Chapter 4: TOWARDS OPTIMAL TRADE-OFFS BETWEEN MATERIAL AND ENERGY RECOVERY FOR GREEN WASTE

Abstract

Green waste, mainly consisting of fresh cuttings, grass and leaves collected from gardens and parks can be used as feedstock for composting or for energy recovery. The EU Waste Directive 2008/98/EC (EP&C, 2008) advocates composting to prevent waste. This directive allows green waste to be used for (renewable) energy valorisation only if a better overall environmental outcome can be demonstrated. The classical life cycle assessment (LCA) approach, in accordance with ISO 14040+44 (ISO, 2006), cannot be used by policy-makers to compare alternatives for the valorisation of green waste since the resulting products perform different functions. In this paper, we propose an alternative assessment procedure based on the Pareto front of optimal trade-off combinations of composting/energy recovery of green waste. The Pareto optimal front is determined by a multi-objective optimization problem that is solved using the 

elitist non-dominated sorting genetic algorithm 

version II (NSGA-II) and the 

ε-constraint method. 

Computational results based on publically available Belgian data show how the optimal valorisation of a batch of green waste is determined by its composition of fresh cuttings and leaves (‘brown mass’) and grass (‘green mass’). Only if no green mass is incinerated with energy recuperation does full allocation of green waste to either energy valorisation or to composting give optimal results. For the case under consideration, the user-friendly ε-constraint method produces the same results as the more complex NSGA-II algorithm. We finally demonstrate that the proposed assessment procedure is capable of supporting decision-makers in allocating green waste to composting and energy recovery in compliance with the EU Waste Directive 2008/98/EC (EP&C, 2008).

Keywords: Multiple Objective Modelling; green waste valorisation; material conservation; waste-to-energy; decision support tool

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1. Introduction

Green waste can be used as feedstock for composting or for renewable energy production. Two different EU Directives encourage both conflicting options. Composting green waste is regarded as waste prevention and is therefore promoted by the Waste Directive 2008/98/EC (EP&C, 2008). Green waste can also be entirely or partially used as feedstock for renewable energy, which favours compliance with EU Directive 2009/28/EC (EP&C, 2009) on the promotion of energy from renewable resources. This paper aims at assisting policy decision-makers in choosing the best overall environmental outcome.

The current version of the European Waste Directive 2008/98/EC (EP&C, 2008) advocates the original waste hierarchy ranking that recommends in decreasing order prevention over re-use, recycling or incineration with energy recuperation and incineration or landfill. It also states that EU Members States shall take measures to encourage the option that delivers the best overall environmental outcome. This may require specific waste streams departing from the waste hierarchy, if the overall impacts of the generation and management of such waste during its entire life cycle justify this.

EU Directive 2009/28/EC (EP&C, 2009) obliges EU Member states to cover at least 20% of energy needs from a renewable energy source (RES) by 2020. However, the current growth rate of renewable energy production is only about a third of what is expected in EU scenarios, which assume heat and power production from biomass to be around 850 TWh higher in 2020 than in 2007 (ECF, 2010). Several other resources such as use of agricultural or forest residues and planting of energy crops will therefore be needed.

It should however be noted that not all EU Member States are under the same pressure to comply with EU Directive 2009/28/EC. In particular, the Scandinavian EU Member States Sweden, Finland and Denmark (and Norway, which does not belong to the EU) have already met the 20% energy RES target. Other EU Member States such as Belgium and the Netherlands, which have been granted a reduction on the average target to respectively 13% and 14% of RES by 2020, currently fail to reach even these more limited goals (Eurostat, 2015). As a result, these countries are under growing pressure to valorise biomass for energy purposes. Energy valorisation of green waste would help them to meet the EU RES targets by 2020.

According to the EU Waste Directive, green waste may only be used for renewable energy valorisation if this is proven to be the best environmental outcome. The EU advocates life cycle thinking and assessment (LCA) to ensure the identification of the best environmental outcome (EC, 2015). An LCA approach (ISO 14040+44, 2006) is traditionally used to assess the environmental impact of products and services. However, ISO 14040+44 only permits comparative assertion\(^8\) of one product as compared with a competing product if both perform

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\(^8\) ISO 14040:2009-11 § 3.6: Comparative assertion: environmental claim regarding the superiority or equivalence of one product versus a competing product that performs the same function.
Consider for example the comparison of the packaging of a beer in a bottle made of aluminium or polyethylene terephthalate (PET). Both options perform the same function, which is to contain and protect the beverage (for more details see www.openica.org/documentation/index.php/Caste_study:_Beer_Bottle).
2. Literature review

According to Morrissey and Browne (2004), waste management models can be divided into three types: those based on cost benefit analysis, those based on life cycle analysis and those based on multi-criteria analysis. As discussed in the introduction, LCA cannot help policymakers to allocate green waste to composting or energy recovery, since the outcomes of these two processes are considered to be different products. Cost benefit analysis is not very suitable either because this method requires the monetization of environmental impacts, which is often the subject of discussion amongst stakeholders. Multi-criteria decision analysis can be seen as the technique with the least shortcomings for environmental policy decision-making, since policymakers and decision-makers spend most of their effort on the selection of the final decision and its implementation. Hence they need decision analysis tools such as multi-criteria decision analysis instead of environmental assessment tools such as LCA (Kiker et al., 2005).

This section starts with a brief introduction to green waste recovery since this will be used as a case study to illustrate the methodology presented in this paper. A discussion of LCA and its shortcomings follows. Since multiple-criteria decision-making is used to alleviate the shortcomings of LCA in comparing the environmental impact for the same product used for different functions, we conclude this section with a brief introduction to multi-objective optimization to accommodate readers with different environmental and mathematical backgrounds.

2.1. Green waste recovery

Green waste is a type of biomass consisting mainly of grass, leaves and fresh cuttings originated from gardens and parks. Biomass resources in general can be considered as organic matter, in which solar energy is stored in chemical bonds. When the bonds between adjacent carbon, hydrogen and oxygen molecules are broken by digestion, combustion or decomposition, the substances release their stored chemical energy. Biomass can be converted into three main types of products: electrical or heat energy, transport fuel or chemical feedstock (McKendry, 2002a). The optimal form of the energy conversion process depends primarily upon the biomass moisture content. High moisture content biomass, such as herbaceous plant sugarcane, lends itself to a “wet/aqueous” conversion process, involving biologically mediated reactions, such as fermentation, while “dry” biomass such as wood chips is more economically suited to gasification or combustion (McKendry, 2002a).

Since green waste consist partially of fresh grass clippings and leaves, which can be considered as having a high moisture content, and partially of wood and dry leaves, which has a high calorific value, multiple conversion technologies can be applied such as combustion, fermentation and anaerobic digestion. An overview of all the conversion technologies for energy production from biomass is presented in McKendry (2002b).
According to Grant (2003), green waste falls somewhere between food waste and timber waste in terms of its potential uses. It is a unique form of waste since it does not have a “product life cycle” as many products do. Green waste generation will vary depending on seasonal factors that affect growth rates and is suitable both for energy recovery and composting purposes.

