CHEMICAL ENGINEERING TRANSACTIONS

VOL. 29, 2012

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at: www.aidic.it/cet

Guest Editors: Petar Sabev Varbanov, Hon Loong Lam, Jiří Jaromír Klemeš

ISBN 978-88-95608-20-4; **ISSN** 1974-9791

DOI: 10.3303/CET1229206

Reducing the Dimensionality of Criteria in Multi-Objective Optimisation of Biomass Energy Supply Chains

Lidija Čuček*[a], Jiří J. Klemeš[b], Petar S. Varbanov[b], Zdravko Kravanja[a]

[a]Faculty of Chemistry and Chemical Engineering, University of Maribor, Smetanova ulica 17, 2000 Maribor, Slovenia
lidija.cucek@uni-mb.si
[b]Centre for Process Integration and Intensification –CPI[2], Research Institute of Chemical and Process Engineering - MÜKKI, Faculty of Information Technology, University of Pannonia, Egyetem utca 10, 8200 Veszprém, Hungary

This contribution presents a novel approach, by which the number of direct environmental footprints is reduced to a minimum number of “independent” ones (INDFs) through correlations among the footprints that show similar behaviour. The correlations are investigated between direct carbon, energy, water, water pollution, and land footprints. Those footprints that show similar behaviour are grouped in subsets of correlated footprints. In each subset only one footprint, an INDF is taken into the multi-objective optimisation, whilst the rest of the “dependent” footprints (DFs) are evaluated after the optimisation from the INDFs. In this way, the dimensionality of the criteria within the multi-objective optimisation is significantly reduced, so that a multi-parametric optimisation is performed with INDFs as parameters. The subjective weighting of environmental and social indicators or footprints is thus avoided. This novel approach is illustrated using a demonstration case study of different biomass energy supply chains.

1. Introduction

The world is currently facing environmental, financial and social challenges, primarily due to human population growth, globalisation, the unsustainable use of resources, and the unsustainable growth of world economy over the last decades (Lior, 2012). Sustainable development requires an integration of economic, environmental and social components at all levels, and thus leading to a multi-objective optimisation problem, as illustrated by De Benedetto and Klemes (2009). Usually ε-constraint method is applied (Pieragostini et al., 2012) and different sets of Pareto optimal solutions are obtained.
In many studies just one objective (e.g., carbon footprint) is considered and evaluated besides an economic criterion, which most likely leads to simplified conclusions. However, more realistic solutions are obtained if more impacts are considered (e.g., carbon, nitrogen, water footprints). Important limitation in this case is that computational burden grows rapidly in size with the number of objectives (Guillén-Gosálbez, 2011). Other limitations are that multi-objective optimisation can be time consuming, and there is difficulty in visualisation and interpretation of the objective space (Pozo et al., 2012). It also prevents the carrying-out of an exact optimization, resulting in only two- or at most three-dimensional Pareto projections, thus providing only a narrow view with underestimated environmental metric estimates (Kravanja, 2012).
Usually, the number of objectives is reduced into aggregated single sustainability indicator (e.g., Kravanja and Čuček, 2012). However, this approach has the drawbacks of subjective weighting and difficulty of selecting the best solution. Reduction of the dimensionality is thus required, and should be based on a systematic mathematical approach. Reduction of the dimensionality is an area of statistical

Please cite this article as: Čuček L., Klemeš J. J., Varbanov P. S. and Kravanja Z., (2012), Reducing the dimensionality of criteria in multi-objective optimisation of biomass energy supply chains, Chemical Engineering Transactions, 29, 1231-1236

multivariate analysis. The methods include principal component analysis, factor analysis, multi-dimensional scaling, clustering systems, etc.

Several papers are dealing with the reduction of the dimensionality of multi-objective optimisation problems. Deb and Saxena (2005) propose an evolutionary multi-objective optimizationpcocedure, while Pozo et al. (2012) developed a method based on principal component analysis. Brockhoff and Zitzler (2009) calculated an approximation error to quantify to which extent the dominance structure of the problem changes when omitting objectives. Guillén-Gosálbez (2011) developed a MILP-based method, where the error of omitting objectives is minimised, and demonstrated that some of objectives behave in a non-conflicting manner, and thus dimension of the problem can be reduced. Vaskan et al. (2012) applied the MILP method for the optimal design of heat exchanger networks considering environmental impacts. Gutiérrez et al. (2010) used principal component analysis and multi-dimensional scaling methodology in order to reduce dimension of the problem.

