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LCA simplification in the context of packaging reuse loops

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ABSTRACT: This paper shows the implementation of the Global Sensitivity Analysis (GSA) as a Life Cycle Assessment simplification (LCA) method to identify the most influential design parameters for the design of packaging reuse loops. The practical execution of GSA relies on Monte Carlo simulations to propagate the input parameter effects in the LCA model and Sobol indexes to quantify the variance contribution of each parameter. This methodology was applied to a case study in the French region of Île-de-France. This method allows identify the key design parameters to prioritize the design key decisions.

KEYWORDS: life cycle assessment simplification, circular economy, modelling, reuse loop, Sobol index

1. Introduction

The escalating global dependence on single-use plastic packaging has generated significant environmental impacts, thereby necessitating a profound and systemic reconfiguration of the food production systems and the current packaging model (Geyer et al., 2017). In response to this, new packaging regulations and policies are emerging worldwide. In the European context, exigent legislative instruments have been introduced, including the Packaging and Packaging Waste Directive (PPWD) and the Packaging and Packaging Waste Regulation (PPWR). These policies are expressly intended to limit the environmental impact of packaging waste, setting clear targets for both reduction and reuse (European Commission, 2022).

Within the circular economy (CE) framework, reuse is prioritized as the most effective strategy for retaining the material value of packaging, taking priority over recycling and recovery in the waste hierarchy (Parlement Européen, 2008). However, the transition from linear single-use models to circular reuse packaging systems is inherently complex, requiring consideration of multiple, interrelated variables for their design to effectively reduce environmental impacts.

From a life cycle assessment (LCA) perspective, reuse loops are primarily driven by the uncertainty of reverse logistics, where the environmental issue of transporting heavier, empty crates in the return trip can outweigh benefits if return distances are not minimized (Accorsi et al., 2014; Levi et al., 2011). Environmental impacts are heavily dependent on the assumed number of rotations (trip rates) and breakage rates, which determine the critical "break-even point" against single-use cardboard (Koskela et al., 2014; Singh et al., 2006). Furthermore, the use phase introduces significant variability through industrial washing and sanitization processes, which consume substantial water and energy resources often exceeding production impacts (Accorsi et al., 2014). Finally, the impact of end-of-life packaging remains difficult to estimate due to the wide range of divergent assumptions regarding closed-loop recycling versus downcycling, which can alter their own environmental performance and that of the loops in which they are used (Tua et al., 2019). Consequently, the environmental performance of reuse loop systems depends heavily on the choices made during their design as even a small inefficiency in loop operations can undermine environmental outcomes

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(Coelho et al., 2020). For this reason, environmental assessment methods capable of rapidly exploring multiple design scenarios are essential, ensuring that conclusions remain robust across the wide range of operational conditions that can arise in real systems.

In this context, the use of full LCA studies to support the design of reuse packaging loops is not practical, as they require substantial time and detailed data that are rarely available during early design stages. To manage the environmental assessment of reuse loops, rather than developing a full LCA analysis itself, it is possible to apply simplification methods to reduce the required data and time (Suppipat et al., 2023). These simplifications are context-specific approximations, and their validity is therefore limited to the specific system for which they are built. In general, Global Sensitivity Analysis (GSA) is the most widely adopted simplification method. GSA enables the identification of the most influential input variables of a model, by quantifying how much of the environmental impact variance can be explained by the variation of each input. It has been extensively applied to simplify energy systems (Di Lullo et al., 2020; Douziech et al., 2021; Gibon & Hahn Menacho, 2023; Paulillo et al., 2023), construction (Belizario-Silva et al., 2023; Rodrigues et al., 2018), and waste management systems (Chen et al., 2023; Wang et al., 2024), but its academic study within the scope of packaging reuse loops is still emerging, with some system specific examples that offer useful early insights (Le Féon et al., 2024; Verghese et al., 2010). Moreover, there is limited practical knowledge as industry has little experience deploying reuse loop packaging at the scale required by new regulations. This combination of industrial limited maturity and absence of rapid environmental assessment tools may restrict the ability to design packaging reuse loops to rapidly respond to regulatory developments while achieving substantial environmental benefits.

