A methodology for assessing eco-efficiency in logistics networks

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Abstract

Recent literature on sustainable logistics networks points to two important questions: (i) How to spot the preferred solution(s) balancing environmental and business concerns? (ii) How to improve the understanding of the trade-offs between these two dimensions? We posit that a visual exploration of the efficient frontier and trade-offs between profitability and environmental impacts are particularly suitable to answer these two questions. The visual representation of the efficient frontier, however, presents two challenges. The first is to obtain a good approximation for such frontier without enumerating all extreme efficient solutions. The second is to obtain a good visual representation of the efficient frontier. We propose a two-phased heuristic to handle these two problems. The algorithm is designed for the multi-objective linear problem with three objectives: minimize costs, cumulative energy demand and waste in a reverse logistics network. We illustrate our approach by designing a complex recycling logistics network in Germany.

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1. Introduction

In the past years, consumers, companies and government have increased their attention towards the environment. In fact, our entire society is more aware of environmental damage caused by human actions due to increased exposure in the media on e.g. global warming and depletion of natural resources. Companies invest more in the assessment and reduction of the environmental impact of their products and services. IBM, for instance, promotes the take-back, recycling, refurbishing and re-use of its computers (Fleischmann et al., 2003). Governments have changed the “end-of-pipe” environmental laws to more comprehensive ones, broadening the responsibility of producers towards a “cradle-to-grave” perspective. The European Union, for instance, has approved the Waste Electrical and Electronic Equipment (WEEE) directive, making producers responsible for their end-of-life products.

Improvement in environmental quality does not come for free. The win-win solutions for business and the environment seem quite elusive in practice, in particular for considerable reductions in environmental impacts (Walley and Whitehead, 1994). The popular saying “there is no such a thing as a free lunch” could not be more true in this case. In the sphere of the “no free lunch” paradigm, some questions should be posed: How much do we have to spend in order to improve environmental quality? Or in more scientific terms, which trade-offs occur between the environmental impacts of an economic activity and its costs? And, what are “best” solutions balancing ecological and economic concerns? (Quariguasi Frota Neto et al., 2007).

In the normative and qualitative field, these questions have led to the concept of trade-offs and efficient frontiers for business and the environment (Huppes and Ishikawa, 2005; Bloemhof-Ruwaard et al., 2004). The rationale is to determine the set of solutions in which it is not possible to decrease environmental damage, or increase total environmental quality of each environmental category, unless increasing costs. These solutions are called eco-efficient.

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The idea of exploring the best alternatives is based on Pareto Optimality. The Pareto-optimal (efficient) frontier, or non-dominated frontier, is composed by the set of the images of all efficient solutions in relation to the objectives: optimize economical and environmental goals. Fig. 1 illustrates the efficient frontier and the trade-offs. The axes represent the indices of the economic value and the environmental quality of an economic activity. The curve represents the efficient frontier, where one cannot decrease either the environmental pressure without decreasing the economic value added (Kuosmanen and Kortelainen, 2005). The area below the curve is eco–eco inefficient: it is feasible to increase economic value without restricting environmental quality or the other way round. We assume that the actual situation represents an inefficient solution. This solution can be improved by moving to the efficient frontier. As each point on the efficient frontier is Pareto-optimal, it is up to the decision maker which improvement path is preferable. Increasing environmental quality without losing economic value means moving to the right, increasing economic value without losing environmental quality means moving up. The trade-off line is chosen by society.

From a methodological perspective, determining such an efficient frontier or assessing the trade-offs in logistic networks is quite new, despite the extensive existing literature in the field of multi-objective programming (MOP). We intend to bridge this gap by an methodology that is sounded to capitalize one of the decision maker’s most
effective cognitive capabilities: visual representation. In order to explore the efficient frontier in feasible CPU-time (for the intractability of finding all extreme efficient solutions see Steuer (1994) and Steuer and Piercy (2005)) and to present a good visual representation of the frontier, we develop a very simple two-phase heuristic. In the first phase, the algorithm determines, for a number of network configurations with same cost, efficient points of the bi-objective frontier regarding Cumulative Energy Demand (CED) and waste. The heuristic tries to obtain equally dispersed points within the frontier. The first phase belongs to the class of methods in Multiple Criteria Decision Making (MCDM) called $\epsilon$-constraint methods. In the second phase, the user selects his preferred solution from the ones provided by phase one. The algorithm then projects this solution into the efficient frontier of the problem with three objectives. The proposed approach can be used by companies to redesign their supply chains in order to balance their environmental footprint and life cycle costs of their products. This approach can also be used by governments to evaluate the effectiveness of environmental regulations.

The paper is organized as follows: Section 2 briefly reviews the main methodologies used to calculate eco-efficiency. Section 3 presents our methodology, the eco-topology. We focus on the users’ interaction in our approach, although the computational results are at least as interesting. Section 4 highlights the comparison between the existing methods and the one we propose. We clearly show the advantages of the latter. In Section 5 we illustrate our method, applying it to the reverse logistics network of end-of-life Electrical and Electronic Equipment in Germany. Section 6 presents the conclusions.

2. A brief literature review on eco-efficiency

The idea of a “frontier” for eco-efficiency was first presented by Huppes and Ishikawa (2005). They also proposed the concept of an eco-frontier with the “optimum” or preferred solution defined by society. Independently, Quariguasi Frota Neto et al. (2007) presented a methodology to assess this frontier and the trade-offs between costs and a single environmental impact factor. This is, as far as we know, the first approach to quantitatively assess the trade-offs between business and the environment, as well as to explore the efficient frontier. The paper of Bloemhof-Ruwaard et al. (2004) advocates the same approach: provide the decision maker with parts or the complete Pareto efficient frontier for economic and environmental objectives.