The main options for green waste material/energy recovery are depicted in Figure 2. Green waste can be composted in the open air by what is known as an aerobic composting process, resulting in only compost. This is considered to be an environmentally friendly procedure as emissions to ground water during composting can be avoided by appropriately designed composting facilities. During the biodegradation of green waste, microorganisms produce nitrate via the nitrification chain. The emission of nitrous oxide cannot be avoided, but can be kept at a low level with sufficient aeration resulting in the lowest contribution to the global greenhouse effect (Hellebrand, 1998).

Partial removal of the wooden part of the green waste is however also possible; this fraction can then be used for co-firing in power plants. Use of biomass as feedstock for co-firing substantially reduces the CO₂ emission of power production and helps to reach the EU 2020 objectives on renewable energy for the Netherlands (Kwant, 2003). Use of the wooden part of the green waste in combined heat and power (CHP) installations yields both power and heat. An anaerobic digestion process can ferment the remaining part. The biogas that results from this process can be enriched to be added to natural gas and the digestate produced can be composted. Vegetable, fruit and garden (VFG) waste can also be processed in the same way. In many cases co-digesting of green waste with VFG waste can improve both the energy yield and the economic yield (Braber, 1995).

Composting and energy recovery from green waste both have their merits. On the one hand, green waste energy recovery can help to close the current gap in generating sufficient renewable energy sources in the EU. On the other hand, compost originating from green waste has a positive environmental impact on the soil and on the reduction of CO₂ emissions. Kranert et al. (2010) report that the valorisation of green waste by energy recovery or material recycling and peat replacement should be considered to be on par in terms of reducing CO₂ emissions. Moreover, Vaughan et al (2011) report that green waste compost has potential to reduce emissions of N₂O, an important greenhouse gas.
Apart from the technologies available for green waste processing discussed above, other approaches such as green waste briquetting, cellulosic ethanol production, bio-plastics production and bio-hydrogen production can also be applied (see for example Bhange et al. (2012) for a complete overview). These technologies are not discussed here since they are considered commercially unviable. Moreover, green waste briquetting is used especially in developing countries to reduce deforestation by providing a substitute for fuel wood. In the European Union it is not considered a viable renewable source of energy. Kabir et al. (2012) also suggest pyrolysis as a suitable conversion process for green waste. Since this conversion process is expensive for green waste valorisation compared to the above-mentioned conversion processes, it is not widely used and hence is not further considered in this paper.

2.2. LCA approach, potential and limitations

Life cycle assessment (LCA) is a well-established analytical method for quantifying the environmental impacts of a product, service or production process. The method is traditionally used to study three types of problems: assessment of individual products to understand their environmental impact, comparison of process paths in the production of substitutable products or processes, and comparison of alternatives for delivering a given function (Jacquemin et al., 2012).

ISO 14040+44 (2006) gives a clear and structured description to practitioners on how to conduct an LCA. However, ISO 14040+44 (2006) states LCA to be “one of the several environmental management techniques (e.g. risk assessment, environmental performance evaluation, environmental auditing and environmental impact assessment) and might not be the most appropriate technique to use in all situations. LCA typically does not address the
economic or social aspects of a product, but the life cycle approach and methodologies described in the ISO 14044 may be applied to these other aspects”. So ISO 14040+44 (2006) does not claim LCA to be the sole methodology for assessment of environmental impact.

Although LCA is a good environmental assessment tool, it does have some drawbacks. Readers interested in a complete overview of the drawbacks and potential solutions to overcome them are referred the literature reviews of Pryshlakivsky and Searcy (2013), Jacquemin et al., (2012), Finnveden et al. (2009), Reap et al. (2008 a, b) and Hertwich et al. (2000). The main drawbacks of LCA can be summarized as follows.

An initial drawback, highly relevant to the subject of this paper, is that ISO 14040 +44 does not permit use of LCA as a basis for a comparative assertion if the products under study do not perform the same function. Even if the products perform the same function, the outcome can still differ significantly. For example, consider the allocation of green waste to compost or energy valorisation by Kranert et al. (2010) with that performed by SenterNovem, an agency of the Dutch ministry of Economic Affairs charged with implementing policies in the fields of innovation, energy and climate, environment and spatial planning (SenterNovem, 2008). Based on separate LCAs, Kranert et al. (2010) conclude that both methods are on par based on CO₂ emissions, while SenterNovem (2008) clearly favours incineration with energy recuperation.

Jacquemin et al. (2012) do not specifically address the use of LCA for competing products with a different function. However they point out that during the past decade the focus of LCA has expanded from a methodology that originally was mostly applied to products into currently an analysis and design tool for processes. In this extended approach, LCA results are used as an input to define environmental objectives in a multi-objective optimization model. Apart from environmental objectives, other objectives related to costs and other factors can also be taken into account. Münster et al. (2015) show that it is feasible to combine LCA methodology with multiple-objective optimization. The value of multi-objective programming in the context of LCA lies in offering a range of choices for environmental improvement of the system, thus enabling preferences to be identified after analysing the trade-offs among the objectives (Azapagic and Clift, 1999).

Reap et al. (2008a) identify another drawback of LCA, relating to the definition of the functional unit considered in the study and the scope of the study. If the functions of a product are not appropriately addressed in an LCA with respect to the study’s goal and scope, the functional unit may fail to reflect the actual trade-offs properly. As an example, consider the failure to take long-term effects on the condition of the soil into account when using green waste compost compared to competing products such as fertilizers made from natural oil. Finnveden et al. (2009) and Reap et al. (2008a) point out that only environmental impacts are addressed in the ISO standard for LCA and not the social and economic impacts which combine to form the dimension. Reap et al. (2008b) state that a consensus on the most appropriate remedy for the problems in each of the four phases of an LCA (definition of goal and scope, life cycle inventory analysis, life cycle impact assessment, and interpretation)
remains elusive. As a decision support tool, LCA combines preference values and science, and hence precludes the existence of uniquely correct methods and results (Hertwich et al., 2000)

2.3. Multiple-Criteria Decision Making (MCDM)

Multiple-criteria decision-making (MCDM) is a sub-discipline of Operations Research that supports decision-makers (DMs) by structuring and solving decision and planning problems involving multiple criteria. The objectives to be achieved in connection with these criteria often conflict with each other. Consequently, there is no single ideal solution that simultaneously satisfies the DM across all criteria. Therefore an optimal trade-off between these objectives must be sought in accordance with the preferences of the DM. Kiker et al. (2005) give an overview of different types of decision support tools based on MCDM in environmental management. Most of them are based on multi-attribute utility theory (MAUT), multi-attribute value theory (MAVT) and analytical hierarchy process (AHP). MAUT and MAVT involve use of utility/value functions that transform the decision criteria into a 0-1 utility scale. By using weightings for the different criteria they provide the DM with a score for each alternative. AHP uses a quantitative comparison method based on pair-wise comparison of decision criteria rather than utility and weighting functions. The above-mentioned MCDM methods are used to identify the most preferred alternative or to rank a finite number of the alternatives explicitly known at the start of the solution process. Another approach to MCDM consists of first mathematically determining the Pareto optimal solutions as alternatives, the choice between which is not explicitly known, and thereafter including the preference of the DM to obtain a final solution. Optimal trade-off solutions are called Pareto optimal or Pareto-efficient if none of the objectives can be improved in value without deteriorating the values of some other objectives. The mathematical process of seeking such a solution is known as multi-objective programming (see e.g. Stadler, 1979 or Steuer, 1986 for an introduction). We prefer to formulate the problem of allocating green waste to composting or energy recovery as a multiple-objective programming problem since there are not a finite number of alternatives explicitly known at the start of the solution process.