To address this research gap, this study aims to establish a robust and efficient methodology for calculating the environmental performance of a secondary plastic packaging reuse loop. Secondary or logistic packaging operates within B2B logistics systems and includes reusable items for bundling, handling, and transporting multiple primary packages. These loops are the first prioritized under the PPWR, which demands B2B transport packaging to become fully reusable by 2030. By applying GSA, this research aims to characterize these systems by assessing the relative importance of key operational variables. This analysis offers actionable insights into the critical decision points and trade-offs encountered during the design phase of these logistic systems. To validate and illustrate the practical application of this approach, the methodology is applied to a case study of a plastic crate reuse loop. This case study is based on the operational data and processes of one of the largest food logistic operators in France.

2. Methodology

2.1. Overview

The present study analyzes the environmental performance of a secondary packaging reuse loop through a full LCA and subsequently simplifies this assessment by applying GSA. Specifically, the analysis evaluates the behavior of the simplest system configuration (a single circuit with the basic plastic refreshing processes) in relation to a comprehensive variable set defined from a real base case study. The steps of the methodology are detailed below:

2.1.1. LCA evaluation

To quantify environmental impacts, the research framework applies the full LCA methodology (ISO, 2006). In the Goal and scope definition and LCI phases, the study establishes input variables and their ranges behaviors based on information from a real operational case study (described in Section 2.2). This enables to define a baseline for environmental performance as well as the parameter space required for the subsequent GSA.

2.1.2. Monte Carlo (MC) experiments

The practical execution of GSA relies on MC simulations, which serve as the computational engine for propagating input uncertainty through the LCA model (Groen et al., 2017). This technique requires defining a probability distribution function (PDF) for every input parameter of the Life Cycle Inventory. During each MC iteration, a value is randomly sampled from the PDF of each parameter,

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defining each time a plausible set of inputs. This set is then used to calculate a full LCA analysis, producing one specific set of output values (Saltelli et al., 2004). The simulation is repeated (hundreds or thousands of times) until a defined confidence threshold is met. The resulting collection of outputs after all the simulations forms a distribution of possible LCA outputs, which are used to calculate the Sobol indexes and identify the most influencing input variables. The concepts used to perform the study are summarized in Table 1.

2.1.3. Sobol indices calculation

Following the MC simulations, the resultant input-output dataset is analyzed using variance-based sensitivity measures with Sobol indices (Sobol, 2001). Sobol indices decompose the total variance of the output into fractional contributions of each individual input variable and their combinations. The resulting indices are normalized, with the sum of all terms equaling unity. Input variables with high Sobol index values are confirmed as the most influential (Groen et al., 2017; Saltelli et al., 2004).

Table 1. Summarized methodological framework concepts used

Stage	Method used	Description
Environmental assessment of the study case	LCA	It is a systematic, "cradle-to-grave" methodology used to quantify the environmental impacts of a product, process, or service throughout its entire lifespan from raw material extraction to final disposal. LCA defines the system boundaries in goal and scope definition phase. Then it assesses environmental impacts of a system by first identifying all relevant resource and energy inputs and emission and waste outputs in the Life Cycle Inventory (LCI) phase; and then translating these flows into specific environmental impact categories like global warming potential, acidification, and human toxicity, among others, in the Life Cycle Impact Assessment (LCIA) phase (ISO, 2006).
Quantification of the design variables contribution to the environmental impact	Global Sensitivity Analysis	Comprehensive framework used to quantify how the uncertainty in a model's output can be apportioned to various sources of uncertainty in its input variables, which are characterized by their respective probability distributions
	Sobol Indices	Sobol indices are variance-based sensitivity measures used to attribute the total output variance of a model to individual input variables or their interactions. The first-order index (S_1) quantifies the main effect contribution of a single variable, while the total-order index (S_T) accounts for both the first-order effect and all higher-order interactions involving that variable.
	Monte Carlo	Monte Carlo Analysis is a stochastic simulation technique that characterizes the uncertainty of a system by performing repeated random sampling of input parameters from their respective probability distributions to generate a range of potential output outcomes