To the best of our knowledge, no other formulation explores the trade-offs between environment and business, as well as the efficient frontier that determines these trade-offs. One stream of research presents a single ratio for eco-efficiency, the single ratio methods. Hellweg et al. (2005) propose a method based on the differences in associated costs divided by environmental impact indices for different projects. The methodology is only suitable for a discrete number of possible solutions. Scholz and Wick (2005) propose a similar approach, also based on ratios. They calculate operational eco-efficiency as the improvement of economic utility divided by the improvement in environmental utility. The project under consideration is compared to the business-as-usual alternative. Kuosmanen and Kortelainen (2005) define eco-efficiency as the ratio of total value added and a damage function, aggregating environmental pressures into a single damage score. Kobayashi et al. (2005) uses Data Envelopment Analysis (DEA) to provide a single measure based on the radial projection of the decision making units (DMUs). These methodologies share two common characteristics. First, they provide a single efficiency measure and implicitly assume the solution with the best ratio is preferred. Second, they are applied to a discrete and small set of possible solutions, mainly to the selection of projects or technologies, whereas most combinatorial optimization problems have many variables and millions of possible solutions. Fig. 2 portrays the Single Ratio Methodology. Note that the alternative black dots, i.e. representing different projects or technologies, serve as inputs for the model. The frontier itself does not map a real solution in this case.

Krikke et al. (2003) provide three efficiency measures to describe eco-efficiency, i.e. costs, energy use and waste. They use weights to explore the efficient solutions in terms of the environment and business. They rely on the assumption that a weighting process captures the preferred solution for business and the environment. Fig. 3 illustrates such a procedure, which in the DEA stream of research, is called Preference Structure Methodology (Zhu, 1996). In the MOP field of research, it is called the weight-sum method. Note that in the case of weight-sum methods, the black dots are supported efficient solutions of the proposed model (for the definition of supported solutions see Ehrgott and Gandibleux (2000)). For the Preference Structure Methodology, the black dots are DMUs. Changing the weights in order to explore the efficient frontier may
lead to an unbalanced exploration, with some regions being well explored while others are left completely untouched. The disadvantages of using weights to select the preferable efficient solution is extensively documented in the MCDM literature. The early seminal works in the field have already documented such disadvantages (Steuer and Choo, 1983; Zions and Wallenius, 1976; Zeleny, 1973).

The two methods do not address the exploration of the efficient frontier or the respective calculation of trade-offs. The assumptions for decision making are that the eco-efficient ratio or the weighting procedure captures the preferred solution(s).

A third methodology is proposed by Quariguasi Frota Neto et al. (2007) using multi-objective programming. The formulation is equivalent to the Preference Structure Method, as it provides the same subset of solutions. For problems with a single environmental impact index, (thus bi-objective; cost optimization and environmental optimization), it also provides alternative solutions, based on the convex combination of the extreme efficient points. Furthermore, this approach gives a visual representation of the trade-offs in the bi-objective case. The approach is, however, impractical for problems with thousands of variables, as the number of solutions exponentially increases with the size of the problem. Fig. 4 illustrates the results of such approach.

3. Exploring eco-efficient solutions, the concept of eco-topology

Quariguasi Frota Neto et al. (2007) describe the first approach to define the theoretical frontier of Huppes and Ishikawa (2005). A cradle-to-grave approach is used to determine the eco-efficient frontier regarding business and the environment for the design of sustainable logistics networks. In this paper, the diverse phases of a product: raw material extraction, manufacturing, transportation, use and end-of-use alternatives are accounted to determine the optimal solutions. In order to assess the trade-offs and determine the optimal configurations, multi-objective programming is used. A multi-objective programming is denoted by (Steuer and Piercy, 2005):

$$\max \{ c_1 x = z_1 \}
\cdots
\max \{ c_k x = z_k \}
\text{s.t.} \{ x \in \mathbb{R}^n | a x \leq b, b \in \mathbb{R}^m, x \geq 0 \},$$

where $k$ is the number of objectives. A solution $x \in S \subset \mathbb{R}^n$ is efficient if and only if there is no $x \in S$ such that $c^T x \geq c^T x$ and there is at least one $c^T x < c^T x$. The efficient solution set is the set of all efficient solutions. The image of such efficient set is referred as the set of efficient points or efficient frontier.

In our formulation (see Section 5), $c_1 x$ represents total profit of a certain configuration, $c_2 x$ the cumulative energy demand, $c_k x$ the respective waste land-filled. The coefficients of the second and third objective function are obtained via Life Cycle Analysis (LCA), a standard technique for evaluating environmental impacts.

