Supply Chains Design for Sustainability: Addressing Correlated Uncertainty in Life Cycle Inventory

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Abstract

The significance of corporate environmental impact has grown in recent years, driven not only by customer expectations but also by emissions reduction regulations that establish a direct connection between emissions and overall profit. Numerous uncertainties can influence the future performance of a supply chain, underscoring the importance of incorporating them into the initial stages of supply chain design. Decision-makers should possess the necessary information on the influence and repercussions of these uncertainties to optimize network outcomes. While existing literature has explored the impact of uncertain factors such as demand and carbon prices, this study considers specifically uncertainty through Life Cycle Impact Assessment data and the correlation among various parameters.

**Keywords**: Multi‐objective, supply chain management, stochastic modelling, Life Cycle Assessment, correlated uncertainty.

* 1. Introduction

In recent years, governments have imposed increasingly stringent environmental regulations, elevating the significance of mitigating the environmental impact within supply chains (SC). This study focuses on the Life Cycle Assessment (LCA) as a key metric among various indicators that measure environmental impact. LCA thoroughly analyzes the environmental effects of complete SC, encompassing processes such as raw material extraction, product manufacturing, transportation, and final disposal. The integration of LCA with tools based on multi-objective optimization (MOO), initially proposed by Azapagic and Clift (1999), has gained increasing popularity. This approach treats the environmental aspect as an additional objective rather than an extra constraint in the model. Many studies integrating LCA and MOO predominantly adopt a deterministic approach, concentrating on analyzing the outcome of a single scenario pre-identified as the most probable. This methodology assumes that all parameters are known, and there is no variability among them. While the solution may be optimal for the specified scenario, its performance becomes unpredictable if the parameters deviate from the expected behavior. Consequently, the role of uncertainty has gained prominence in the decision-making process for effective supply chain management. Many key parameters, such as demand and prices, are susceptible to uncertainty, making the precise prediction of future values challenging. This study concentrates on uncertainties within the Life Cycle Inventory (LCI) data obtained from the ECOINVENT database, commonly identified as the primary source of uncertainty in LCA analyses.

To the best of our knowledge, Guillén‐Gosálbez and Grossmann (2009) were the first to introduce a robust mathematical programming tool that considers the uncertainty of LCI emissions, using uncorrelated, normally distributed data. In this study, the SC design problem is formulated under uncertainty as a multi-objective stochastic Mixed Integer Linear Program (MILP). The objectives are to maximize profit and minimize environmental impact. The main novelty of this work lies in investigating the influence of the correlation among uncertain LCI emission parameters on the economic and environmental performance of a supply chain.

* 1. Case study

The proposed model has been applied to the SC structure introduced by Guillén‐Gosálbez and Grossmann (2009). The three-echelon European supply chain comprises 7 plants located in Germany (Frankfurt and Leuna), Italy (Mantova), Spain (Tarragona), Poland (Wloclawek), the Czech Republic (Neratovice), and Hungary (Kazincbarcika). Each plant is associated with a warehouse and allows for chemical production using six different technologies. These technologies generate acetaldehyde, acetone, acrylonitrile, cumene, isopropanol, and phenol. The resulting products are distributed and sold across ten European markets situated in Belgium (Brussels), Romania (Pitesti), Germany (Stade), Hungary (Kazincbarcika), Italy (Mantova and Ferrara), the Czech Republic (Neratovice), Spain (Tarragona), Poland (Wloclawek), and Portugal (Sines), in accordance with their respective demands. The interested reader can find the full data describing the supply chain and all constraints in tables 1 to 7 of the original publication by Guillén‐Gosálbez and Grossmann (2009).

* 1. Methodology and mathematical formulation

The goal of this study is to identify a SC design that simultaneously maximizes the expected total Net Present Value (NPV) and minimizes its environmental impact, which is subject to uncertainty. Given are the capacity constraints, the prices of raw materials and final products, a fixed time horizon divided into a set of time periods, a set of possible locations for SC facilities, the investment and operational expenses, as well as the demand. Additionally, the environmental data, subject to uncertainty, is represented through a set of scenarios with assigned probabilities. The approach proposed in this work relies on a two‐stage stochastic MILP model, based on that introduced by Guillén‐Gosálbez and Grossmann (2009). The model encompasses two types of decision variables. Firstly, the structural decisions encode characteristics of the plants and warehouses, such as their locations, capacities, and the types of installed technologies. The second type of decision variables involves the operational ones, which include the production rate at each plant and in each time period, material flows between plants, warehouses and markets, as well as the amounts of sales of final products. These decisions are made after the uncertainty is revealed and impact operational variables in the model, enabling it to adapt to the new circumstances.