2.2. Case study definition

The case study concerns a reuse loop that delivers chilled food from a storage platform to catering sites. The food is transported in plastic crates in a logistic loop comprising the following stages: crate production, usage (food cold storage and distribution), adequacy and assessment for reuse (washing), and crate disposal. For the case study the system manages 1112 plastic crates per day which corresponds to the transport of 5 tons of food. Material, process energy, and transport related exchanges are defined as flows. The model system boundaries are shown in Figure 1. The specific assumptions and parameters used to simulate the system are synthesized in Table 2.

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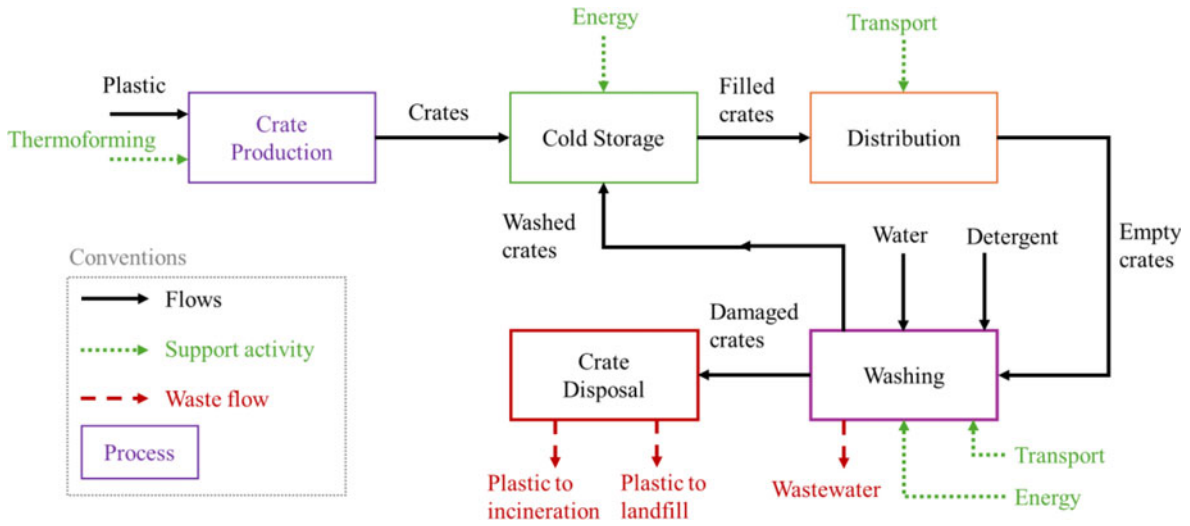


Figure 1. Packaging reuse loop processes and flows scheme

Table 2. Summary of key assumptions and operational parameters for the crate life cycle stages

Life Cycle Stage	Key Parameters & Assumptions	Sensitivity Parameter	Data Source/ Reference
Crate Production	Material: Polypropylene (PP) Manufacturing: Thermoforming Unit Crate Mass: 0.69 kg Crate Lifetime: 3 years. Function of number of crates required which in turn is defined based on crate lifetime.		Logistic Operator
Cold Storage	Energy Model: $e = 0.163663(i \cdot n)^{0.8173}$ e is the storage facility energy consumption, i the inventory turnover time, and n the number of crates stored. Function of facility size which in turn is function of the inventory turnover time.	Inventory turnover time	(Evans et al., 2014)
Distribution	Full Load: 4.5 kg food/crate; 1112 crates/truck; 64 crates/pallet. Pallet Mass: 25 kg Function of the average full-load and return-load weights and distances.	Distance	Logistic Operator
Washing	Process: Automatic washing is defined based on three parameters: water, detergent, water temperature. a quality control assessment of the crate's integrity is simultaneously performed. For the model, number of rejected units depends on crate lifetime.	Water usage Detergent concentration Water temperature.	(Christeyns, 2025; Elpress, 2020, 2025b, 2025a; HEIM, 2023, 2025)
Crate Disposal	End-of-Life: 34% Incineration; 66% Landfill. Allocation: Based on French national rates. Function of the number of crates rejected in Washing stage, which is defined based on crate lifetime.		(INRAE, 2023)