Solving the MOLP problem, or finding every extreme efficient solution has two major drawbacks. The first concerns CPU-time. Steuer (1994), Steuer and Piercy (2005) and Papadimitrou and Yannakakis (2001) present computational difficulties in finding every extreme efficient solution. One way to overcome this problem is to interactively explore points on the frontier via weight-sum methodologies.\(^\dagger\) The drawback of such a formulation is well known in the MCDM literature: complete regions of the frontier may stay completely unexplored. This approach does not ensure the number of efficient solutions found or the distance between them. The second drawback regards the visualization and interpretation of results. Dividing the environmental impact to three or more sub-

\(^\dagger\) The equivalence between a weighted single objective LP and a multi-objective one defined in the same feasible polyhedron is a well known result in MOP. Let $\Lambda = \{ \lambda | \lambda \in \mathbb{R}^k, \sum_{i=1}^k \lambda_i = 1 \}$, $i = 1, \ldots, k$ and the LP problem be defined as the $\max_{x \in X} \sum_{i=1}^k \lambda_i \cdot f_i (x)$ subjected to $x \in X$. Defining $X^*(\lambda)$ as the subset of $x \in X$ that maximizes the function $\lambda (x)$, we have that $U_{\lambda \geq 0} \lambda_1 x = X ' \subseteq \bigcup_{\lambda \geq 0} \lambda_1 x (\lambda)$ (see Zeleny, 1974).
categories would lead us to a frontier which, besides being very difficult to completely define, is not easy to visualize.

Another way to overcome the intractability of finding all extreme efficient solutions is to look for approximations of the frontier. For the bi-objective problem, Bernd et al. (2001), Liu et al. (1999), Fruhwirth et al. (1989) proposes approximations for the non-dominated frontier. To the best of our knowledge, no approximation has been proposed for non-dominated frontier of higher dimensions.

In order to overcome two aforementioned problems, CPU-time intractability and visual representation, we propose a very simple heuristic to explore the non-dominated efficient frontier. We call this method eco-topology. In the first phase of the model, we generate a number of non-dominated frontiers for the bi-objective problem regarding the minimization of CED and waste. We call them iso-pre-tium curves. In the second phase, the user defines his preferred target without the use of interactive processes or constraints. The second phase can be classified as a weight-setting. The algorithm performs in polynomial time. It is easy to see, however, that the number of points on the frontier that are explored, and therefore the better the representation of the frontier, the higher the number of points on the frontier that are explored, and therefore the better the representation of the frontier.

3. For $j = 1$ to $\frac{1}{3}$ do
   3.1. $\hat{z}_2 = \min\{z_2|z_1 = \hat{z}_1 \land z_2 = \hat{z}_2\}$, $\hat{z}_3 = \min\{z_3|z_1 = \hat{z}_1 \land z_2 = \hat{z}_2\}$.

4. Connect pairwise the $f \in F$ with the same profit
   5. end

where

- $z_1$ is the first objective function: marginal revenue of the network
- $z_2$ is the second objective function: cumulative energy demand,
- $z_3$ is the third objective function: land-filled waste,

$\epsilon$ is an auxiliary variable: the smaller this variable the higher the number of points on the frontier that are explored, and therefore the better the representation of the frontier.

$F$ is the set of solutions for our formulation. It is easy to see that at least one solution exists for each $\hat{z}_1 = \{\min z_1|z_1 = \hat{z}_1 \land z_2 \leq \hat{z}_2\}$, and that this solution is Pareto-Optimal for the bi-objective case. We first proof the following lemmas:

**Lemma 3.1.** If $\max\{z_1\}$, $\min\{z_2\}$, $\min\{z_3\}, z_1 = 0$ exists, then $\hat{z}_1, \hat{z}_2, \hat{z}_2, \hat{z}_3$, exist.

**Proof.** Let $S \subset \mathbb{R}^n$ and $f : S \rightarrow \mathbb{R}^k$, it is a well know fact that if $S$ is convex and $f$ is linear, the image of $S$ under $f$ is also convex. It implies that $f : \mathbb{R}^k$ is also connected. Once $\max\{z_1\}$ is limited and $z_1 = 0$, any solution $\hat{z}_1 = \max\{z_1\} \cdot \epsilon$ exists for $0 \leq \epsilon \leq 1$. Once $\hat{z}_1$ and $\min\{z_2\}$ exist, $\hat{z}_2$ exists. The proof for $\hat{z}_3, \hat{z}_2, \hat{z}_3$ is analogous.

**Lemma 3.2.** If $\min\{z_2\}$ and $\min\{z_3\}$ exist, all efficient solutions of the original problem with the constraint $z_1 = \hat{z}_1$ are linear combinations of $(\hat{z}_1, \hat{z}_2, 0)$, $(\hat{z}_1, 0, \hat{z}_3)$, $(\hat{z}_1, \hat{z}_2, \hat{z}_3)$ and $(\hat{z}_1, \hat{z}_2, \hat{z}_3)$.

**Proof.** Any solution $(\hat{z}_1, \hat{z}_2, \hat{z}_3)$ given $\hat{z}_2 < \min\{z_2\}$ is unfeasible. The same rationale is valid for $z_1 < \min\{z_1\}$. All solutions $(\hat{z}_1, \hat{z}_2, \hat{z}_3)$ given $\hat{z}_2 > \hat{z}_2$ and $\hat{z}_3 \geq \hat{z}_3$ and $\hat{z}_2 \geq \hat{z}_2 \land \hat{z}_3 \geq \hat{z}_3$ are non-Pareto-optimal. The same rationale is valid for $\hat{z}_1 \land \hat{z}_2 \land \hat{z}_3 \geq \hat{z}_2$ and $\hat{z}_3 \geq \hat{z}_3 \land \hat{z}_2 \geq \hat{z}_2$. The remaining solutions are enclosed in a square with vertices $(\hat{z}_1, \hat{z}_2, 0)$, $(\hat{z}_1, 0, \hat{z}_3)$, $(\hat{z}_1, \hat{z}_2, \hat{z}_3)$ and $(\hat{z}_1, \hat{z}_2, \hat{z}_3)$.

