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Dimensionality reduction applied to the simultaneous optimization of the economic and life cycle environmental performance of supply chains

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ABSTRACT

The design and planning of more sustainable supply chains should take into account several impacts for a proper assessment of the environmental performance of the logistic activities. Unfortunately, minimizing several environmental objectives simultaneously leads to hard optimization problems. This paper presents a rigorous computational framework for solving complex multi-objective optimization (MOO) problems encountered in the optimization of logistic tasks under economic and environmental indicators. The key ingredient of our method is the use of an objective reduction algorithm that allows identifying redundant objectives that can be omitted while still preserving the problem structure to the extent possible. The advantages of our method are illustrated by means of two case studies that address the multi-objective optimization of supply chains that produce bioethanol and hydrogen for vehicle use.

1. Introduction

Over the past decade, the minimization of the environmental impact of supply chains (SCs) has received much attention in both academia and industry. Such interest has been mainly motivated by the growing consumer demand for "greener" products along with tighter environmental protection laws.

Despite the efforts made so far in this area, there is still nowadays a lack of agreement concerning the impacts to be minimized to achieve better environmental performance. Ideally, the optimization model should minimize simultaneously a set of impacts in several damage categories of concern for decision-makers. However, given the large number of metrics that currently exists, this approach leads to complex formulations that are hard to solve in short CPU times. Furthermore, there is the added difficulty of visualizing and analyzing the solutions produced in a high-dimensional space. In this paper, we present a method that reduces the complexity of multi-objective optimization models by identifying redundant objectives that can be omitted while still preserving the problem structure to the maximum extent possible. Our approach allows dealing with complex models that assist in the design and planning of more sustainable processes.

The paper is organized as follows. We first review the literature on this topic, with emphasis on the use of multi-objective optimization in the design and planning of more sustainable supply chains. The problem under study is formally defined in the next section. The modeling framework and the solution procedure follow. Some numerical results are then presented, while the conclusions of the work are drawn in the last section of the paper.

2. Literature review

The incorporation of environmental aspects in supply chain management (SCM) has led to the concept of green supply chain management (GrSCM), which aims to integrate environmental decisions into elementary SC phases including product design, material selection, manufacturing processes, delivery of final products to customers, and end-of-life management of products after their useful life (Hervani et al., 2005; Srivastava, 2007). In his

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Abbreviation: EU ETS, European Union Emission Trading Scheme; GHG, Greenhouse gas; GrSCM, Green supply chain management; GWP_{100}, Global warming potential over a 100-year time horizon; DEQ, Damage to eco-system quality; DHH, Damage to human health; DR, Damage to resources; EI_{99}, Eco-indicator 99; LCA, Life cycle assessment; MILP, Mixed integer linear programming; MOO, Multi-objective optimization; MO(X), Multi-objective model; MOSS, Minimum objective subset; PCA, Principal component analysis; SC, Supply chain; SCM, Supply chain management; SMR, Steam methane reforming; $SO_e(X)$, Single objective model; TDC, Total discounted cost; X, Feasible decision variables space

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Notation

Indices

e	ε-iterations
i	objectives
n	inequality constraints
n'	equality constraints
p	Pareto solutions

Sets

E_i	ε-values for objective f_i
F_0	original set of objectives
F	reduced set of objectives
S	set of Pareto solutions
S''	set of Pareto solutions of bi-criteria and single criterion models
S'	set of unique Pareto solutions of bi-criteria and single criterion models
$S^{(bi)}$	set of Pareto solutions of bi-criteria models
$S^{(ex)}$	set of extreme solutions
$S^{(final)'}$	final set of Pareto solutions
$S^{(final)'}$	final set of unique Pareto solutions
$S^{(norm)'}$	set of normalized elements of S'
$S^{(red)'}$	set of Pareto solutions of reduced space model