This step defines the ranges and probability distributions of the input variables, which will be sample in the Monte Carlo simulation. Adjusting the underlying assumptions allows the proposed framework to adapt to various operational contexts. For instance, modifications to the spatial configuration of distribution points allow recalibration of the corresponding distance probability distributions. Thus, this scheme establishes a foundational architecture that supports both the parametric variation of the recovery loop and the systematic integration of additional complexities to enhance model fidelity.

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2.3. Life Cycle Assessment calculation and Global Sensitivity Analysis setup

The Life Cycle Assessment (LCA) of the reuse loop was performed utilizing the Brightway2 Python library as the computational framework. The Ecoinvent 3.11 database provided the necessary life cycle inventory data for modeling the energy and service flows illustrated in Figure 1. The LCA functional unit (FU) was defined as the one-year operation of a plastic crate reuse loop, processing 1112 crates per day within the Île-de-France region. The chosen LCA methodology was the ReCiPe 2016 V1.03, Midpoint (H) methodology (Huijbregts et al., 2016).The system analysis was parameterized using the five input variables shown in Table 2. These variables summarize the operational decisions of the involved processes as shown in Table 3.

For Monte Carlo simulation, each input variable was stochastically characterized using specific PDFs. A Normal distribution was assigned to parameters with well-defined mean operational values, while a Uniform distribution was employed for variables where only a feasible range of interval values was available.

Table 3. System process input variable description

Process	Variable	Description	Distribution	PDF Parameters	Source
Cold Storage	Inventory turnover time	Number of days required to replace all the stored crates. It is related to the required storage volume and the number of crates required.	Uniform	[5, 7] days	First assumption from logistic operator
Distribution	Distance	Total travelled distance in kilometers during the distribution of the crates to the different customers.	Normal	$\mu = 15$ km $\sigma = 5$ km	Average from distribution locations in the case study
Washing	Soap concentration	Concentration of the cleaning or disinfecting agent used during the crate washing expressed as mass percentage of the cleaning solution.	Normal	$\mu = 0.015$ % m/m $\sigma = 0.0015$ % m/m	(Code of Federal Regulations, 2025)
	Water consumption	Average liters of water consumed per crate washed.	Uniform	[0.3, 0.6] l/crate	(Christeyns, 2025; Elpress, 2025a; HEIM, 2023)
	Water temperature	Temperature in degrees Celsius used during the rinsing stage.	Normal	$\mu = 70$ °C $\sigma = 7$ °C	(Christeyns, 2025; Elpress, 2025a; HEIM, 2023)

For the LCA process and flow setup, the flows not connected to a process inside Figure 1 (e.g., Energy, Transport) denote background system exchanges, representing inputs of materials, processes, and services. Energy service is modelled as electricity consumption from the French energy mix. The transport service is differentiated: distribution uses a 7.5-ton, Euro 6, refrigerated truck (R134a), while post-washing transport uses a similar but non-refrigerated truck. Life Cycle Inventory (LCI) data for all background services were extracted from the Ecoinvent v3.11 database.

Sampling in the MC simulation for parameter space exploration employed Sobol's sequence, extended by Saltelli (2002), as implemented in the SALib Python library. The number of samples (N) was systematically varied across powers of two, ranging from 2 to 2048, consistent with the recommended practice for this method. The generation of each sample set requires the evaluation of the underlying model, specifically the Life Cycle Assessment (LCA), a total of $N(D+2)$ times, where D represents the number of dimensions (parameters) in the model space. For this study, the dimensionality was fixed at $D = 5$. The sampling was configured to calculate the first order and total order Sobol indices for sensitivity analysis. To quantify the uncertainty in each estimation a confidence interval of 95% was computed for each resulting Sobol index. The experiments were executed on a computational platform featuring an Intel® Core™ Ultra 7 155H processor and 16 GB DDR5 memory. The computational efficiency of the LCA model was characterized by an average CPU time of 0.98 s per single LCA evaluation.