This paper presents the novel approach, by which the footprints that show similar behaviour are grouped in subsets of correlated footprints. Different criteria are proposed for determining the correlations among footprints and selecting the INDFs: i) ratio between pair of footprints, ii) overlap of footprints in process variables, and iii) average absolute normalised deviation. INDFs are then taken into multi-objective multi-parametric optimisation. The DFs are thus evaluated from the INDFs using linear or nonlinear correlations. Methodology for the development of linear and nonlinear correlations among different footprints within a multi-objective optimisation approach presented in Čuček et al. (2012a) is applied.

2. Description of the proposed approach

The dimensionality reduction in multi-objective optimisation consists of three steps. First, the correlations among footprints are identified, and INDFs are selected. Then, multi-parametric optimisation is performed for the INDFs using the ε-constraint method. Finally, non-linear quadratic-based correlations are performed for DFs, which are evaluated after the optimisation from the INDFs.

2.1 Identification of correlations among footprints

Identification of correlations among footprints is performed directly from the matrix of the process variables and footprints. The direct environmental footprints (burdening of the environment) are thus obtained using the following equation:

$$\mathrm{ENVB}_f^{\mathrm{d}} = \sum_{v \in V} \mathrm{a}_{v,f} \cdot x_v \tag{1}$$

where $\mathrm{a}_{v,f}$ are the matrix coefficients, and x_v are the corresponding process variables at their optimal values, where profit is maximised.

Three measurements were proposed:

i) Ratio between pairs of footprints (f and ff):

$$R_{f,ff} = \frac{\sum_{v \in V} \left(\frac{\mathrm{a}_{v,f}}{\mathrm{a}_{v,ff}} \cdot \frac{\mathrm{a}_{v,f} \cdot x_v}{\mathrm{ENVB}_f^{\mathrm{d}}} \right)}{\frac{\mathrm{ENVB}_f^{\mathrm{d}}}{\mathrm{ENVB}_{ff}^{\mathrm{d}}}} \qquad \forall f \in F \wedge \forall ff \in F \wedge \mathrm{a}_{v,ff} \neq 0 \tag{2}$$

For perfect correlation the ratio between footprints is 1. Because $R_{f,ff}$ can differ from $R_{ff,f}$, geometric mean is calculated using the following equation:

$$GR_{f,ff} = \sqrt{R_{f,ff} \cdot R_{ff,f}} \qquad \forall f \in F \wedge \forall ff \in F \tag{3}$$

ii) Overlap of pair of footprints (f and ff) in process variables:

$$O_{f,ff} = \sum_{v \in V} \frac{\mathrm{a}_{v,f} \cdot x_v}{\mathrm{ENVB}_f^{\mathrm{d}}} \qquad \forall f \in F \wedge \forall ff \in F \wedge \mathrm{a}_{v,f} \neq 0 \wedge \mathrm{a}_{v,ff} \neq 0 \tag{4}$$

This measurement represents a similarity between pairs of footprints. If footprint f is defined by the same process variables as footprint ff, then the overlap coefficient is 1. Because $O_{f,ff}$ can be different from $O_{ff,f}$, geometric mean is calculated:

$$GO_{f,ff} = \sqrt{O_{f,ff} \cdot O_{ff,f}} \qquad \forall f \in F \wedge \forall ff \in F \tag{5}$$

iii) Average absolute normalised deviation between pair of footprints (f and ff):

$$D_{f,ff} = \frac{\sum_{v \in V} \left(\left| \frac{1 - \frac{\mathrm{a}_{v,f}}{\mathrm{a}_{v,ff}}}{\frac{\mathrm{ENVB}_f^{\mathrm{d}}}{\mathrm{ENVB}_{ff}^{\mathrm{d}}}} \right| \cdot \frac{\mathrm{a}_{v,f} \cdot x_v}{\mathrm{ENVB}_f^{\mathrm{d}}} \right)}{\left(\sum_{v \in V} 1 \right) - 1} \qquad \forall f \in F \wedge \forall ff \in F \wedge \mathrm{a}_{v,ff} \neq 0 \tag{6}$$