Directly from Lemma 3.1, we can always find a solution $f = (\max\{z_1\} \cdot \epsilon, i, z_i(z_i))$. If $\min\{z_2\}$ and $\min\{z_3\}$ are bounded, there is a solution for $\hat{z}_2$ and $\hat{z}_3$. Using Lemma 3.2, and the fact that all extreme efficient solutions are con-
connected \((\hat{z}_1, \hat{z}_2, \hat{z}_3)\) and \((\hat{z}_1, \hat{z}_2, \hat{z}_3)\) are also Pareto-optimal, there is a path from \(\hat{z}_2\) to \(\hat{z}_1\) that can be expressed as the linear combination of \((\hat{z}_1, \hat{z}_2, 0)\), \((\hat{z}_1, 0, \hat{z}_3)\), \((\hat{z}_1, \hat{z}_2, \hat{z}_3)\) and \((\hat{z}_1, \hat{z}_2, \hat{z}_3)\). Therefore for any \(\hat{z}_2 = \hat{z}_2 + (\hat{z}_2 - \hat{z}_2) \cdot \epsilon \cdot j\) there will be one and only one Pareto-optimal point (not necessarily a vertex) \((\hat{z}_1, \hat{z}_2, \hat{z}_3)\). Once \(\hat{z}_1\) and \(\hat{z}_2\) are constants, this point is \(\hat{z}_3 = \{\min z_3 | z_1 = \hat{z}_1 \land z_2 = \hat{z}_2\}\).

The problem with the added constraint is an \(\epsilon\)-constraint method, with the particularity that for the respective LP, feasibility is guaranteed. Ehrigott and Gandibleux (2000) proves that for any closed solution space, the solution for the \(\epsilon\)-constraint, if existent, is at least weakly efficient. For the bicriteria linear problem, it is easy to see that the solutions generated in the inner loop of the heuristic are Pareto-optimal, however not necessarily extreme. The Fig. 5 illustrates the first phase of the algorithm.

The solutions \(F\) are not necessarily Pareto-optimal with respect to the original MOLP, due the constraint \(z_1 = \hat{z}_1\), but they are Pareto-optimal for the original problem plus constraint \(z_1 = \hat{z}_1\). In our case study (Section 5) we test efficiency “a posteriori”. The next phase of our procedure works as follows. First, the user differentiate, in the graphical representation, the Pareto-optimal from the non-Pareto-optimal solutions. This process could be also performed “a priori”, cleaning the solutions that are dominated by some other solution in the graph. We believe, however, that leaving such solutions gives the decision maker a better “intuition” of the topology of feasible solutions. Second, the user decides on his preferred solution. Third, an algorithm finds an efficient solution by, in this order, increasing profitability and decreasing CED and generated waste. The procedure of the aforementioned algorithm works as follows:

1. Normalize the objective functions.
2. With the preferred solution \((\hat{z}_1', \hat{z}_2', \hat{z}_3')\) \(\max \{\lambda_1 \cdot z_1 + \lambda_2 \cdot [z_2 + z_3]\}\) s.t. \(Ax \leq b, z_1 \geq \hat{z}_1', z_2 \leq \hat{z}_2', z_3 \leq \hat{z}_3'\) and \(\lambda_1 \gg \lambda_2, \lambda_3\).

It is easy to see that the final solutions is Pareto-optimal.

4. Comparison between eco-topology and the existing methods

We compare the eco-topology methodology with the three methodologies presented in Section 2: (1) the single ratio methods, (2) the Preference Structure methods based on weighting and (3) the multi-objective methods based on the complete exploration of the extreme efficient vertices. We also draw parallels between the different methodologies.

The single ratio methodology proposes a single efficiency measure to select one solution out of a set of solutions, according to the highest Economic value Environmental pressure ratio. The main drawbacks of such formulation are:

- It is not possible to differentiate between different environmental impacts or to add new variables to the model, such as social aspects or performance levels.
- It does not give any information on the theoretical trade-offs between the dimensions of analysis (in our case business and planet).
- The decision maker has no flexibility to choose targets according to his preferred solution. A high rate could, for example, be possible only via a cheap and environmentally unfriendly process; or alternatively, an extremely environmentally friendly process with extremely high costs. Both could be undesirable, if not unrealistic.

In mathematical terms, the ratio procedure is nothing but a DEA model with two variables and constant returns of scale. It can only be applied to a discrete set of alternatives. The eco-topology approach allows the decision maker to freely decide on the best trade-offs or location on the optimal frontier. It also allows an increment on the number of objectives, allowing discrimination between the different environmental pressure classes and the insertion of new variables, such as performance levels. The trade-offs between those variables can be determined and easily visualized via the iso-premium curves. In the case of discrete solutions, the model should be adjusted for DEA formulations.

The Preference Structure Methodology, partial exploration, is equivalent to an interactive version of the eco-curves. It is a heuristic approach as it provides a subset of solutions. First, it only explores the efficient vertices, not the corresponding hyperplanes. Second, it is not possible to ensure that all extreme points are explored. The number of alternatives is then diminished. The weighting procedure is another drawback, since the weights may not correspond to their implicit importance. A weight of
70% for the environment does not necessarily mean a solution which takes the environment for 70% into account, contrary to common belief. Furthermore, it is also not possible to determine any trade-off between different dimensions.