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3. Results and analysis

3.1. Samples number assessment

The convergence of the estimated Sobol indices was systematically assessed to ensure statistical robustness. This analysis involved incrementally increasing the number of samples from 2 to 2048 in powers of two. The predefined convergence criterion required that the width of the 95% confidence interval (CI) for each estimated index value must be at most 10% of the index value itself. Achieving this tolerance for statistical stability required a total sample size of 2048 samples for the analyzed loop configuration. Given the computational cost associated with the Sobol index estimation method, this sample size corresponded to a total of 14,336 evaluations of the underlying LCA model.

Figure 2 illustrates the stabilization of the index value of Global Warming Potential (GWP100) and the narrowing of its 95% CI as the sample size increases. Essentially, this convergence trend observed for the GWP100 index is representative of the characteristics found across all 18 environmental indicators assessed within the ReCiPe methodology. Consequently, a sample size of 2048 was adopted for the following analysis of the Sobol indices across all environmental impact categories to guarantee consistent statistical reliability.

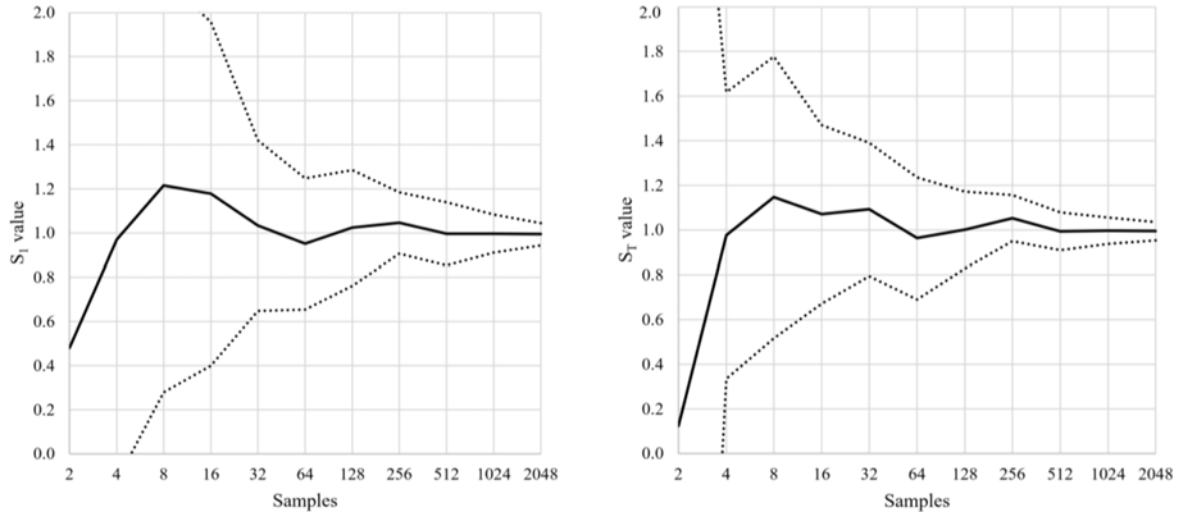


Figure 2. First and Total order Sobol index convergence diagram for GWP100 and the distance input parameter. The evolution of the Index value is represented through a continuous line while the 95% confidence interval is represented with a dotted line

3.2. LCA evaluation and Sobol index calculation

A preliminary extreme case analysis was executed to estimate the expected variation in the indicator values. The parameter values selected for this evaluation were determined by their assumed probability distributions. For uniformly distributed parameters, the evaluation included the minimum, mean, and maximum values (lower, average, and upper bounds). For normally distributed parameters, the bounds were set at a distance of two standard deviations (2σ) from the median, effectively covering approximately 95% of the distribution's probability. These results are detailed in Appendix A.