Small values indicate good agreement between pair of footprints. Again, geometric mean is calculated because $D_{f,ff}$ can be different from $D_{ff,f}$, :

$$GD_{f,ff} = \sqrt{D_{f,ff} \cdot D_{ff,f}} \qquad \forall f \in F \wedge \forall ff \in F \tag{7}$$

From above criteria two or three INDFs are selected.

2.2 Multi-objective optimisation

In the second step a multi-objective optimisation is performed for selected N_{fi} INDFs, $fi \in FI$. ε-constraint method is applied to this multi-parametric optimisation where sequences, one for each footprint, of constrained single-objective mixed-integer non-linear programming $(\mathrm{MINLP})_{fi_1,\dots,fi_{N_{fi}}}$ problems are thus solved for INDFs as the maximisation of the profit subjected to relative INDFs. Relative INDFs are being defined as the INDFs divided by their reference values. A multi-dimensional graph of Pareto optimal solutions is thus obtained.

2.3 Correlations among "dependent" and "independent" footprints in group

A few INDFs can be selected applying criteria i)-iii). In this way, two or three groups with similar behaviour are identified. DFs are evaluated from INDFs in each group using linear or nonlinear correlations (Čuček et al., 2012a). For better curve fitting quadratic-based non-linear correlations is used.

3. Demonstration case study

The concept described above is applied within a case study of regional biomass and bioenergy supply chains (Čuček et al., 2010) extended for simultaneous assessment of footprints (Čuček et al., 2012b). It follows a four layer structure, which consists of harvesting, collection and pre-processing, core processing, and usage of products including the transportation flows within and between the layers. Different biomass sources are considered, corn grains and stover, wood chips, municipal solid waste, manure and timber. Dry-grind process, anaerobic digestion, incineration and sawing convert biomass into valuable products, heat, electricity, bioethanol, and distillers dried grains with solubles, digestate, and boards. Besides processed products, also food can be produced. Supply chains incorporate different environmental pressures, and consider different direct footprints, carbon, energy, water, water pollution and land footprints.

3.1 Results and discussion

Applying criteria i) – iii), similarity among footprints was estimated. With greater accuracy three INDFs should be selected, carbon, water, and land footprints. When less exact, only two INDFs can be selected. In this way, two groups with similar behaviour are identified. Three-dimensional problem is obtained with selected two INDFs, where the profit is the main criterion, and carbon and water footprints are identified as INDFs. Figure 1 shows the results, obtained by multi-parametric optimisation.

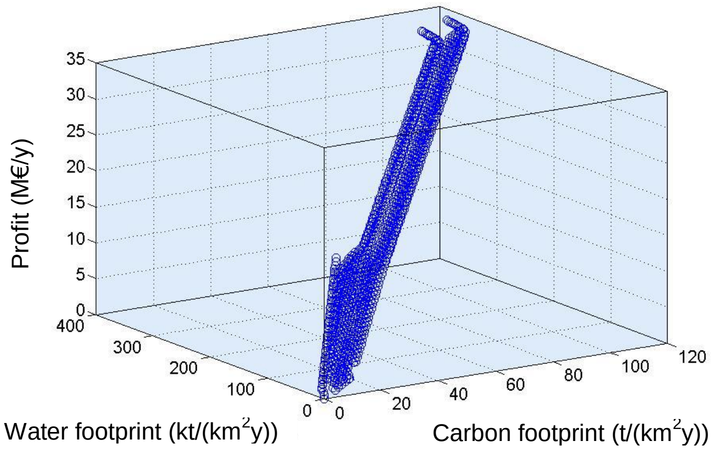

Figure 1: Profit versus INDFs

DFs are evaluated from INDFs using nonlinear quadratic-based correlations (Čuček et al., 2012a). Carbon footprint (CF) is grouped with energy footprint (EF). Water footprint (WF) is grouped with water pollution (WPF) and land footprints (LF). Nonlinear correlations based on quadratic function for carbon footprint are taken from Table 2 in Čuček et al. (2012a). The correlations among the first group – carbon and energy footprints are presented on Figure 2 and the corresponding profit – dependent footprint 2D projection on Figure 3.

