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Objective dimensionality reduction method within multi-objective optimisation considering total footprints

Lidija Čuček [a,*], Jiří Jaromír Klemeš [b], Zdravko Kravanja [a]

[a] *Faculty of Chemistry and Chemical Engineering, University of Maribor, Smetanova ulica 17, 2000 Maribor, Slovenia*
[b] *Centre for Process Integration and Intensification – CPI^2, Research Institute of Chemical and Process Engineering – MŰKKI, Faculty of Information Technology, University of Pannonia, Egyetem utca 10, 8200 Veszprém, Hungary*

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A B S T R A C T

This contribution presents a simplified and more practical version of an objective dimensionality reduction method within multi-objective optimisation – a Representative Objectives Method. This method is based on similarities between several objectives in order to reduce the number of objectives to a minimum number of representative objectives. This method can be applied to different direct and total objectives. In this contribution the selected objectives are annual profit and total footprints. Total footprints are the sum of direct and indirect footprints where the direct footprints only consider the burdening of the environment, whilst the total footprints consider both the burdening and unburdening of the environment.

This dimensionality reduction method is applied during a demonstration case study of regional supply chains regarding the evaluations of different total environmental footprints. This case study indicates that this simplified version of the Representative Objectives Method is easy to apply and enables the user to more easily understand multi-objective optimisation solutions. It represents a practical tool for performing the dimensionality reduction of criteria during the economic and environmental optimisation of different problems when considering total environmental footprints.

1. Introduction

Depletion of resources, their generally-increasing prices – see e.g. Nemet et al. (2013) - and environmental and social issues, such as global warming, water pollution, food supply, security of energy supply (Lam et al., 2010) and many others, are becoming important issues to be faced with today (Lior, 2012). It is for those reasons that many different methods and tools have been developed over recent decades for measuring and monitoring sustainability and sustainable development to assess and evaluate progress towards more sustainable systems (De Benedetto and Klemeš, 2008). Key aspects of sustainability are avoidance, reuse, mitigation and minimisation (Klemeš et al., 2012). As the most sustainable solutions, closed-loop supply chains are considered (Rashid et al., 2013). System's approach based on life-cycle thinking has become widely used. Life-cycle thinking has also become a key element in different policies (European Commission; Directorate-General for the Environment, 2010). Life Cycle Assessment (LCA) is a set of tools and ideas for evaluating mostly the environmental (U. S. Environmental Protection Agency (EPA), 2012) but also social sustainability (United Nations Environment Programme, 2009) of systems (products, processes or services). LCA takes into account the whole supply chain, and the full life-cycle of the system.

In many cases just global warming potential (GWP) or carbon footprint (CF) are evaluated as criteria for environmental sustainability – 'castrated type' of LCA (Finkbeiner, 2009). Most of the effort and resources are spent in order to reduce CF. Several countries have set ambitious targets in order to reduce their greenhouse gas (GHG) emissions, such as the European Union (European Commission, 2009), China (Leggett, 2011), Australia (Australian Government; Department of Climate Change and Energy Efficiency, 2012) and others. However, more comprehensive analysis need to be performed that should consider all aspects of the natural environment, human health, and resources (Finkbeiner, 2009). A comprehensive list of objectives (potential impacts or footprints) should be taken into account and evaluated. However, if several objectives are considered, there are limitations such as:

- Increased time spent in obtaining the entire solution space;
- Difficulty regarding visualisation of the solution space;

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[*] Corresponding author. Tel.: +386 2 22 94 455; fax: +386 2 25 27 774.
E-mail address: lidija.cucek@um.si (L. Čuček).

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- Difficulty regarding interpretation of the objective space;
- Providing only the narrow views of two, three, or at most four-dimensional (4-D) Pareto projections (Čuček et al., 2013);
- Computational burden in some cases – see e.g. (Guillén-Gosálbez, 2011).

There is then a need to apply a criteria dimensionality reduction technique in order to facilitate the comprehension of the solution space when many objectives are involved within multi-objective optimisation (MOO) problems.

On the other hand usually only the direct effects of systems on the environment are considered. They represent the direct burdens of those systems due to the extraction and conversion of resources, materials' production, usage, maintenance, re-use, recycling, energy recovery, and/or disposal, including all the flows between the LCA stages (Azapagic, 1999). However, when considering only the direct effects that different footprints have on the environment; this may result in misleading solutions. Almost all systems seem to be unsustainable, even if they provide benefit to the environment, see e.g. Čuček et al. (2012a). A more realistic picture can be obtained if the indirect effects caused by product's substitutions, and the utilisations of harmful products are considered, too (Čuček et al., 2012b). The indirect effects are those sets of impacts that indirectly unburden or benefit the environment, e.g. due to the usage of harmful raw-materials that otherwise would be deposited or replacement of harmful products with benign ones. It is important that footprints account for both direct and indirect effects. The total effect is the sum of the direct and indirect effects (Kravanja and Čuček, 2013).