In general, three types of approaches to the solution of a multiple-objective optimization problem (MOOP) can be distinguished based on the timing of making the preferences by the DM (Van Veldhuizen and Lamont, 2000): (i) an a priori preference articulation where the DM decides how to combine the differing objectives into a scalar function prior to the optimization process, (ii) a progressive preference articulation where the decision-making and optimization are intertwined and (iii) an a posteriori preference articulation where the DM is presented with a set of Pareto optimal candidate solutions and chooses from that set. Type (i) and (iii) solution approaches for a MOOP are commonly used and will be discussed further below.
If the DM defines his relative preferences at the start of the process (a priori), the relative preference vector is used to scale the multiple objectives into a single-objective optimization problem with one single solution as outcome. Well-known methods for determining upfront relative preferences are the analytical hierarchy process (Saaty, 2008) and goal programming (Jones et al., 2002; Tamiz et al., 1998), which are based on the construction of a value function that expresses DM preferences. Once the objective function is constructed, the resulting single objective mathematical program is solved to obtain a preferred solution. Standard solution techniques for these models have been available for some time and are mostly simplex-based methods. A drawback of defining the relative preferences at the start of the optimization process is the high sensitivity of the solution to the relative preference vector used in forming the composite function (Deb, 2009). To alleviate this drawback, one can first generate as many trade-off solutions as possible (the a posteriori approach). Once a sufficient number of these Pareto points have been determined, the DM can select one amongst these solutions by adding information to the problem. This process of generating a subset of the Pareto optimal solutions can basically be carried out using classical gradient-based exact optimization methods or meta-heuristic methods such as simulated annealing, taboo-search or genetic algorithms.

In the group of exact methods, the MOOP is solved by constructing several scalarizations with the aim of obtaining a subset of Pareto points that are distributed as evenly as possible within the full set of Pareto optimal points. This group of methods includes the normal boundary intersection (NBI), modified normal boundary intersection (NBIm), normal constraint (NC), successive Pareto optimization (SPO) and directed search domain (DSD) methods. Another widely used method is the \( \varepsilon \)-constraint method and the augmented \( \varepsilon \)-constraint method (AUGMECON), which is a novel version of the conventional \( \varepsilon \)-constraint methods providing remedies for its well-known pitfalls (Mavrotas, 2009). In the \( \varepsilon \)-constraint method, one of the objective functions is optimized while the other objective functions are used as constraints. It has several advantages over the weighting method (Mavrotas, 2009), such as obtaining a richer representation of the Pareto optimal front and being fit for use in multi-objective integer and mixed integer programming problems. Compared to the \( \varepsilon \)-constraint method, the AUGMECON method avoids generating weakly Pareto optimal solutions and accelerates the optimization process by avoiding redundant solutions. The AUGMECON method is available in a number of different modelling languages, including GAMS (general algebraic modelling language, www.gams.com). The interested reader is referred to Mavrotas (2007, 2009) for further details of the AUGMECON method. The \( \varepsilon \)-constraint method has also been used by Azapagic and Clift (1999), among others, in an evaluation of possible options for environmental management of five boron products.

Meta-heuristics solution methods have become increasingly important in MCDM for their ability to solve many highly nonlinear multiple-criteria problems. In the nineties three evolutionary algorithms were suggested by three different groups of researchers: the multi-objective genetic algorithm (Fonseca and Fleming, 1993), the non-dominated sorting genetic algorithm (Srinivas and Deb, 1994), and the niched Pareto genetic algorithm (Horn et al., 1994), as reviewed by Wallenius et al. (2008). Increases in computing power have been at the
heart of many of the advances in MCDM (Wallenius et al., 2008). Along with algorithmic advances, larger and more complex problems have become solvable in reasonable computation times.

Probably the most popular meta-heuristics for MCDM are genetic algorithms, which emulate the way species breed and adapt in the field of genetics; simulated annealing, which emulates the way in which material cools down to its steady state in the field of physics; and taboo search which draws on the social concept of ‘taboo’ in order to provide an effective search technique which avoids returning to local optima (Gonzalez, 2007). The main advantage of evolutionary algorithms, when applied to solve multi-objective optimization problems, is the fact that they typically generate sets of solutions that approximate the entire Pareto front. The main disadvantage of evolutionary algorithms is that the Pareto optimality of the solutions cannot be guaranteed. Only the solutions generated are guaranteed not to dominate the solutions on the Pareto optimal front. In general, evolutionary algorithms are considered a good alternative to exact methods for large MCDM instances. The observed Pareto fronts determined by evolutionary algorithms have a better spread of solutions with a larger number of non-dominated solutions when compared to the classical multi-objective techniques (Li, 2010).

Given the fact that ISO 14040+44 (2006) does not permit the use of comparative LCA in case of different product functions and given the fact that the allocation of green waste to composting and/or energy recovery is not to be classified into a finite set of alternatives in advance, the optimal trade-off if green waste is used for both products may be formulated as a MOOP. Depending on the situation, decision-makers can allocate green waste to composting or energy recovery, or a combination of both.

3. A MOOP formulation for the Green waste valorisation problem

In the case of green waste, a complete life cycle approach in which the closed loop supply chain has to be evaluated is not very suitable since its prior life cycle is a relatively natural one that is generally not considered to be a “product life cycle” at all (Grant, 2003). This process can be better evaluated on its own as a gate-to-gate process. Therefore we consider only the processes that deal with composting and incineration with energy recuperation (referred to from now on simply as incineration) subject to several constraints. Depending on the preferences of the decision-makers, the green waste can be allocated to one or a combination of both options. The outcome of the MOOP is a set of Pareto optimal solutions guaranteeing the best outcome for the options under study and complying with the EU waste Directive 2008/98/EC that allows diversion from the waste hierarchy preferring
composting to incineration with energy recuperation if it leads to an equivalent or a better environmental outcome.

The problem consists of finding the optimum between two conflicting objectives: the first objective function maximizes the compost output and the second objective function maximizes the waste to energy output in a given planning period for a given mass of green waste, as detailed below.

Let:
- \( x_t \): total incoming mass of green waste to be composted/incinerated [ton]
- \( x_{bc} \): brown mass (mainly leaves and cuttings) in green waste batch \( x_t \) to be used for composting [ton]
- \( x_{gc} \): green mass (mainly grass) in green waste bath \( x_t \) to be used for composting [ton]
- \( x_{bi} \): brown mass (mainly leaves and cuttings) in green waste batch \( x_t \) to be used for incineration [ton]
- \( x_{gi} \): green mass (mainly grass) in green waste batch \( x_t \) to be used for incineration [ton]
- \( x_c \): total mass resulting from the composting process [ton]

The mass of the green waste \( x_t \) to be composted or incinerated equals the sum of the brown mass and the green mass. This is expressed in (3.1)

\[
x_t = x_{bc} + x_{gc} + x_{bi} + x_{gi}
\]  

(3.1)

3.1. First objective: maximizing composting yield

The yield obtained from composting a certain mass of green waste \( (x_{bc} + x_{gc}) \) derived from the incoming batch of green waste of mass \( x_t \) can be modelled by an approximate empirical function (3.2) derived from publically available data for Belgium reported by Vlaco (2010). The data was based on experiments carried out at a composting site in Flanders, Belgium (Vlaco, 2010), where two 350-ton batches with a different green waste content were composted in the open air (aerobic composting) every season. This resulted in four experiments, each with a different seasonal composition of brown mass, \( x_{bc} \), and green mass, \( x_{gc} \), leading each to a composting yield, \( \gamma_c \), expressed in (3.2) and a final amount of compost \( x_c \), expressed in (3.3). The empirical parabolic function, depicted in Figure 2, agrees with insights of composting practitioners that the maximum compost yield is reached when the amount of brown mass in the green waste blend equals the amount of green mass \( (x_{bc} = x_{gc}) \), and that high-quality composting is impossible if only brown mass \( (x_{bc} \neq 0 \text{ and } x_{gc} = 0) \), or only green mass \( (x_{gc} \neq 0 \text{ and } x_{bc} = 0) \) is used in the green waste blend. Both extremes are represented in Figure 2 by \( x_c = 0 \) in case of \( x \) equals 0% (only green mass) or 100% (only brown mass) of the total mass of incoming green waste, \( (x_{bc} + x_{gc}) \), assigned for composting. Composting green waste needs a proper ratio of carbon-rich materials called ‘browns’ such as
dried leaves and cuttings, and nitrogen-rich materials called ‘greens’ such as grass. If the C (carbon)/N (nitrogen) ratio of compost deviates from the optimal ratio, negative environmental impact arises. A too high C/N ratio results in a loss of nitrogen in the soil and a too low C/N ratio results in a compost product that does not help to improve the structure of the soil (Bhange et al., 2012). Material with a carbon/nitrogen (C/N) ratio larger than 30 is called ‘brown’ mass and material with a C/N ration less than 30 is called ‘green’ mass (www.homecompostingmadeeasy.com).

\[
\gamma_c = \left( -1.4 \cdot x^2 + 1.4 \cdot x \right) \cdot 100\% \]  \hspace{1cm} (3.2)

\[
x_c = \left( -1.4 \cdot x^2 + 1.4 \cdot x \right) \cdot \left( x_{bc} + x_{gc} \right) \text{ [ton]} \]  \hspace{1cm} (3.3)

Where \( x = \left( \frac{x_{bc}}{x_{bc} + x_{gc}} \right) \cdot 100\% \); \( x \in [0,100]\% \) \hspace{1cm} (3.4)

![Figure 2: Empirical function for composting yield of green waste, \( \gamma_c \), based on the fraction of brown mass \( x_{bc} \) and green mass \( x_{gc} \) in the green waste blend and results of the composting experiment Vlaco (2010)](image)

In this paper we use a blend of green waste as detailed in Table 1 for our calculations. If a more detailed composition of a batch of green waste is available, more detailed calculations can be made, for example on the basis of data from the Phyllis\(^{10}\) database.

For the blend in Table 1, the mass for 1 m\(^3\) of brown mass equals approximately the mass of 1 m\(^3\) of green mass, which is optimal for composting: \( x_p = 0.6 \cdot 0.15 + 0.1 \cdot 0.4 = x_g = 0.3 \cdot 0.45 \)

\(^{10}\) Energy Research Center Netherlands. Phyllis database for biomass and waste, http://www.ecn.nl/phyllis/
Table 1: Characteristics of main components of green waste (C/N ratio: carbon/nitrogen ratio; LHV: lower heating value). (a) Jenkins (2005); (b) NVRD, 2010; (c) LNE (2002); (d) LNE (2014); (e) based on SenterNovem (2008) and Vlaco (2010).

<table>
<thead>
<tr>
<th>Component</th>
<th>C/N ratio</th>
<th>LHV [GJ/ton]</th>
<th>Bulk density [ton/m$^3$]</th>
<th>Volume share in green waste</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry cuttings (25% moisture)</td>
<td>641$^{(a)}$</td>
<td>14.0$^{(b)}$</td>
<td>0.15$^{(d)}$</td>
<td>0.6$^{(e)}$</td>
</tr>
<tr>
<td>Dry leaves</td>
<td>54$^{(a)}$</td>
<td>17.2$^{(c)}$</td>
<td>0.40$^{(d)}$</td>
<td>0.1$^{(e)}$</td>
</tr>
<tr>
<td>Wet clippings (grass) (50% moisture)</td>
<td>12-19$^{(a)}$</td>
<td>8.0$^{(b)}$</td>
<td>0.45$^{(d)}$</td>
<td>0.3$^{(e)}$</td>
</tr>
</tbody>
</table>

3.2. Second objective function: maximizing waste to energy

Since the aim is to find the optimal mix of $x_{bc}$, $x_{gc}$, $x_{bi}$ and $x_{gi}$ that maximizes green waste as feedstock for energy recovery and composting, the objective function for the energy valorisation of green waste by incineration, $E_i$, is given by (3.5) using the lower heating values (LHV)$^{11}$ also known as net calorific values (NCV) or lower calorific values (LCV) for dry pruning wood and wet grass (see Table 1).

$$E_i = 14 \cdot x_{bi} + 8 \cdot x_{gi} [Gj]$$

(3.5)

Note that since wood is mostly used dry in co-firing, the dry LHV value is used and since grass is mostly not dried when used for energy recuperation, the wet LHV is used.

The effect of the moisture content in biomass on the LHV is expressed by (3.6) (see Fowler et al., 2009) in which MC is the moisture content of the biomass expressed in %.

$$LHV_{wet} = LHV_{dry} \cdot (1 - MC) - 2.442 \cdot MC$$

(3.6)

To give an example, using leaves with moisture content MC of 50% reduces the LHV from 17.2 [GJ/ton] to 7.4 [GJ/ton]. Given the low proportion of leaves in the blend and the seasonal variation in collecting the leaves, we assume in this paper that the average annual LHV of the leaves is the same as that of dry cuttings.

The functions (3.3) and (3.5) represent opposing trends. The more brown mass $x_{bi}$ and green mass $x_{gi}$ are removed from the total incoming green waste mass $x_i$ for incineration, the less compost will be made according to (3.3), but the more renewable energy will be made according to (3.5). Moreover, if the equal balance of brown mass and green mass is disturbed in the green waste mixture, for example to favour the conversion of brown mass to renewable energy, the output of compost will also be reduced as depicted in Figure 2 and expressed in (3.2).

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$^{11}$ LHV calculations assume that the water component of a combustion process is in a vaporous state at the end of combustion and that the latent heat of vaporization of water in the fuel and the reaction products is not recovered.
The objectives of GWVP can be expressed by (3.7) and (3.8), where \( x \) is expressed by (3.4).

\[
\text{Maximize } f_1 = x_c = (-1.4x^2 + 1.4x) \cdot (x_b - x_{bi} - x_{gi}) \text{[ton] (3.7)}
\]
\[
\text{Maximize } f_2 = E_t = 14 \cdot x_{bi} + 8 \cdot x_{gi} \text{[GJ] (3.8)}
\]

3.3. Constraints

(1) Space restrictions: Constraint (3.9) represents the fact that the mass to be composted in a single batch is limited to a maximum mass of \( x \) ton given the physical constraint of the space where the green waste is composted.

\[
x_{bc} + x_{gc} + x_{bi} + x_{gi} \leq x \text{[ton]} (3.9)
\]

(2) Limitations on the energy valorisation of green waste: since a conventional blend of green waste consists of half brown and half green mass, the fraction brown \( x_{bi} \) and green \( x_{gi} \) are limited to half the amount of green waste \( x \) as represented by constraints (3.10) and (3.11).

\[
0 \leq x_{bi} \leq \frac{x}{2} \text{[ton]} (3.10)
\]
\[
0 \leq x_{gi} \leq \frac{x}{2} \text{[ton]} (3.11)
\]

(3) Guaranteeing an acceptable yield for the composting process: According to the empirical function (3.2), the composting yield drops when the ratio of brown to green mass to be composted deviates increasingly from the preferred balance. Constraint (3.12) therefore lays down boundaries guaranteeing an acceptable composting yield.

\[
35 \leq \frac{x_{bc}}{x_{gc} + x_{bc}} \cdot 100 \leq 65\% (3.12)
\]

This can be rewritten as:

\[
35x_{gc} - 65x_{bc} \leq 0 (3.13a)
\]
\[
35x_{bc} - 65x_{gc} \leq 0 (3.13b)
\]

(4) All masses are positive numbers.

\[
x_{bc}, x_{gc}, x_{bi}, x_{gi}, x, \geq 0 \text{[ton]} (3.14)
\]

4. Solving the Green waste valorisation problem

The green waste valorisation problem, GWVP, has two conflicting objective functions (3.7) and (3.8), of which (3.7) is non-linear. All constraints apart from (3.4) are linear. We use the genetic algorithm NSGA-II and the \( \varepsilon \)-constraint method to generate the efficient frontier and solve the bi-objective problem. Both methods are widely used a-posteriori methods permitting generation of the Pareto optimal front for decision-makers. The NSGA-II method is the most generic one, but is less popular because of the computational effort required and the lack of widely available software (Mavrotas, 2009). The problem solving approach will be
illustrated using the practical case of green waste valorisation in the Low Countries (Belgium and the Netherlands). The optimal allocation of a batch of green waste with \( x_t = 150 \) ton to composting or energy recovery will be taken as an example.

4.1. The NSGA-II GA algorithm used for solving the GWVP MOOP

Given its good performance, the NSGA-II GA has been used in many MOOP solving problems in the last decade (Konak et al., 2006; Murugan et al., 2009; Jeyadevi et al., 2011; Lin and Yeh, 2012). According to Murugan et al. (2009), it is one of the most efficient algorithms for multiple-objective optimization on a number of benchmark problems. It generates a set of solutions close to the Pareto optimal front (Deb, 2009).

The NSGA-II algorithm and its detailed implementation are described in Deb (2009). Unlike the case with the \( \varepsilon \)-constraint method that can easily be used with the aid of freely available GAMS software, there is no widely available free tool for the NSGA-II algorithms as far as we know. The basic working principles of the NSGA-II algorithm will therefore be briefly explained in the appendix to this paper. Software commonly used to implement the NSGA-II algorithm includes Visual Basic (Montazer-Rahmati and Binaee, 2010; Hani et al., 2008) Mathlab (Dehghanian and Mansour, 2009) and Python (De Rainville et al., 2012).

In order to solve the GWVP with the NSGA-II method, the objective functions have to be formulated as minimization problems. Functions (3.7) and (3.8) are therefore transformed into (4.1) and (4.2) respectively, using the duality principle. It should be noted that NSGA-II could deal with nonlinear objective functions and constraints unlike the \( \varepsilon \)-constraint method, which requires linear objective functions and constraints. The NSGA-II method is thus the more generic version of the two. The constraints (3.4) and. (3.9) – (3.14) are transformed into (4.3) – (4.8) in this case.

\[
\begin{align*}
\text{Minimize } f_1 &= (1.4 \cdot x^2 - 1.4 \cdot x)(x_t - x_{bi} - x_{gi}) \text{ [ton]} \\
\text{Minimize } f_2 &= -14 \cdot x_{bi} - 8 \cdot x_{gi} \text{ [GJ]}
\end{align*}
\]

Subject to:

\[
\begin{align*}
x &= \frac{x_{bc}}{x_{bc} + x_{gc}} = \frac{75 - x_{by}}{150 - x_{by} - x_{gi}} \\
x_{bc} + x_{gc} + x_{mt} + x_{gt} &\leq 150 \text{ [ton]} \\
0 \leq x_{by} &\leq 75 \text{ [ton]} \\
0 \leq x_{gi} &\leq 75 \text{ [ton]} \\
35x_{gc} - 65x_{ub} &\leq 0 \\
35x_{wc} - 65x_{gc} &\leq 0 \\
x_{bc}, x_{gc}, x_{bi}, x_{gi} &\geq 0 \text{ [ton]}
\end{align*}
\]
4.1.1. Basic situation: grass and wood in green waste allowed for green waste valorisation.

Solution of the GWVP with the aid of the NSGA-II algorithm yields the Pareto optimal front shown in Figure 3. The NSGA-II algorithm was programmed in Visual Basic. Each variable was binary coded in a 10-bit chromosome string. As a point of comparison for the implementation, the Matlab code of Lin (2011) was used. The NSGA-II algorithm was executed using Matlab R2014b and Microsoft Visual Basic 6.5 on a personal computer with a 1.66 GHz processor and 10.99 GB Ram memory. The results shown were obtained after 500 iterations, starting with an initial population of 20 solutions using a single crossover probability $P_c=0.8$. The Pareto optimal solutions in Figure 3 represent all combinations with maximum compost yield $\gamma_c=35\%$ with $x=50\%$ for the range $x_{bi} = [0, 75]$ ton and $x_{gi} = [0, 75]$ ton, while $x_{bc}=x_{gc}$. All solutions on the Pareto optimal front represent equal combinations in terms of lowest environmental impact for green waste valorisation. The shape of the Pareto curve indicates the perfect complementary nature of the trade-off between the two different objective functions when the fixed maximum compost yield $\gamma_c=35\%$. The Matlab and Visual Basic programs of NSGA-II generate comparable results. The Pareto optimal front generated by the NSGA-II algorithm results in a combination of negative values of compost and energy production because of the dual representation of the objective functions as expressed in (4.1) and (4.2).

![Figure 3: Pareto optimal front for the Green Waste Valorisation Problem, GWVP, representing the optimal combinations for Energy valorisation, $E_i$, and Compost, $x_c$, in case of equal amounts of brown mass, $x_{bc}$, and green mass, $x_{gc}$, in the green waste batch, obtained with NSGA-II (elitist non-dominated sorting genetic algorithm version II) after 500 iterations using a single cross-over probability, $P_c=0.8$, using Matlab and Visual Basic (VB).]
Since we want to compare the outcome of NSGA-II, which minimizes the objective functions with that of the $\varepsilon$-constraint method that maximizes objective functions, the results of the NSGA-II algorithm will be presented as positive values in Figure 3 using the duality principle so that the outcomes reflect the maximization of both objective functions.

4.1.2. Only brown mass of green waste allowed for energy valorisation

Because the brown mass of the green waste is most suited for incineration, it is more likely that no green mass will be incinerated in practice (i.e. $x_{gi}=0$). The partial removal of especially the wooden mass from the green waste batch $x_i$ will bring about a change in the composition of the green waste used for composting from the empirical optimal proportions of 50% green and 50% brown mass. Depending on the amount of brown mass used for incineration, the amounts $x_{bi}$, $x_{hc}$ and $x_{gc}$ will then differ in accordance with constraint (4.4). Constraints (4.7 a and b) limit the imbalance between $x_{hc}$ and $x_{gc}$ to a $\pm 15\%$ range around $\gamma_c=35\%$. This results in the Pareto optimal front shown in Figure 4. This does not differ appreciably from the result shown above for the basic situation, since the parabolic function (4.1) is almost linear in the range defined by constraints (4.7 a and b). If the composting yield constraints (4.7 a and b) are alleviated, the Pareto optimal front will be seen to deliver worse results outside the range defined by constraints (4.7 a and b). This is shown by the option “$x_{gi}=0$, no composting yield constraints” in Figure 4. In this case, composting and Waste-To-Energy are no longer perfect complements.

Figure 4: Pareto optimal front for the Green Waste Valorisation Problem, GWVP, representing the optimal combinations for Energy valorisation, $E_i$, and Compost, $x_c$, in case of only the brown mass, $x_{bc}$, of green waste is allowed for energy valorisation, obtained with NSGA-II (elitist non-dominated sorting genetic algorithm version II) after 500 iterations using a single cross-over probability, $P_c=0.8; (x_{gi}: amount of incinerated green mass; x_{hc}: amount of composted brown mass; x_{gc}: amount of composted green mass; VB: Visual Basic).
4.2. The ε-constraint method

In the ε-constraint method, one of the objective functions is optimized using the other objective functions as constraints. For the GWVP case, the non-linear objective function (3.7) for composting will be optimized, and the second linear objective function (3.8) will be incorporated with the other constraints. As a result, the set of constraints remains linear. The problem can then be reformulated as follows:

Maximize \[ f_1 = (-1.4x^2 + 1.4x) \cdot \left(150 - x_{bc} - x_{gi}\right) [ton] \]  
Subject to: \[ 14 \cdot x_{hi} + 8 \cdot x_{gi} \geq \epsilon \]

The other constraints (4.3) – (4.8) remain unchanged.

Efficient solutions of the problem are obtained by parametric variation of the variables on the right-hand side (RHS) of the second constrained objective function (e) (see Mavrotas, 2009). The ε-constraint module of GAMS (www.gams.com) is used to solve the problem expressed above. This solver is based on linear programming, which means that (4.9) and (4.3) have to be linearized. This can be done using the algorithm of Frank-Wolfe (1956) or by the approach suggested below.

In the basic situation, the maximum composting yield will be subject to the constraint \( x_{bc} = x_{gc} \) as explained in section 4.1.1. In this case constraint (4.3) becomes \( x = 0.5 \) and function (4.9) is reduced to the linear function shown in (4.11).

\[ f_1 = 0.35 \cdot \left(150 - x_{hi} - x_{gi}\right) [ton] \]

In the second scenario where no green mass from the green waste is incinerated, as expressed by \( x_{gi} = 0 \), constraint (4.11) can no longer be used since \( x_{bc} = x_{gc} \) if \( x_{hi} \neq 0 \). Due to constraints (4.7 a and b), only the part of the parabolic function that is quite linear will be used. We therefore approximate to (4.9) by considering only \( x_{hi} \) and assuming that \( x_{gi} = 0 \) in (4.3). This leads to the expression (4.12) for \( x_{hi} = [0, 34.62] \) ton.

\[ f_1 = -0.45x_{hi} + 53.13 [ton] \quad ; \ R^2 = 0.995 \]

The results of the GAMS optimization procedure for 10 grid points for \( e \) and for the two situations discussed above leads to the two Pareto optimal fronts shown in Figure 5. The results of the NSGA-II method are also included in Figure 5 for the sake of comparison, showing that both methods result in similar Pareto optimal fronts. If the constraints (4.7 a and b) were alleviated, the Pareto optimal front would deviate from the one in (4.11) for \( x_{hi} > 34.62 \) ton. This effect is modelled by the option “\( x_{gi} = 0 \), no composting yield constraints”.

\[ 4.1 \]
Figure 5: Overview of the Pareto optimal fronts of the Green Waste Valorisation Problem, GWVP, representing the optimal combinations for Energy valorisation $E_i$ and Compost $x_c$ in case of equal amounts of brown mass, $x_{bc}$, and green mass, $x_{gc}$, in the green waste batch and in case of no green mass allowed for incineration with energy recuperation, $x_{gi}=0$, generated with the aid of the $\varepsilon$-constraint method in GAMS. ($x_{bc}$: amount of composted brown mass; $x_{gc}$: amount of composted green mass; VB: Visual Basic).

The pay-off table for the basic run using the $\varepsilon$-constraint method is given in Table 2, and that for the special case with $x_{gi}=0$ is given in Table 3. Table 2 shows that in the basic run the extreme solutions for the valorisation of an incoming batch of 150 ton of green waste are given by complete composting of the batch resulting in 52.5 ton of compost or complete incineration resulting in 1650 GJ of energy. Table 3 shows, for the same incoming batch of 150 ton of green waste, that if no green mass is incinerated and constraints (4.7 a and b) on composting yield are taken into account, the maximum energy valorisation is limited to 484.68 GJ. The maximum composting yield is still possible in the absence of incineration. It will be noted that the maximum composting yield of 53.13 ton differs from the value of 52.5 ton given in Table 2 because the estimated function (4.12) is used.

<table>
<thead>
<tr>
<th>Compost $x_c$ [ton]</th>
<th>Energy $E_i$ [GJ]</th>
</tr>
</thead>
<tbody>
<tr>
<td>52.5</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1650</td>
</tr>
</tbody>
</table>

Table 2: Pay-off table for GAMS basic run

<table>
<thead>
<tr>
<th>Compost $x_c$ [ton]</th>
<th>Energy $E_i$ [GJ]</th>
</tr>
</thead>
<tbody>
<tr>
<td>53.13</td>
<td>0</td>
</tr>
<tr>
<td>37.44</td>
<td>484.68</td>
</tr>
</tbody>
</table>

Table 3: Pay-off table for GWVP GAMS special case $x_{gi}=0$ (no green mass is incinerated).
4.3. Comparison of the NSGA-II and $\varepsilon$-constraint methods for the GWVP

The $\varepsilon$-constraint method needs linearization of the non-linear objectives and constraints in the green waste valorisation problem. The NSGA-II method permits nonlinear multi-objective programming and is therefore better suited to deal with the green waste valorisation problem as such. The computing time for the NSGA-II method is however higher than that for the $\varepsilon$-constraint method (see Table 4). Use of Matlab gives faster generation of the population on the Pareto optimal front thanks to the efficiency of the built-in functions that can be used.

The grid points in the NSGA-II method are less evenly distributed than those in the $\varepsilon$-constraint method, which does yield an even distribution of the grid points. The grid points of the population representing the Pareto optimal front in NSGA-II may deviate slightly from those of the $\varepsilon$-constraint method, which are based on an exact calculation. This is because the heuristic underlying the NSGA-II algorithm guarantees only Pareto optimality for the set of solutions generated on the Pareto optimal front.

<table>
<thead>
<tr>
<th>Method</th>
<th>Basic run time in seconds</th>
<th>Run time (seconds) for $x_{gi}=0$</th>
<th>Population size</th>
<th>Number of generations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon$-constraint</td>
<td>2</td>
<td>2</td>
<td>10</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>4</td>
<td>20</td>
<td>N/A</td>
</tr>
<tr>
<td>NSGA-II (Visual Basic)</td>
<td>173</td>
<td>153</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>772</td>
<td>756</td>
<td>10</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>1003</td>
<td>969</td>
<td>20</td>
<td>500</td>
</tr>
<tr>
<td>NSGA-II (Matlab)</td>
<td>8</td>
<td>8</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>42</td>
<td>41</td>
<td>10</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>45</td>
<td>45</td>
<td>20</td>
<td>500</td>
</tr>
</tbody>
</table>

Table 4: Comparison of computing times for the NSGA-II (elitist non-dominated sorting genetic algorithm version II) and $\varepsilon$-constraint methods; $x_{gi}$ is the amount of green mass that is incinerated.

4.4. Determining a final single solution

If a single optimal solution is to be determined, a decision-maker can fix the values of two weighting factors ex-post by assigning to each objective function a weighting factor, $w_j$, representing its importance so that the total of all weighting factor equals 1. According to Deb (2009), the optimal objective values of each single-objective optimization model form the components of the ideal point vector $f^*$ for the multi-objective problem under investigation. Next, for each single-objective solution of the optimal solutions set, the distance to the ideal point $f^*_j$ is weighted by the chosen weights $f^*_j$ to obtain a weighted percentage deviation factor (WPD). The value $f^*_j$ of the $j^{th}$ objective function is then calculated for all solutions $s$ of the Pareto optimal set, and compared with the ideal point value of the $j^{th}$ objective function $f^*_j$. This ideal point value is formed by the optimal results per objective function of each assessed alternative.

$$WPD_s = \sum_{j=1}^{2} w_j \cdot \left| \frac{f^*_j - f^*_s}{f^*_j} \right|$$

(5.1)

This method is applied to the Pareto optimal front population of the basic case generated by the $\varepsilon$-constraint method. When $w_1=w_2=0.5$, all solutions are identical; in other words, all
combinations belonging to the Pareto optimal front are equally optimal from a waste management policy standpoint. The results are depicted in Table 5. The outcome with the highest WPD factor is the preferred outcome.

<table>
<thead>
<tr>
<th>Solution s</th>
<th>( f_1 = x, ) [ton]</th>
<th>( f_2 = E, ) [GJ]</th>
<th>( WPD_s )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( w_1 = w_2 = 0.5 )</td>
<td>( w_1 = 0.4; w_2 = 0.6 )</td>
<td>( w_1 = 0.6; w_2 = 0.4 )</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1650</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td>5.25</td>
<td>1485</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>10.5</td>
<td>1320</td>
<td>0.5</td>
</tr>
<tr>
<td>4</td>
<td>15.75</td>
<td>1155</td>
<td>0.5</td>
</tr>
<tr>
<td>5</td>
<td>21</td>
<td>990</td>
<td>0.5</td>
</tr>
<tr>
<td>6</td>
<td>26.25</td>
<td>825</td>
<td>0.5</td>
</tr>
<tr>
<td>7</td>
<td>31.5</td>
<td>660</td>
<td>0.5</td>
</tr>
<tr>
<td>8</td>
<td>36.75</td>
<td>495</td>
<td>0.5</td>
</tr>
<tr>
<td>9</td>
<td>42</td>
<td>330</td>
<td>0.5</td>
</tr>
<tr>
<td>10</td>
<td>47.25</td>
<td>165</td>
<td>0.5</td>
</tr>
<tr>
<td>11</td>
<td>52.5</td>
<td>0</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 5: influence of the weighting factors on the outcome in the basic case (\( x, \) amount of compost; \( E, \) amount of energy; \( w_1, w_2, \) weighing factor for function \( f_1, f_2; \) \( WPD_s, \) weighted percentage deviation factor for solution \( s \))

The optimal allocation of the incoming green waste to composting and energy valorisation will vary, depending on the relative weighing factors \( w_j. \) If \( w_2 \geq 0.5, \) material valorisation will be favoured, while if \( w_2 \geq 0.5, \) energy recuperation will be favoured.

In the case of a \( GWVP \) with a linear Pareto optimal front combination between the two objective functions \( f_1 \) and \( f_2, \) the results are obvious. Other criteria may be used to select the optimal allocation of green waste to composting and energy valorisation. We demonstrate the power of the WPD method by choosing the optimal green waste conversion method if the green mass of the green waste may not be used for incineration (that is, \( x_{gi} = 0 \)) and when no constraint is enforced on maintaining the composting yield. As depicted in Figures 4 and 5, there is no linear relationship between \( f_1 \) and \( f_2 \) in this case. If equal weight is allocated to composting \( (f_1) \) and energy valorisation \( (f_2), \) then complete composting or complete incineration of the green waste is optimal (see Table 6). All other solutions \( s \) on the Pareto optimal front will result in a composting yield loss.
5. Conclusions

According to ISO 14040+44 (2006), comparative life cycle assessment (LCA) cannot be used to assist policy decision-makers in obtaining the best environmental outcome for green waste recovery when choosing between composting and incineration with energy recuperation. This paper therefore develops an alternative solution approach using multi-objective optimization. Both types of green waste recovery methods have positive environmental impacts. Composted green waste has a positive long-term effect on the soil and avoids the use of peat or natural–oil-based fertilizers, both of which have a negative environmental impact. Incineration of some or all of the green waste can also generate a considerable amount of renewable energy, which can help in achieving EU targets for renewable energy. Multi-objective optimization offers a methodology to assist decision-makers in making an optimal trade-off between these two options.

In this paper, the green waste valorisation problem (GWVP) is formulated as a non-linear multi-objective optimization problem (MOOP) with the objective of maximizing the generation of compost and of renewable energy. The NSGA-II genetic algorithm method and the computationally more efficient ε-constraint method have been used to solve this problem. The outcome is a Pareto optimal front taking into account the trade-off of both conflicting sustainable objectives. In this sense, the outcome represents a balanced approach that is beneficial for both material conservation and renewable energy generation. Moreover, this approach satisfies the requirement of the EU Waste Directive 2008/98/EC that EU Member States shall select the waste recovery method that delivers the best overall environmental outcome. Finally, the presented methodology also contributes to the goal of the EU Directive 2009/28/EC on the promotion of energy from renewable resources.

Computational results based on publically available Belgian data show that when equal importance is attached to composting and energy valorisation, the optimal valorisation of a
batch of green waste is determined by its share of brown (cuttings and leaves) versus green (grass) mass. Green waste is optimally allocated to composting for all combinations with an equal share of green and brown mass. The uncomposted remainder may be allocated to incineration with energy recuperation.

If a batch of green waste consisting of green and brown mass can be incinerated with energy recuperation, then combinations with an equal share of green and brown mass give optimal results. If no green mass from the green waste batch is incinerated, then it is optimal to fully allocate the brown mass from the batch to either energy valorisation or to composting.

ACKNOWLEDGMENTS

This research was partially funded by research project 5598 of the University of Antwerp, Belgium. This support is gratefully acknowledged.

DISCLAIMER

The views presented in this paper reflects the view of the authors on this subject and have no other intention than stimulating the debate on the use of Operations Research techniques in achieving sustainable development. These views do not necessarily reflect the opinions of the organizations cited or the stakeholders involved.
Appendix: Basic explanation of the NSGA-II algorithm

In this appendix we explain the basic principles of the NSGA-II algorithm. For a more detailed explanation, see Deb (2009).

Variables in a genetic algorithm (GA) are represented by binary strings. For example, a variable denoted as (8, 10) will be represented in a 5 bit binary format as a chromosome denoted as 01000 01010. Each chromosome is made of genes. In this example the chromosome has 10 genes. Binary GAs use chromosomes representing the decision variables instead of the decision variables themselves.

Three genetic operators are used to find the Pareto optimal solutions in a GA: (i) reproduction; this operator duplicates good solutions and eliminates bad ones in a population while keeping the population size constant; (ii) crossover operator; during crossover two chromosomes or strings are exchanged from the mating pool and some portion of the strings are exchanged between the strings to create new strings; (iii) mutation; during mutation, the binary value of some genes changes according to a pre-defined schema.

A GA can begin its search with a random set of solutions. Each population of solutions is evaluated in the context of the underlying MOOP and fitness is assigned to each solution. Solutions are evaluated by calculating the objective value and constraint violations. The fitness is the relative merit that is assigned to the objective value and constraint violations. As long as the termination criterion is not met, the three genetic operators used to create an offspring population $Q_t$ modify the population of solutions. The generation counter is incremented for each completed generation of the GA.

An elite-preserving operator favours the better solutions in a population by giving them an opportunity to be directly carried over to the next generation. In NSGA-II, the offspring population using the parent population $P_t$ first creates $Q_t$. Applying a crossover and mutation operator to the parent population in the mating pool generates an offspring population. The two populations $Q_t$ and $P_t$, both of size N, are combined to form the entire population $R_t$ of size $2N$. Then a non-dominated sorting is used to classify the entire population $R_t$. On completion of this non-dominated sorting, solutions from different non-dominated fronts fill the new population one at a time. The filling starts with the best non-dominated front and continues with solutions of the second non-dominated front, and so on. All fronts which could not be accommodated in N slots are simply rejected (Figure A.1d).
Figure A.1 NSGA-II Procedure. (a) Decision variable \( x \) in the Decision space \( D \) and the corresponding point \( z \) in the Objective space \( Z \); (b) A, B, C and D are Pareto optimal solutions and E is a Pareto non-optimal solution; (c) classification into non-domination fronts; (d) NSGA-II procedure (figures based on Deb (2009)).

The non-dominated sorting method used in the NSGA-II algorithm is known as the crowding-sort procedure. In this sorting procedure, the crowded comparison operator, \( <_c \), compares two solutions and returns the winner of the “tournament”. It assumes that every solution \( i \) has two attributes: (i) a non-domination rank \( r_i \) in the population and (ii) a local crowding distance, \( d_i \), which is a measure of the search space around \( i \) which is not occupied by any other solution in the population.

The crowded comparison operator is designed so that a solution \( i \) wins a tournament against another solution \( j \) if any of the following conditions are true: (i) if solution \( i \) has a better rank, that is \( r_i < r_j \) or (ii) if they have the same rank but solution \( i \) has a better crowding distance than solution \( j \), that is \( r_i = r_j \) and \( d_i > d_j \).

Let \( I_j \) denote the solution index of the \( j^{th} \) member in the sorted solution list. \( I_1 \) and \( I_l \) denote the lowest and highest objective function values respectively. For \( m = 1, 2... M \), the crowding distance of the \( j^{th} \) solution in its front is calculated as in (A.1):
The crowding sort \( \langle f_i, c \rangle \) procedure that assigns the crowding distance is the following:

**Step a:** Call the numbers of solutions in \( F \) as \( l = |F| \). For each \( i \) in the set, first assign \( d_i = 0 \).

**Step b:** For each objective function \( m = 1, 2, \ldots, M \), sort the set in worse order of \( f_m \).

**Step c:** For \( m = 1, 2, \ldots, M \), assigning a large distance to the boundary solutions, or \( d_{i+} = d_{i-} = \infty \), and for all other solutions \( j = 2 \) to \((l-1)\) assign \( d_j \) according to (A.1).

The NSGA-II procedure is as follows (see Figure A.1d):

**Step 1:** Combine parent population \( P_t \) and offspring populations \( Q_t \) and create \( R_t \) and identify different fronts \( F_i, i = 1, 2, \ldots \) etc.

**Step 2:** Set new population \( P = \emptyset \). Set a counter \( i = 1 \). Until \( |P_t+1| + |F_i| < N \), perform \( P_t+1 = P_t \cup F_i \) and \( i = i + 1 \).

**Step 3:** Perform the crowding-sort \( \langle f_i, c \rangle \) procedure and include the most widely spread \( \left(N - |P_t+1|\right) \) solutions by using the crowding distance values in the sorted \( F_i \) to \( P_t+1 \).

**Step 4:** Create offspring population \( Q_{t+1} \) from \( P_{t+1} \) by using the crowded tournament selection, crossover and mutation operators.

Up to now the algorithm described assumed that the underlying optimization problem is free from any constraint. A popular constraint-handling strategy is based on use of penalty functions. Minimization of all objective functions is assumed here (Deb, 2009). Before the constraint violation is calculated, all constraints \( g_j(x_i) \) are normalized, denoted by \( \bar{g}_j(x_i) \).

For each solution \( x_i \), the constraint violation for each constraint \( j \) in is calculated as follows:

\[
\sigma_j(x_i) = \left| \bar{g}_j(x_i) \right|, \text{If } \bar{g}_j(x_i) < 0 \text{ or } 0 \text{ otherwise}
\]  

(A.2)

The overall constraint function \( \Omega(x_i) \) is the sum of all the constraint violations:

\[
\Omega(x_i) = \sum_{j=1}^J \sigma_j(x_i)
\]

(A.3)

This constraint violation is finally multiplied by a penalty parameter \( R_m \) and this product is added to each of the objective function values as in (A.4):

\[
F_m(x_i) = f_m(x_i) + R_m \cdot \Omega(x_i)
\]

(A.4)

For a feasible solution the corresponding \( \Omega \) term is zero and for an infeasible solution \( F_m > f_m \) due to the addition of the penalty function. The penalty parameter \( R_m \) in this penalty function has to be chosen so that it has the same order of magnitude as \( f_m(x_i) \).