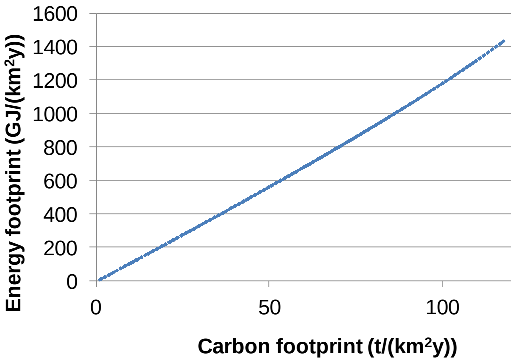

Figure 2: EF versus CF

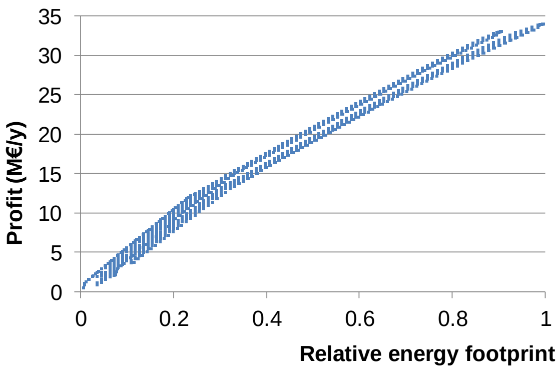

Figure 3: Profit versus relative EF at changing WF

In the second group water footprint is selected as INDF. DFs in the second group are expressed through water footprint. Linear and non-linear correlations among footprints, where water footprint is selected as INDF are presented in Table 1.

The correlation among the second group – water and water pollution, and water and land footprints are presented on Figures 4 and 5, respectively. These corresponding profit – dependent footprint projections are given on Figures 6 and 7.

Table 1: Obtained linear and non-linear correlations among footprints, where water footprint is selected as INDF

Footprint	Linear correlation	Non-linear correlation based on quadratic function
ENF	$f^{r}_{j,\mathrm{ENF}} = 1.002 \cdot f^{r}_{j,\mathrm{WF}} - 2.135 \cdot 10^{-3}$	$f^{r}_{j,\mathrm{ENF}} = 1.580 \pm \sqrt{0.907 \cdot (f^{r}_{j,\mathrm{WF}})^{2} - 3.071 \cdot f^{r}_{j,\mathrm{WF}} + 2.500}$
CF	$f^{r}_{j,\mathrm{CF}} = 1.002 \cdot f^{r}_{j,\mathrm{WF}} - 2.135 \cdot 10^{-3}$	$f^{r}_{j,\mathrm{CF}} = 2.050 \pm \sqrt{1.303 \cdot (f^{r}_{j,\mathrm{WF}})^{2} - 4.409 \cdot f^{r}_{j,\mathrm{WF}} + 4.208}$
WPF	$f^{r}_{j,\mathrm{WPF}} = 1.025 \cdot f^{r}_{j,\mathrm{WF}} - 2.469 \cdot 10^{-2}$	$f^{r}_{j,\mathrm{WPF}} = 2.564 \pm \sqrt{1.774 \cdot (f^{r}_{j,\mathrm{WF}})^{2} - 6.005 \cdot f^{r}_{j,\mathrm{WF}} + 6.679}$
LF	$f^{r}_{j,\mathrm{LF}} = 1.077 \cdot f^{r}_{j,\mathrm{WF}} - 7.687 \cdot 10^{-2}$	$f^{r}_{j,\mathrm{LF}} = 3.667 \pm \sqrt{2.860 \cdot (f^{r}_{j,\mathrm{WF}})^{2} - 9.681 \cdot f^{r}_{j,\mathrm{WF}} + 13.932}$