The preliminary analysis performed on the life cycle impact assessment (LCIA) results demonstrated significant variation across all evaluated environmental categories. The relative variation, resulting from the tested parameter perturbations, spanned a considerable range, extending from a minimum of 29 % for IRP (Ionizing Radiation Potential) to a maximum of 54 % for TETP (Terrestrial Ecotoxicity Potential). These quantitative findings feature the strong dependence of the environmental indicators on the selected modelling parameters.

To assess the contribution of each of the parameters to the environmental indicators, the first order (S_1) and total order (S_T) Sobol indices were calculated. The results of this analysis are presented in Figure 3, and their corresponding values are shown in Annex B. In each of the sections of the plot both values of Sobol indices are shown for each environmental indicator. This global sensitivity analysis reveals crucial insights into the system's structure and the dominant drivers of uncertainty across the 18 environmental outputs.

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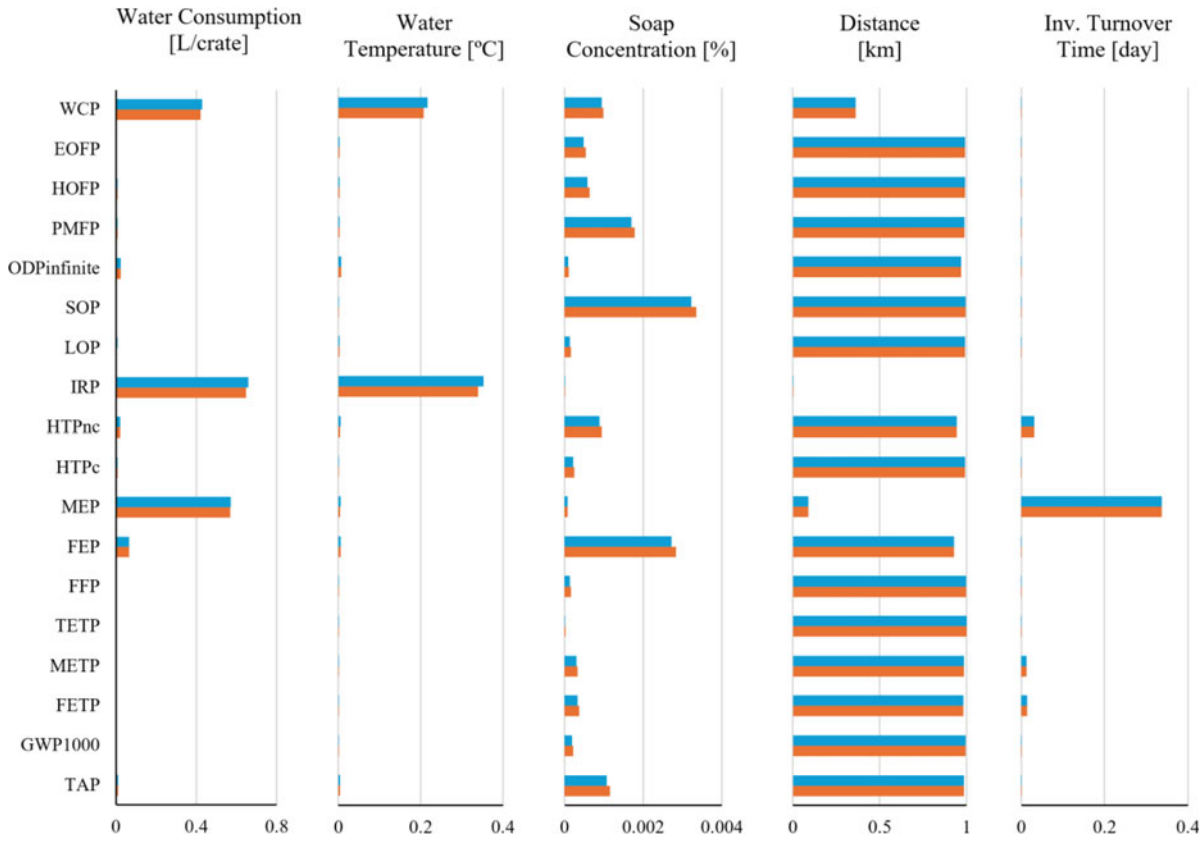