The multi-objective methodology is the one most closely related to the concept of eco-topology. Here, the objective is to completely explore the set of all efficient extreme solutions. This formulation gives the DM a set (in worst case with exponential size) of efficient solutions. In this case flexibility is given to the decision maker to decide between a given number of alternatives. There is one serious drawback: it cannot be applied to big instances. An increase in the number of variables, therefore, may turn the problem unsolvable from a CPU-time perspective. The eco-topology is runs in polynomial time, at least within a constant number of objective functions. The main drawback of the proposed method is the computational complexity as compared to the Preference Structure Methodology.

The models referred and presented in this paper, however, clearly do not exhausted the application of MCDM methodologies in the field of eco-efficiency. Literature in this stream of research is extremely rich, and a number of other methods are suitable for the exploration of the eco-efficient frontier. So far we have not mentioned, for instance, a number of articulated approaches. In the articulated methods the Decision Maker interacts with the model until he finds a satisfying solution. An example of such approach is the Pareto Race, or STEM, which promotes a “walk” on the facets of the frontier (Korhonen et al., 2003). The Pareto Race enables a decision maker to freely search any part of the efficient frontier by controlling the speed and direction of motion. The values of the objective functions are presented during the Race as bar graphs on a display. For discrete problems, multi-attribute methods may also be used. We have found no literature on the application of articulated methods for eco-efficiency analysis, but it seems to be another fruitful area of research.

Table 1 describes the different types of methodologies, their applicability, main advantages and limitations.

5. The German waste electrical and electronic (WEEE) case

In the following, the algorithm described in Section 3 is applied to a real-world case study regarding the implementation of the Directive for recycling waste electrical and electronic equipment (WEEE-directive). It is the aim of this part of the paper to show the applicability of the eco-topology method, and to demonstrate how the method helps in the decision making process by visualization of efficient alternatives and calculation of trade-offs.

5.1. Description of the problem

According to the European Commission, the amount of waste electrical and electronic equipment (WEEE) is growing rapidly. Since WEEE contains hazardous as well as valuable substances, it must be treated properly. The directive of the European Parliament and the European Council on waste electrical and electronic equipment (WEEE-directive, 2003) is aiming at prevention, re-use, material recycling and energy recovery of WEEE. The overall goals of the directive are to reduce the amount of waste that is disposed of, and to improve the environmental performance of all processes along the life cycle of electrical and electronic equipment. As a result of the directive, recycling systems have to be implemented in countries with a poorly developed recycling infrastructure like in Spain or the East European countries. However, in other countries like Germany or The Netherlands, there already exists an adequate infrastructure, and the main question is how to allocate WEEE using the given infrastructure. In the following, we will focus on the latter case, and show how to support decision makers like politicians, recyclers, and manufacturers of electronic products by calculating efficient solutions and trade-offs for optimal operation of a given recycling system. In order to determine the efficient frontier aiming at economic as well as ecological objectives, we apply the algorithm presented in chapter 3. The algorithm is applied based on a model describing all the material flows and processes possible within the given infrastructure, which is presented in the following. As material flows and processes within the reverse logistics network system, various tasks like acquisition and collection, transportation, sorting, disassembly, re-use, recycling and recovery of products, as well as storage and selling of material fractions are conducted as is presented in Fig. 6. As can be seen, discarded electronic products are first transported from collection points to treatment companies. There, products are disassembled, i.e. harmful substances are removed, and valuable materials as well as re-usable spare parts are gained.

<table>
<thead>
<tr>
<th>ID</th>
<th>Family</th>
<th>Papers</th>
<th>Trade-off?</th>
<th>Flex.?</th>
<th>C. Class?</th>
<th>Visual Trade-off?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Single ratio</td>
<td>Kuosmanen and Kortelainen (2005) Hellweg et al. (2005)</td>
<td>NO</td>
<td>NO</td>
<td>–</td>
<td>NO</td>
</tr>
<tr>
<td>2</td>
<td>Weighting LP</td>
<td>Bloemhof-Ruwaard et al. (2004)</td>
<td>NO</td>
<td>YES</td>
<td>P</td>
<td>NO</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Krikke et al. (2003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Multi-objective</td>
<td>Quariguasi Frota Neto et al. (2007)</td>
<td>YES/NO</td>
<td>YES</td>
<td>NP-hard</td>
<td>YES/NO</td>
</tr>
<tr>
<td>4</td>
<td>Eco-topology</td>
<td>–</td>
<td>YES</td>
<td>YES</td>
<td>P</td>
<td>YES</td>
</tr>
</tbody>
</table>
Different disassembly depths as well as mechanical processing activities can be applied. After treatment, tradable material fractions of defined quality are sold or are disposed of. Metal fractions are supplied to metal or steel works for material recycling, plastics are either utilized for energy recovery or land-filled.

According to the WEEE-directive, all electronic products coming back from the end-user have to be treated properly. Thus, this WEEE amount is given as fixed input to be treated by the system. However, there are many decisions that are to be decided on with regard to how to treat these products. Decisions to be made when implementing the WEEE-directive within an existing infrastructure are:

- Masses of product type $i$ transported from source $q$ to treatment company $u$ ($y_{iqu}$), and between treatment companies ($y_{imu}$).
- Number of treatment activities $j$ to be applied, i.e. how often is a certain disassembly depth or mechanical processing activity chosen ($x_{ju}$).
- Masses of material fraction $i$ generated depending on the treatment activities, and recovery or disposal site $r$, these fractions are transported to $y_{iru}$ depending on current market prices.

Based on all material flows possible within a given infrastructure, the target is to select the best allocation out of all possibilities. To be able to do so, objectives are to be known. Often, companies as well as politicians are aiming at the most efficient economic solution. In such a case, the contribution margin is to be maximized as result of all product and recycling revenues minus variable disassembly, transportation, and sorting costs (see (1)). For this single objective problem, the model and results are described in Walther and Spengler (2005).

However, if the environmental aims of the WEEE-directive are to be taken into account, more than one objective function is to be regarded. The WEEE-directive is aiming at two different environmental aims: reduction of ecological impacts on the one hand, and resource protection respective waste minimization on the other hand.

In the following, the Cumulative Energy Demand (CED) is chosen as aggregated screening indicator for ecological impacts. CED represents the primary energy used over the life cycle of a good or for a certain process (VDI4600, 1997), and has shown good correlations to different ecological impact categories, e.g. global warming potential (Huijbregts et al., 2005). For our example, CED is calculated for transportation processes by multiplying total masses to be transported ($y_{iqu}$, $y_{iru}$, $y_{imu}$) with distance and mode specific CED-coefficients for transportation processes ($ced_{iqu}$, $ced_{imu}$, $ced_{iru}$). For treatment processes, the number of activities ($x_{ju}$) is multiplied with activity specific CED-coefficients (e.g. energy used per disassembly activity). For calculation of the CED-coefficients, we used on the one hand generic data of data bases like SimaPro (CED for transportation processes, energy production based on a national energy mix), and on the other hand specific data determined by empirical analyses (e.g. specific energy demand of a shredder). The equation for calculation of CED is given in (2). Another goal of the WEEE-directive is to minimize waste. Thus, the total amount of waste (i.e. materials that are sent to landfills and incinerators) is to be minimized. This amount is calculated as total input masses entering the treatment system ($y_{iqs}$) minus total output masses that are recycled. Recycled masses are calculated multiplying total output masses with recycling coefficients. These recycling coefficients have values between 0 and 1, and determine the part of a material fraction that is assumed to be recycled. Coefficients are determined at national level, and depend on quality of the material fraction.
i as well as on the facility type r this fraction is sent to (oekopol, 2004). The equation for waste minimization is given in (3).

\[
\begin{align*}
\max U & \{ \sum_{i=1}^{n} \left( \sum_{q=1}^{Q} \left( e_{iq}^{O} - e_{iq}^{U} \right) \times y_{iq}^{O} \right) + \sum_{u=1}^{U} \left( \sum_{j=1}^{J} \left( c^{e} \cdot x_{ju} \right) \times y_{iu}^{U} \right) \} \\
& + \sum_{q=1}^{Q} \left( \sum_{j=1}^{J} \left( c^{e} \cdot x_{ju} \right) \times y_{iq}^{Q} \right) - \sum_{j=1}^{J} x_{ju} \times c_{ju}^{2} \} \\
\min U & \{ \sum_{i=1}^{n} \left( \sum_{q=1}^{Q} \left( c^{e} \cdot x_{ju} \right) \times y_{iq}^{Q} \right) + \sum_{u=1}^{U} \left( \sum_{j=1}^{J} \left( c^{e} \cdot x_{ju} \right) \times y_{iu}^{U} \right) \} \\
& + \sum_{q=1}^{Q} \left( \sum_{j=1}^{J} \left( c^{e} \cdot x_{ju} \right) \times y_{iq}^{Q} \right) - \sum_{j=1}^{J} x_{ju} \times c_{ju}^{2} \} \\
& \leq 0
\end{align*}
\]

These objectives are to be followed taking certain restrictions of the recycling system into account. First, material balances are set up for every single disassembly company of the network. The output of a treatment company \(y_{iu}^{Q}\) is given by the net result of all inputs of appliances from sources outside the network \(y_{iq}^{Q}\), the input of appliances and material fractions from other treatment companies \(y_{iuu}\), and the transformation of masses related to treatment. Latter is expressed as the number of executions of a treatment activity \(x_{ju}\) multiplied with an input–output-coefficient \(v_{ju}\) specifying the input–output-relationships of products and material fractions \(i\) of this activity \(j\).

\[
\begin{align*}
\sum_{j} x_{ju} \times v_{ij} + \sum_{q=1}^{Q} y_{iq}^{Q} + \sum_{u=1}^{U} y_{iuu}^{U} = y_{iu}^{D}, \\
i = 1, \ldots, I; \ u = 1, \ldots, U
\end{align*}
\]

According to (5) the output of a treatment company \(y_{iu}^{D}\) is either delivered to recovery companies or disposal sites \(y_{iu}^{R}\) or to other (specialized) treatment companies \(y_{iuu}\).

\[
\begin{align*}
y_{iu}^{D} & = \sum_{u=1}^{U} y_{iuu}^{U} + \sum_{r=1}^{R} y_{iuu}^{R}, \ i = 1, \ldots, I; \\
u = 1, \ldots, U
\end{align*}
\]

In addition to these material balances, different external and internal restrictions exist. All products available at sources must be accepted and properly treated (6). Additionally, restrictions exist regarding treatment capacities at companies (7), which are described in maximal costs the company is able to spent because of capacity restrictions. For example, the number of employees (or working stations) available at one company times the costs for one worker for one month determines the capacity (given in costs) that is available for manual recycling. This description is chosen, since capacity depends on durability of activities performed. Additionally, capacities at recovery and disposal sites are to be regarded (8).

\[
\begin{align*}
\sum_{u=1}^{U} y_{iu}^{Q} & = y_{iu}^{Q_{\text{MAX}}} , \ i = 1, \ldots, I; \ q = 1, \ldots, Q \\
\sum_{j=1}^{J} \sum_{u=1}^{U} c_{ju}^{e} \times x_{ju} & \leq C_{u}^{Q_{\text{MAX}}} \\
\sum_{j=1}^{J} \sum_{u=1}^{U} y_{iuu}^{U} & \leq y_{iuu}^{U_{\text{MAX}}} , \ i = 1, \ldots, I , \ r = 1, \ldots, R
\end{align*}
\]

Additionally, the non-negativity constraints are set (9)

\[
\begin{align*}
y_{iuu}^{Q}, y_{iuu}^{U}, y_{iuu}^{R}, y_{iu}^{D} & \geq 0
\end{align*}
\]

5.2. Application of the algorithm

In the following, the algorithm of Section 3 is applied to the WEEE case study. With regard to the given objectives, it is the overall aim to calculate the optimal allocation and treatment processes within a given infrastructure with regard to the requirements of the WEEE-directive following economic as well as ecological goals. Since we want to calculate efficient allocations based on decisions about masses (kg), the solution space is continuous. As stated in Section 3, it is not our intention to determine one preferred solution (as would be done by a-priory weighting of the different goals of the decision makers), but to visualize all efficient solutions and trade-offs between the different goals. Since we have three objectives, it is a three-dimensional efficient frontier, but we want to present it as two-dimensional trade-offs on iso-pretum curves (thus, keeping the contribution margin constant for every curve). Based on the visualization of the efficient frontier and the trade-offs, a discussion process can start which of the solutions to chose (subjective part). We do not want to replace this discussion, but rather help in the decision making process by an presentation and visualization of all alternatives and trade-offs to the decision makers (objective part). The application of the algorithm is done for a sample region, the federal state of Lower Saxony in Germany. Actors, activities and material flows were determined within an empirical study. As a result of this analysis, 47 public waste collection points, 46 disassembly and mechanical processing companies, and 56 recycling and disposal sites with their location, specialization as well as treatment capacities were determined. Since electronic products are very heterogeneous, seven reference products resembling the average of several products were defined according to product similarities based on empirical data. Four to six disassembly depths and mechanical processing activities with corresponding quality and quantity of materials fractions were determined for every reference product. The resulting optimization problem consists of approximately
71,000 linear variables and 11,000 constraints. For the one objective case, the problem can be solved using common solution procedures for linear optimization problems in few seconds.

When applying the algorithm the profit (objective 1) is first maximized ignoring all other objectives. In the WEEE case, the maximum attainable profit is 1.1 Mio €/y if CED and waste are not taken into account. This solution would be the result of a single (economic) objective optimization model, and would be chosen by a decision maker following purely economic targets. A certain number of iso-pretium curves is then calculated by multiplying the maximum profit with coefficients for all . Thus, each iso-pretium is representing a certain fraction of the maximum profit. In the WEEE case, 10 iso-pretium curves are calculated ( ), which means that the lowest profit iso-pretium curve (110,000 €/y) is representing 1/10th of maximum profit. For each of these ten fractions of the maximum profit, CED (objective 2) as well as waste (objective 3) are minimized separately. Doing so, the solution space is limited since infeasible solutions (i.e. all results representing less than the minimum attainable CED and waste) can be eliminated for each iso-pretium curve. In the WEEE case for example, it is not possible to reach less than 5700 GJ/y CED and 2380 t/y waste if a profit of 220,000 €/y is at least aimed at. Thus, if at least 220,000 €/y must be reached, the given input amount of WEEE that is collected cannot be processed generating less than 5700 GJ/y CED and 2380 t/y waste. Keeping the profit as well as the minimal attainable CED unaltered, the minimal waste is now calculated. For a profit of 220,000 €/y and 5700 GJ/y of CED this results in 5830 t/y of waste. The same is done keeping the objective value of the profit as well as the minimal waste unchanged, which is for the example a profit of 220,000 €/y and waste of 2380 t/y resulting in 8940 GJ/y of CED. Note that there is a trade-off between CED and waste minimization in the WEEE case. Therefore, the minimization of CED and the minimization of waste each lead to maximum values for the other objective for a given profit. Applying these calculations, the solution space is bounded, and the starting and ending points of the iso-pretium curve are now known. Thus, the curve connecting these two points can be calculated. This is done by slowly raising the CED by a certain fraction for all and each time calculating the minimized waste for this combination of maximized profit/minimized CED until the maximum CED (and thus in the WEEE case the minimum waste) is reached for this iso-pretium. The results are stored, and the algorithm is repeated by slowly raising the profit objective by 110,000 €/y (maximum profit) until the maximum profit is reached. Fig. 7 illustrate the search for a 220,000 €/y iso-pretium.

5.3. Results

Results are shown within Fig. 7. In this figure, direct trade-offs between CED and waste are given on every iso-pretium curve. However, trade-offs between profit and CED (respectively profit and waste) can also be deduced when changing from one iso-pretium curve to another if the other ecological impact is kept constant. For our case study, the solution space is continuous. Thus, every point on the iso-pretium curve belongs to one or several solutions with a certain characteristic of decision variables. For instance, to a certain combination of CED, waste and profit belongs a certain amount of products that is delivered from collection point to treatment company , where a certain number of disassembly activities is applied and as result certain material fractions are generated that are then sent to recycling facility . Since there are millions of possible (and even efficient) solutions, we will not focus on the solution itself, but rather on the efficient frontier and the trade-offs. A more sophisticated analysis of different solutions is given in (2005).

The results of the iso-pretium curves are represented in Fig. 8. The curve ending on the right of the others represents the iso-pretium for a profit of 90% of the maximum profit, or 990,000 €/y. The one ending on the left of all other represents the iso-curve for a profit of 20% the maximum profit, 220,000 €/y. The curves in between represent, respectively 30%, 40%, 50%, 60%, 70% and 80% of the maximum profit. The maximum profit (100%) has a single point (5488 t/y and 5892 GJ/y).

Looking at the iso-pretium curves, it can be observed that decreasing landfill is only possible via increasing in the CED. Our results show that there is very little room for trade-off between the two environmental indicators, and the profit of the reverse supply chain. In other words, selecting less profitable supply chains do not render improvements in both environmental indicators. The reason seems to be the energy spent with transportation: the electrical and electronic equipment being diverted from
landfill to other end-of-use alternatives (i.e. recycling) results in higher transportation efforts. Two facts help to explain this phenomena. First, the fact that landfills are usually more abundant than recycling facilities, and therefore, in average close to the consumer centers helps to explain the inverse correlation of transportation (and therefore CED) and amount of end-of-life electronic ending at landfills. As land-filled waste decreases, therefore, CED increases. Second, the level of reduction on land-filling due to other end-of-life activities (i.e. recycling) are different for the different end-of-life facilities. In order to get a higher recycling percentage the equipment may have to travel longer distances.

Another interesting result is that the reduction in waste due to an unitary increase in CED rapidly deteriorates with the increase in CED. This particular result holds for all iso-pretium curves. At a 220,000 Mio €/y profit, and a CED of 5700 GJ/y, an increase of one MJ reduces 6.11 kg of waste land-filled. For the same unitary reduction, and a CED of 8770 GJ/y, the reduction is only 0.08 kg. In order to get a higher recycling percentage the equipment may have to travel longer distances.

Looking at the results for shadow price of CED, one can note that they rapidly increase with the increase in profitability. From iso-pretium with profit of 330,000 €/y to iso-pretium with profit of 220,000 €/y at a 8620 GJ/y CED, the unitary reduction costs 0.12 €/MJ. The same reduction from iso-pretium with profit of 880,000 €/y to 770,000 €/y results in unitary cost of 0.46 €/MJ for a 6710 GJ/y CED. Both results seem quite high compared to normal take-back prices. A 12 kg computer would cost between 12 € to 20 €.

Comparing these different iso-pretium curves, one can infer that minimizing land-filled waste can only be achieved

![Fig. 8. Eco-efficient frontier. The pairs (a,b) are, respectively, the land-filled waste and CED. The number at the end of the lines are profit for the iso-pretiums.](image-url)
if a low profit is taken into account, or if transportation (and therefore CED) is increased. This is an interesting result with regard to the European WEEE-directive, which is aimed at minimizing the amount of EEE waste that is sent to landfill.

If the aforementioned transparency of trade-offs could be provided before legislative procedures start, political decision makers could gain a deeper insight into the impacts of legal measures. Non-intuitive results (e.g. increase in CED with a lower amount of land-filled waste) could be anticipated. Additionally, the level of effort necessary to fulfill new legal measures (e.g. high recycling costs necessary for minimizing the land-filled waste or high shadow prices for CED) could be shifted to other processes or other product life-cycle phases, where higher environmental gains could be achieved with the same monetary efforts.

The proposed model provides decision makers with an easy tool for selecting the preferred solution regarding business and environmental indicators. For the German WEEE case, the decision maker can visually inspect the solutions and point his preferred one, and the model will indicate a network with decisions regarding end-of-life destination (i.e. recycling, landfill) and respective allocations. Furthermore, the model provides the trade-offs between waste ending in landfills and CED for supply chains with same costs. It is also possible to calculate the costs for reducing CED and land-filled waste, for different levels of the environmental indicators. Those results are not available for the aforementioned models based on single efficiency measures or methods based on linear programming weighting.

6. Conclusions and outlook

In this paper we develop a methodology to explore Pareto-optimal solutions for business and the environment. Our methodology allows decision makers to assess their preferred solution via one of the decision makers’ most effective cognitive capabilities, visual inspection. Furthermore, the resulting iso-premium curves permit the assessment of the trade-offs among the environmental impact indicators and the profit of a given logistics network. In other words, the methodology helps to answer the questions: (i) How to determine the preferred solution(s) balancing environment and business? and (ii) what are the trade-offs between the aforementioned two dimensions? The emerging streams of research on eco-efficiency, namely, (1) methods based on single efficiency index, (2) methods based on weighting or (3) multi-objective methods based on the complete exploration of the extreme efficient vertices, do not provide satisfying solutions for the proposed questions. Furthermore, for the multi-objective methods, CPU-time grows fast with the size of the problem.

Identifying future research in this area is simultaneously an easy and a hard task. Easy because the methodologies available for MCDM and MOP have yet barely been applied for these specific problems. Methodologies such as Pareto Race and STEM have not yet been explored for the assessment of preferred solutions for business and the environment. Hard because it is not clear which existing methods will bring better results. Further research on the most relevant phases for improving eco-efficiency (i.e. in a logistics network, transportation, manufacturing, procurement, end-of-use) has to be carried out, as well as on the computational difficulties of the models.

References