The model consists of three main sets of equations: mass balance equations, capacity constraints, and equations describing the objective functions governing both the economic and environmental performance of the system.

Throughout the manuscript, the subscript *p* denotes a plant, and the set of plants is denoted *P*. Similarly,  denotes a warehouse. The chemical products are represented by , and markets by  k. The set of main products for technology  is denoted . The time horizon is discretized into a finite number of timesteps, , and scenarios are given by .

* + 1. Mass balances and capacity constraints

Mass balances are defined for every node in the supply chain network. In the case of plants, the sum of purchased chemicals and the produced chemicals must equal the quantity transported from the plant, *p,* to the warehouses, *w,* across all time steps and scenarios. The production rate of each technology at each plant, across each time period and scenario, is restricted to be below the corresponding capacity. This capacity is defined by the sum of the previous timestep's capacity and a capacity expansion, which is constrained within specified bounds. For warehouses, in each scenario and at every time step, the inventory at the previous time step, when added to the amount of product transported from the plants, must equal the inventory in the current time period plus the quantity of product sent from the warehouse to the markets. The capacity of a warehouse can also be expanded in each timestep. The quantity of products sold on a market is constrained with a minimum threshold ensuring satisfaction of demand.

* + 1. Objective function

The model under study has two objectives. The economic performance, measured in terms of the NPV, is to be maximized, while the quantified environmental performance is to be minimized (eq.).



where *WC* represents the worst case of the environmental impact of the system, *x* and *xs* denote first and second stage continuous variables, respectively, and *y* are binary variables.

* + - 1. Economic objective function

The NPV(s) is calculated for each scenario  as the sum of the discounted cash flows over all time periods. The expected value of the NPV is then calculated as



where  denotes the probability of scenario s.

* + - 1. Environmental impact assessment

In this study, the Global Warming Potential indicator (GWP) was employed to assess the environmental impact. This indicator measures how much one kilogram of a specific greenhouse gas contributes to global warming relative to the emission of one kilogram of carbon dioxide. To quantify the amount of global warming emissions throughout the entire life cycle of the SC, we consider three main sources of emissions: emissions due to the consumption of raw materials; emissions due to transportation of products from plants to warehouses and from warehouses to markets; and emissions due to energy consumption.



In eq. is the amount of raw materials purchased, represents the cumulative life cycle impact assessment (LCIA) associated with the consumption of 1 kg of the corresponding raw material.  is the cumulative LCIA associated with the transportation of 1 ton of product over a distance of 1 km, , and,are the distances and transported flows from plants to warehouses and from warehouses to markets for all timesteps and scenarios, respectively. is the cumulative LCIA associated with the consumption of 1 MJ of energy,  denotes the consumption of energy used by each technology *i* and the amount of chemical *j* produced at plant *p* with technology *i*. The total GWP is calculated as (eq. )



* + 1. Uncertainty and scenario generation

The LCI and LCIA parameters are obtained from the ECOINVENT database. However, these parameters are uncertain, and the values presented in the database represent their expected values. Analytical information regarding their probability distribution is unavailable. Nonetheless, in accordance with the recommendation by Weidema and Wesnæs (1996), the parameters can be modelled using a lognormal distribution, defined by a location parameter μ and an arithmetic scale parameter σ. This allows for the sampling of uncertain parameters, resulting in a set of scenarios used to address the stochastic SC design problem. The initial step involves utilizing the correlation matrix and standard deviation of the lognormally distributed uncertain parameters to establish a covariance matrix. Subsequently, this matrix, in conjunction with the Monte Carlo technique, is employed to generate samples of normally distributed correlated random variables. The multivariate cumulative density function of the transformed variables is then computed for the impact factors. Finally, the inverse of this multivariate cumulative density function is calculated to assign a probability to each of the generated samples. Scenarios for the stochastic problem are obtained by backtransforming these samples onto the original, lognormally distributed probability spaces. This methodology for handling correlated uncertainty has been employed in previous studies. For instance, Salcedo-Diaz et al. (2020) optimized a water distribution network considering correlated uncertainty in nodes' demand, and Garcia-Castro et al. (2023) addressed the design of SC under correlated uncertainty in energy and carbon prices.