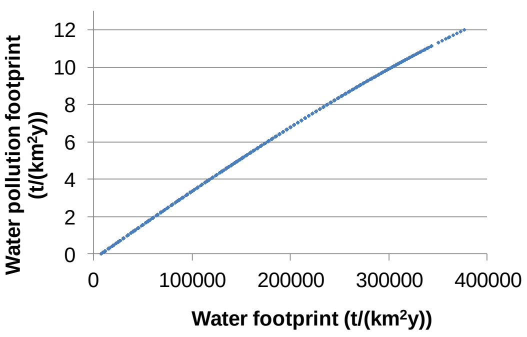

Figure 4: WPF versus WF

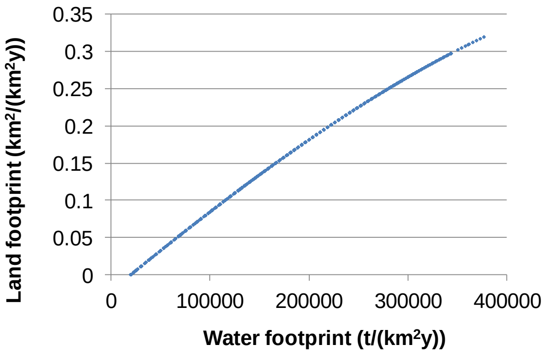

Figure 5: LF versus WF

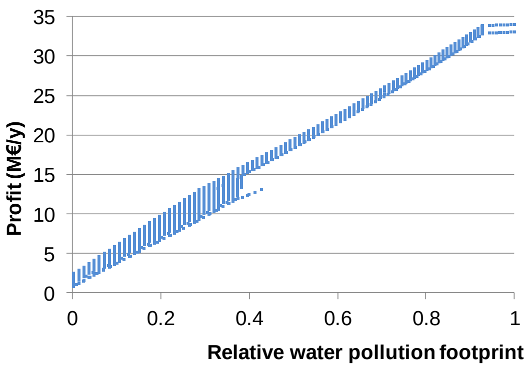

Figure 6: Profit versus relative WPF at changing CF

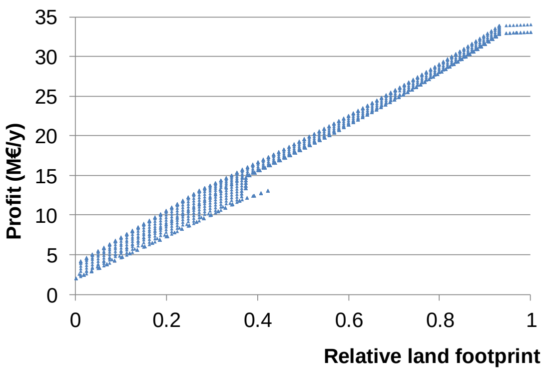

Figure 7: Profit versus relative LF at changing CF

4. Conclusions and future work

In the presented contribution, a methodology (principle and procedure) for identification of correlations among different objectives (footprints) has been introduced. Following this procedure, the dimensionality of the criteria set can be reduced significantly to a minimum of INDFs. The methodology was successfully applied to a demonstration case study of biomass energy supply chains where the dimensionality of footprints has been reduced from five to two.

For future work, the correlations from other footprints should also be investigated, such as nitrogen and phosphorus footprints, and the issue of biodiversity, measured by biodiversity footprints. In order to achieve more realistic solutions, also indirect (unburdening) effects should be included, therefore obtaining total effects (burdening and unburdening) (Čuček et al., 2012b).

The application to heat and power generation and distribution should also be pursued, as one of the problem areas of great impact on the environment and the economy.

Acknowledgement

The authors are grateful for the financial support from the EC FP7 project “Design Technologies for Multi-scale Innovation and Integration in Post-Combustion CO2 Capture: From Molecules to Unit Operations and Integrated Plants" – CAPSOL, Grant No. 282789, the Slovenian Research Agency (Program No. P2-0032 and PhD research fellowship contract No. 1000-08-310074) and from the Hungarian project Társadalmi Megújulás Operatív Program (TÁMOP) ‘Tudományos képzés műhelyeinek támogatása’ TÁMOP-4.2.2/B-10/1-2010-0025.

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