fp_{0,3}(t)0000000000 \\ fp_{0,4}(t)0000000000 \\ fp_{0,5}(t)0000000000 \\ fp_{0,6}(t)0000000000 \\ 0fp_{1,7}(t)0000000000 \\ 00fp_{2,8}(t)0000000000 \\ 000fp_{3,9a}(t)00000000 \\ 0000fp_{4,9b}(t)00000000 \\ 00000fp_{5,10}(t)0000000 \\ 000000fp_{6,11}(t)000000 \end{bmatrix} \quad (10)$$

Table 2

Temporal distribution of the elementary flows of NO_x

double glazed PVC window (day "0" : end of assembly)							
day	-38	...	-18	...	-4	...	0
$fe_0(t)$ (kg)	0	...	0	...	0	...	3,27
$fe_1(t)$ (kg)	0	...	0	...	5.50E-03	...	0
$fe_2(t)$ (kg)	0	...	0	...	1.54E+00	...	0
$fe_3(t)$ (kg)	0	...	0	...	2.68E-01	...	0
$fe_4(t)$ (kg)	0	...	0	...	2.45E-01	...	0
$fe_5(t)$ (kg)	0	...	0	...	8.49E-02	...	0
$fe_6(t)$ (kg)	0	...	0	...	1.65E-03	...	0
$fe_7(t)$ (kg)	0	...	3.95E-03	...	0	...	0
$fe_8(t)$ (kg)	0	...	1.04E-02	...	0	...	0
$fe_{9a}(t)$ (kg)	0	...	3.12E-04	...	0	...	0
$fe_{9b}(t)$ (kg)	0	...	2.88E-04	...	0	...	0
$fe_{10}(t)$ (kg)	0	...	3.06E-04	...	0	...	0
$fe_{11}(t)$ (kg)	0	...	8.90E-02	...	0	...	0

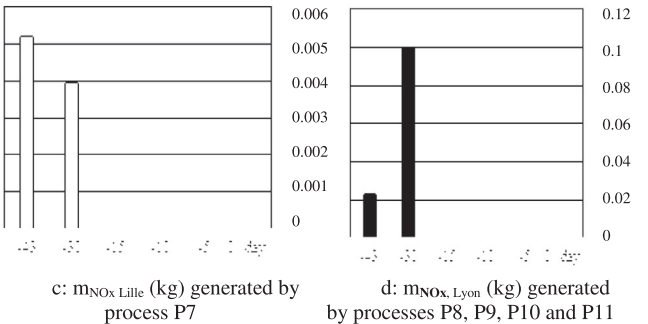
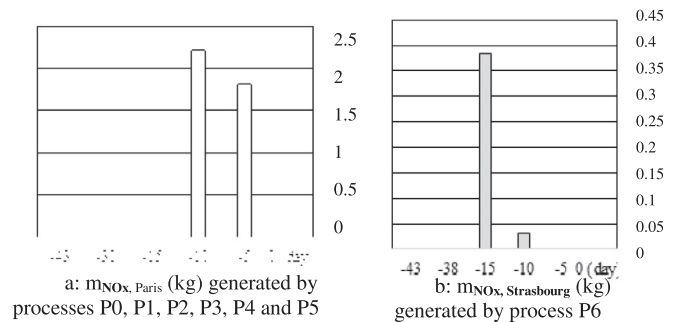


Fig. 5. .

The elementary distribution flows $fe_i(t)$, see Table 2, are built using OpenLCA database, Ecoinvent 3.4.

The ESPA method uses convolution product on temporal and spatial dimension between different elements of equation (1). An algorithm written under MATLAB performs calculations. Thus, all elements of matrices and vectors are "discretized" in time and space. Figures 5a, 5b, 5c and 5d show the results obtained with Dynamic LCA. Emission rates are much lower than the single value obtained with a traditional LCA (Fig. 6). Indeed, the huge difference is due to the fact that traditional LCA performs the sum of the emission rates generated by manufacturing processes which do not take place in one place (Fig. 3 and Fig. 4) and in a single day. Consequently, the dynamic LCA used in this study gives much more realistic emission rates than those of the traditional LCA. Furthermore, when it's known that the alert threshold for a substance is measured in micrograms/m³ as an hourly average, the presence of the time scale in the Dynamic LCA is interesting.

Pollutant rates indicated in Figures 5a, 5b, 5c and 5d being spatialized, they therefore relate to the processes located in each of the regions:

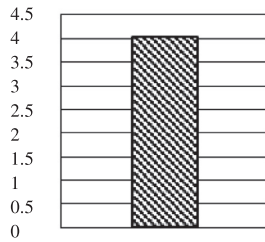


Fig. 6. NO_x emission with traditional LCA (kg)

Table 3a
Results $FF_{NO_{x_k}}$ site-dependent

NO _x	Paris	Strasbourg	Lille	Lyon
$FF_{NO_{x_k}}$ (day)	1.10-3	4.60.10-4	1.19.10-3	6.19.10-4

Table 3b
Results $IF_{NO_{x_k}}$ site-dependent

NO _x	Paris	Strasbourg	Lille	Lyon
$IF_{NO_{x_k}}$ [kg _{intake} /kg _{emitted}]	1.10E-06	2.14E-07	3.16E-07	4.33E-07

- P0 + P1 + P2 + P3 + P4 + P5: region 1
- P6: region 2
- P7: region 3
- P8 + P9 + P10 + P11: region 4

The color indication used in these figures respects that of fig. 4.

Tables 3a and 3b show results concerning Fate Factor ($FF_{NO_{x_k}}$) and Intake Factor ($IF_{NO_{x_k}}$) of NO_x. They are obtained using step 2 (Fig. 2) of the methodology developed in this article. To perform the calculations, an algorithm written under MATLAB is used.

The advantage of the last coupling is to estimate the concentration of pollutants in an area downstream of an emission source. Thus, the use of a coupling with the dispersion model of the Gaussian plume guarantees to take into account the parameters that govern the dispersion of pollutants in the atmosphere and specific weather conditions (wind direction, etc.). The calculation of the two factors, the FF and the IF, is therefore contextualized.

The value of $IF_{NO_{x_k,Paris}}$, relative to that of the other selected cities, indicates that Paris, with its population, will be the most impacted in human toxicity during the manufacture of the double glazed window. In comparison, the traditional USEtox model, after a rough calculation, proposes for an intra-urban intake fraction (IF) of an "average" world city of an emitted pollutant an IF value of the order of 24 ppm (Humbert et al., 2014). Therefore, one single value would be proposed with traditional LCA, whereas in our study the different values are consistent with the fact that spatial and meteorological contexts differ.

Conclusion and Outlook

Nowadays, critical levels of morbidity reached by atmospheric pollution make it important to provide effective foresight tools to stem growth of the phenomenon.

A state of the art has pointed out that systemic tool exist for modeling impacts of human toxicity: traditional LCA. It is still criticized because of results which do not take into account spatial specificities and temporal parameters. This indigence creates loss of information for a rigorous assessment of local impacts. A functional and physical conceptual method is therefore proposed in this research work. It is based on a multi-coupling. It is carried out between a traditional LCA software, OpenLCA, a temporal and spatial dispersion method, ESPA, and a digital pollutant dispersion

model, the Gaussian model. The ESPA method uses a convolution product which generalizes the idea of sliding average. It applies to temporal and spatial data. Despite a distribution of random emission rates, the values being temporally and spatially disaggregated, become more realistic than those proposed by traditional LCA.

Pollutant flows and their dependence on spatial specificities (meteorology, topography, etc.) make it interesting to use a digital dispersion model to assess the concentrations of pollutants that infect the geographic areas observed. Although USEtox already includes urban, regional and global environments, it does not have detailed spatial resolution. In our study, our multi-coupling makes it possible to calculate a site-dependent Fate Factor (FF) and a site-dependent Intake Fraction (IF). The IF represents the fraction of the emitted mass which enters the human population. The final purpose of this work will be to calculate a more robust and more realistic spatial-temporal impact of human toxicity by than that proposed by conventional LCA.

LCA is the best suited tool to bring the environment back to the center of design for a company. It must then make it possible to assess the risks in greater compliance and also greater performance. Looking at the results, it is more judicious to use a dynamic site-dependent LCA than a traditional LCA to carry out the assessment of the impact of toxicity for humans in an eco-design approach. The first one therefore leads to an eco-design approach in the context of continuous improvement. The organization concerned can then propose more effective solutions to prevent high levels of anthropogenic air pollutants.

The intrinsic complexity of urban pollution, which depends on both urban planning and "immission" - the result of emission after modification by urban morphology and meteorological parameters - leads to think about improving the Gaussian dispersion model chosen in this research work. Hence the outlook of considering the use of a weather modeling system and advanced air quality: CALPUFF. The CALPUFF model is designed to simulate the dispersion of floating point sources, puffs or continuous as well as the dispersion of floating continuous linear sources. The model also includes algorithms to manage the effect of washout by nearby buildings on the way to the plumes of pollution. Consequently, in an unstable state,

CALPUFF associated with ESPA and the OpenLCA software can improve the results and enable more complex studies. In this paper, the contextualization of our study was limited to 4 regions.

Thus, CALPUFF will allow it to be extended more conveniently to a larger number.

The use of regional geographic data in GIS software is envisaged in order to cross-reference precise geographic information on the location of emission sources and reception areas.

Credit author statement

Patrice MEGANGE: Conceptualization, Methodology, Writing, Software, Contextualizing, Computation, Investigation

Pierre NGAE: Methodology, Software, Supervision, Computation

Amir FEIZ: Visualization, Supervision

Thien Phu LE: Supervision, Writing- Reviewing

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