Parameters

$\overline{\delta}$	upper limit for δ-error
$\overline{f_i}$	maximum value of objective f_i
$\underline{f_i}$	minimum value of objective f_i
$f_i^{(norm)}$	normalized value of objective f_i
J	number of Pareto solutions
K	number of objectives in the original space
L	number of ε-values
L_{max}	maximum number of ε-values
N	number of inequality constraints
N'	number of equality constraints
$\underline{s_i}$	solution at which objective f_i attains its minimum value
$\overline{s_i}$	solution at which objective f_i attains its maximum value
$YP_{p,p',i}$	binary parameter that takes the value of 1 if solution s_p is better than solution $s_{p'}$ in objective function f_i and 0 otherwise

Variables

$ZD_{p,p'}$	binary variable (1 if solution $s_{p'}$ dominates solution s_p in the reduced Pareto space and 0 otherwise)
ZO_i	binary variable (1 if objective f_i is removed from F_0 and 0 otherwise)
$ZOD_{i,p,p'}$	auxiliary binary variable
$\delta_{p,p',i}$	difference between the value of objective f_i in solutions s_p and $s_{p'}$

extensive review, Srivastava (2007) recognized two main approaches in the area of GrSCM: empirical studies and mathematical modeling techniques. Among mathematical modeling tools, multi-objective optimization (MOO) has gained wider interest in the research community, as it offers the possibility of balancing economic and environmental concerns in a systematic manner.

The overwhelming majority of MOO models applied in SCM minimize the amount of emitted greenhouse gases (GHGs), mainly because carbon emissions are regulated by the European Union Emission Trading Scheme (EU ETS), the world's largest emissions trading mechanism, whose main purpose is to mitigate climate change. Hugo et al. (2005) presented a bi-objective model for the optimal design of hydrogen SCs that maximizes the net present value (NPV) and minimizes the GHG emissions. Zamboni et al. (2011) proposed a bi-objective model for optimizing biofuel networks that minimizes the amount of GHG. Giarola et al. (2011, 2012) proposed bi-objective models for the design of bioethanol SCs in Italy that minimize the emitted CO_2. More recently, Akgul et al. (2012) adopted a similar approach for optimizing bioethanol SCs in the UK.

Some authors have claimed that optimizing GHG emissions as unique criterion can lead to solutions where this metric is reduced at the expense of increasing other negative environmental effects (Scharlemann and Laurance, 2008; Vries et al., 2010; Cooper and Sehlke, 2012). A possible manner to avoid this consists of optimizing aggregated environmental metrics obtained by attaching weights to single impact indicators (see Huppes and van Oers, 2011). Particularly, aggregated metrics based on life cycle assessment (LCA) principles (Curran, 2006) have gained wider interest in the recent past, as they allow assessing the environmental impact considering all the stages in the life cycle of the process. The Eco-indicator 99 is one of these LCA metrics (Goedkoop and Spriensma, 1999) that has been widely used in SCM. Guillén-Gosálbez and Grossmann (2009) used the Eco-indicator 99 in the design of petrochemical SCs and hydrogen SCs for vehicle use (Guillén-Gosálbez et al., 2010). The same metric was employed by Duque et al. (2010) and Pinto-Varela et al. (2011) for optimizing industrial networks in Portugal. Neto et al. (2008) applied another aggregated metric that weights seven single impacts for optimizing paper logistic networks, while Bojarski et al. (2009) applied the IMPACT2002+, which is quantified following LCA principles, in the optimization of SCs.

The computation of aggregated metrics involves two main steps: normalization and weighting. The aim of normalization is to refer the original impact values to a common basis before being aggregated into a single metric. Weighting procedures range different indicators according to some targets. They are typically defined by a panel of experts that reflect the views of the society or a group of stakeholders. The weakness of the aggregation procedure is that it uses fixed normalization and weighting parameters that may not represent the decision-makers' interests. Moreover, when used in an MOO framework, aggregated metrics may change the dominance structure of the problem in a manner such that some solutions may be left out of the analysis (Brockhoff and Zitzler, 2010).

The use of aggregated indicators in environmental MOO problems is a common practice in environmental engineering that was originally motivated by the numerical difficulties associated with the optimization of a large number of objectives simultaneously (Ehrgott, 2000). An alternative approach that avoids the use of aggregated metrics consists of optimizing approximated