Figure 3. First and Total order Sobol index values per environmental category and parameter. S1 in orange and ST in blue

This global sensitivity analysis identifies the Transport Distance as the main driver for the majority of environmental impact categories, including Global Warming Potential (GWP) and Terrestrial Acidification (TAP), where it accounts for over 90% of the total variance ($S_1 > 0.9$). This indicates that for the reuse loop configuration under analysis, the most effective design strategy to mitigate the system's general environmental footprint is supply chain optimization and facility localization, rather than process engineering. Conversely, the washing process parameters, Water Consumption and Water Temperature, are specifically decisive for specific categories such as Water Depletion (WCP) and Ionizing Radiation (IRP). Therefore, unless the design is strictly constrained by water scarcity or specific energy grid mixes, efforts to improve washing machine efficiency are secondary to the critical need for reducing logistical expenses.

Finally, the comparison between first order (S_1) and total order (S_T) indices demonstrates that the reuse loop behaves as a highly linear system with negligible interaction effects. Across almost all categories, the sum of S_1 indices approximates 1.0, and S_T values closely track their corresponding S_1 values (e.g., $S_{1,\,\text{Distance}} \approx S_{T,\,\text{Distance}}$ for GWP100). This lack of higher-order interactions implies that the environmental impact of logistics and washing are additive rather than multiplicative in the reuse loop configuration under analysis. From a design perspective, this linearity allows for the separate optimization of the logistical network and the washing unit, simplifying the overall optimization problem by eliminating the need to account for complex cross-variable dependencies. This also implies that in systems where the processes are modelled in detail, it is possible that the current representation cannot manage the feasible complex interactions that the detailed model might imply. At a more advanced stage of the research, the analysis will be extended to more accurate representations of the processes, and an attempt will be made to characterize more complex configurations of the reuse cycle (i.e. multi-loop system, closed vs open loop, logistic networks with pooling sites, among others) in order to expand the solution space and capture the effects of additional cycle provisions and process combinations.

4. Conclusions

This study utilized extreme case and Sobol sensitivity analyses to definitively characterize the uncertainty landscape of the LCIA model. The analysis confirmed the suitability of the system for a

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simple main-effects approach, as the variability in outcomes is mainly governed by the independent, direct effects of the parameters, with negligible interaction contribution (ST ≈ S1). Quantitatively, the Distance parameter is confirmed as the dominant source of variance for most environmental outputs in the case study. In a future step of the research, the influence of other operational variables will be examined in greater depth, by focusing on the effect of transport differentially (e.g. assessing the additional transport generated by reusable packaging and not the total transport that would also exist in the single-use loop systems) to capture the effect of the other variables more accurately.

In the presented case study, since transport distance governed the variance for the majority of environmental impact categories, including Global Warming Potential and Acidification, design efforts must prioritize the optimization of reverse logistics routes to minimize the packaging distribution loop radius. Conversely, investments in washing machine efficiency, specifically targeting water consumption and temperature, should be reserved for scenarios strictly constrained by water scarcity (WCP) or nuclear energy dependence (IRP), as these parameters exert negligible influence on the system's broader carbon footprint. Furthermore, the demonstrated linearity of the model and the irrelevance of soap concentration validate a decoupled optimization framework, allowing engineers to fix chemical variables and optimize the logistical network independently of the washing unit without the risk of significant cross-subsystem trade-offs. Also, this linearity limits the model conclusions to simplified cases where the considered variables effects have not high order interactions.

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Appendix A. LCA extreme values evaluation

Impact	Unit	Low	Mid	Upper	Variation	% Variation
TAP	kg SO2-Eq	48.64	60.83	73.43	24.78	41%
GWP1000	kg CO2-Eq	25181.27	32132.84	39249.39	14068.12	44%
FETP	kg 1,4-DCB-Eq	1184.96	1508.11	1837.33	652.37	43%
METP	kg 1,4-DCB-Eq	1607.54	2048.65	2497.95	890.41	43%
TETP	kg 1,4-DCB-Eq	128911.11	176178.76	224046.55	95135.45	54%
FFP	kg oil-Eq	7963.09	10079.40	12238.63	4275.54	42%
FEP	kg P-Eq	4.61	5.76	6.95	2.34	41%
MEP	kg N-Eq	4.16	5.12	6.11	1.96	38%
HTPc	kg 1,4-DCB-Eq	4678.46	6034.34	7422.40	2743.94	45%
HTPnc	kg 1,4-DCB-Eq	30986.79	38188.37	45622.77	14635.99	38%
IRP	kg Co-60-Eq	57317.80	66576.04	76823.22	19505.42	29%
LOP	m2*a crop-Eq	574.85	728.60	887.77	312.91	43%
SOP	kg Cu-Eq	629.52	819.15	1012.71	383.19	47%
ODPinfinite	kg CFC-11-Eq	0.01	0.02	0.02	0.01	41%
PMFP	kg PM2.5-Eq	21.13	26.56	32.17	11.04	42%
HOFP	kg NOx-Eq	43.25	54.27	65.63	22.38	41%
EOFP	kg NOx-Eq	47.07	59.18	71.63	24.56	42%
WCP	m3	374.97	440.42	511.66	136.69	31%

Appendix B. Sensitivity analysis Sobol index values

	S_1						S_T					
	Water Consumption [l/crate]	Water Temperature [°C]	Soap Concentration [% m/m]	Distance [km]	Inventory Turnover Time [day]	Sum	Water Consumption [l/crate]	Water Temperature [°C]	Soap Concentration [% m/m]	Distance [km]	Inventory Turnover Time [day]	Sum
TAP	0.010	0.004	0.001	0.986	0.000	1.000	0.010	0.004	0.001	0.986	0.000	1.000
GWP1000	0.003	0.001	0.000	0.994	0.001	1.000	0.003	0.001	0.000	0.994	0.001	1.000
FETP	0.003	0.001	0.000	0.982	0.014	1.000	0.003	0.001	0.000	0.982	0.014	1.000
METP	0.002	0.001	0.000	0.983	0.013	1.000	0.002	0.001	0.000	0.983	0.013	1.000
TETP	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.999	0.000	1.000
FFP	0.002	0.001	0.000	0.997	0.000	1.000	0.002	0.001	0.000	0.997	0.000	1.000
FEP	0.065	0.006	0.003	0.926	0.000	1.000	0.066	0.006	0.003	0.926	0.000	1.000
MEP	0.570	0.005	0.000	0.088	0.337	1.000	0.570	0.005	0.000	0.088	0.337	1.000
HTPc	0.009	0.001	0.000	0.990	0.000	1.000	0.009	0.001	0.000	0.990	0.000	1.000
HTPnc	0.020	0.005	0.001	0.942	0.032	1.000	0.020	0.005	0.001	0.942	0.032	1.000
IRP	0.648	0.339	0.000	0.001	0.000	0.988	0.660	0.353	0.000	0.001	0.000	1.014
LOP	0.006	0.003	0.000	0.991	0.000	1.000	0.006	0.003	0.000	0.991	0.000	1.000
SOP	0.003	0.001	0.003	0.993	0.000	1.000	0.003	0.001	0.003	0.993	0.000	1.000
ODPinfinite	0.023	0.006	0.000	0.969	0.001	1.000	0.023	0.007	0.000	0.969	0.001	1.000
PMFP	0.007	0.003	0.002	0.988	0.000	1.000	0.007	0.003	0.002	0.988	0.000	1.000
HOFP	0.007	0.003	0.001	0.990	0.000	1.000	0.007	0.003	0.001	0.990	0.000	1.000
EOFP	0.006	0.002	0.001	0.991	0.000	1.000	0.006	0.002	0.000	0.991	0.000	1.000
WCP	0.421	0.208	0.001	0.362	0.000	0.992	0.429	0.217	0.001	0.362	0.000	1.009

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