* + 1. Solution procedure

The solution to the MOO problem can be depicted through a collection of Pareto points, each of which represents a trade-off between both objectives. To compute these Pareto points, the ε‐constraint method is utilized (eq.), transforming the primary problem into a single‐objective problem that is solved for different values of the ε‐parameter.



* 1. Results and discussion

The MILP problem formulated has been implemented in the General Algebraic Modeling System (GAMS) and solved to global optimality using IBMs CPLEX v12.9 optimization algorithm. Given the vast number of scenarios resulting from the consideration of mean values, standard deviation, and correlation among the 35 impact factors in the database, only the five impact factors with the highest contribution to emissions are considered to be correlated and uncertain. These impact factors are carbon dioxide (fossil), carbon monoxide (fossil), dinitrogen monoxide, Methane (biogenic), and Methane (fossil), which are responsible for more than 99% of the total emissions. In each simulation, the correlation between several subgroups of the 5 parameters can either be low, medium, or high. This variability results in distinct correlation matrices for each simulation, serving as input for the sampling algorithm to generate 170 corresponding scenarios. The obtained results reveal a pronounced impact of accounting for correlation among the impact factors on the network's performance. Furthermore, depending on the level of correlation, the economic performance can worsen while maintaining the level of emissions. Therefore, it is crucial to account for correlation among the LCI parameters, as treating them as independent can result in an overestimation of the network's performance. A simulation was conducted to pinpoint the two impact factors whose correlation has the most substantial influence on the overall network performance. The findings reveal that these impact factors are carbon dioxide and fossil methane. Figure 1 displays the Pareto curves obtained without correlation and with a notably high correlation factor of 0.98 between carbon dioxide and fossil methane. It is evident that accounting for correlation between these two impact factors results in a poorer economic performance for a given level of emissions in the network.



Figure 1. Pareto curve representing the economic and environmental performance of the network without correlation and with high correlation between carbon dioxide and fossil methane.

In a subsequent simulation, a high correlation between these two impact factors was exclusively considered in one component of the global warming potential, namely raw material consumption, transportation, and energy consumption. The outcomes indicate that, as expected, raw material consumption exerts the most significant influence on the overall result, given that the largest proportion of emissions occurs during this stage. Finally, the study examined the dispersion of solutions with and without correlation, considering three values for the σ parameter: 1.7, 1.487, and 1.216. Consistently across all these values, the same trend was observed, that is, the economic performance for a specific GWP is more conservative when considering correlation. Moreover, for lower values of σ, the resulting network is more robust concerning emissions but exhibits a larger variation in economic performance (Figure 2). This suggests that σ, and consequently the dispersion of scenarios, significantly influences the performance of the network.



Figure 2. Pareto points for the stochastic model without correlation and with correlations of 0.98 between carbon dioxide and fossil methane for σ = 1.7 and 1.216, respectively.

In a broad sense, the Pareto optimal set of solutions reveal that SC strategic decisions, encompassing the locations and capacities of its entities, exhibit minimal variations among them. However, differences surpassing a 1% threshold arise in the NPV and GWP due to fluxes between nodes, particularly when accounting for correlations among uncertain parameters that.

* 1. Conclusions

In this study, the focus is on the design of sustainable SC under correlated uncertainty in the LCI data. The findings reveal that accounting for the correlation between uncertain LCI factors can significantly influence the overall performance of the network. Not considering this correlation may result in a supply chain design that underperforms in potential future scenarios. Introducing correlation among the burdens with the highest contribution to overall emissions is crucial, as precise modelling of these factors is essential. The results emphasize that considering correlation generally leads to more conservative outcomes, implying that the economic performance for a fixed GWP may be compromised. Additionally, the dispersion of scenarios has a substantial impact on the network's performance.

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