This contribution therefore represents an extension of the novel objective dimensionality reduction method – a Representative Objectives Method (ROM) (Čuček et al., 2013) from direct to total footprints. Different total environmental footprints are considered, and different measurements are proposed for determining the correlations amongst footprints and selecting the representative ones: i) the ratios between pairs of footprints, ii) the overlapping of pairs of footprints in process variables, and iii) the average absolute normalised deviation between pairs of footprints.

The dimensionality reduction in MOO is solved over three steps. Firstly, the environmental footprints are obtained from the matrix of the process variables and direct and indirect footprints. In the second step the similarities amongst footprints are identified. Based on similarity amongst the footprints which are determined from proposed measurements i)–iii), several groups are formed consisting on one representative "independent" footprint and remaining "dependent" footprints. In the final step, a multi-objective multi-parametric optimisation is performed for the selected representative footprints using the ε-constraint method (Haimes et al., 1971). This approach is illustrated using a demonstration case study of synthesising biomass energy supply chains (Čuček et al., 2010) when considering total footprints (Čuček et al., 2012b).

It should be noted that this contribution represents a more practical version of the ROM within MOO when compared to the method presented in Čuček et al. (2013). Only the optimistic scenario is considered with respect to handling the remaining non-representative footprints as suggested in Čuček et al. (2013), and more relaxed Pareto solutions are obtained in terms of environmental burdens and profit. The obtained solutions are those with higher profits, but also exhibit rather good environmental indicators. In addition the error of the dimensionality reduction approach is excluded as the error should be small when properly applying the proposed measurements for identifying similarities amongst footprints. However, for safety reasons one can still apply the calculation of the error as by Čuček et al. (2013) rigorously or only by calculating a few pessimistic solutions in order to avoid exhausting iterative optimisations. This simplified version of the ROM is easy to apply and enables the user to more easily understand MOO solutions. It is called "objective dimensionality reduction method" since it reduces the dimensionality of optimisation criteria during the procedure. The ROM represents a more practical tool for performing the dimensionality reduction of criteria during the economic and environmental optimisations.

2. More practical representative objectives method

The dimensionality reduction method, a ROM (Čuček et al., 2013), is used within the mathematical programming approach during MOO when applying the ε-constraint method. MOO is comprised of several objectives $o \in O$, including economic and environmental ones. The main criterion is the economic-one, such as the annual profit, P. Environmental objectives such as environmental footprints $F_{f,k}(x), f \in FP$ are additional objectives. The application of ROM within MOO is solved over three main steps:

(i) Generation of the optimal points x_k in order to analyse similarities amongst footprints (see Section 2.1);

(ii) Identification of similarities amongst footprints for selected optimal points x_k by considering the partitioning criteria (see Section 2.2):
  - Normalised ratios between pairs of footprints (f and ff);
  - Overlapping pairs of footprints (f and ff) in process variables;
  - Average absolute normalised deviation between pairs of footprints (f and ff).

Using those criteria the representative $fr_s \in FS_s^{fr}$ and remaining unrepresentative $fu_s \in FS_s^{fu}$ footprints are selected within a given subset $s \in S$. The N_S subsets $s \in S$ of similar footprints are identified: $FS_s = FS_s^{fr} \cup FS_s^{fu}$.

(iii) Performing MOO within a reduced set of footprints by maximisation of the profit vs. representative footprints only (see Section 2.3). All the feasible solutions of the profits' and footprints' combinations can be read directly from multi-dimensional (multi-D, ideally 2-4 dimensions) Pareto solutions.

2.1. Generation of optimal points

Optimal points for analysing similarities amongst footprints are obtained from matrix coefficients (specific environmental footprints) – $a_{f,v}$, and corresponding process variables at iteration $k \in K$, $x_{v,k}$. By multiplying them, the environmental footprints $F_{f,k}(x)$, $f \in FP$ are obtained:

$$F_{f,k}(x) = \sum_{v \in V} a_{f,v} \cdot x_{v,k} \quad \forall f \in FP, \forall k \in K \tag{1}$$

The multi-criteria approach is applied along the whole range of footprints. The synthesis model including different environmental footprints is solved within MOO by maximising profit as the main objective, whilst the footprints are constrained by ε when applying the widely-used technique ε-constraint method (Pieragostini et al., 2012). The footprints at iteration k are normalised in order to adjust their values to a common scale. In this way the relative footprints are obtained: