MIXED POLICIES FOR RECOVERY AND DISPOSAL OF MULTIPLE-TYPE CONSUMER PRODUCTS

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ABSTRACT: New European government policies aim at the closure of material flows as part of integrated chain management (ICM). One of the main implementation instruments is extended producer responsibility, which makes original equipment manufacturers (OEMs) formally responsible for take-back, recovery, and reuse of discarded products. One of the key problems for OEMs is to determine a recovery strategy, i.e., determine to what extent return products must be disassembled and which recovery and disposal (RD) options should be applied. On a tactical management level, this involves anticipation of problems such as meeting legislation, limited volumes of secondary end markets, bad quality of return products, and facility investments in recycling infrastructure. In this paper, a model is presented that can be used to determine a recovery strategy for multiple-type consumer products. The objective function incorporates technical, ecological, and commercial decision criteria and optimization occurs using a two-level optimization procedure. First, a set of potential product recovery and disposal (PRD) strategies is generated for each separate product type. Secondly, optimal PRD strategies are assigned to the products within a coherent multiproduct or product group policy. The aim is to find an optimal balance between maximizing net profit and meeting constraints like recovery targets, limited market volumes, and processing capacities. A TV case is worked out to illustrate the working of the model. Also, the managerial use of the model is discussed in view of establishing an economically and ecologically sound base for achieving ICM.

1 INTRODUCTION

Traditionally, manufacturers retrieved discarded products and components selectively, if at all. Products were usually returned to the original equipment manufacturer (OEM), due to contractual obligations (lease products), technical failure, etc. However, the growing public interest in environmental issues causes customer demand for recycling and the implementation of new government policies in Europe, which aim at the closure of material flows as part of integrated chain management (ICM). As a result, many industrial businesses will be confronted with large volumes of discarded products within the foreseeable future. Although many OEMs may at first react rather cautiously to the concept of extended producer responsibility, opportunities do exist for commercial exploitation of return flows. However, a number of managerial problems of an entirely new nature will have to be solved. Some critical problem areas are as follows:

- Design for recycling (DFR): product design must enable cost effective disassembly and processing as well as high quality recovery.
- The development of secondary end markets to sell the recovered waste.
- The set up of collection systems: products must be returned in sufficient quantity and quality.
- Data acquisition: relevant information must be available to decision makers.
- Taking make or buy decisions and establishing strategic alliances.
- Choosing optimal recovery and disposal (RD) options.

For more details refer to Thierry et al. (1995) and Pohlen and Farris (1992).

The problem studied in this paper concerns the formulation of a tactical recovery plan. In such a plan, decision rules are formulated on the handling of return products in terms of disassembly, recovery, and disposal. A recovery plan is determined for a tactical planning period, because it serves as a basis for other tactical decisions like facility investments, buy-back agreements with suppliers, and negotiations with the government with respect to environmental legislation. This paper focuses on OEMs who produce multiple types of consumer products and who are confronted with legislative take-back and recovery obligations. It is assumed that products have a complex assembly structure, are durable, and that the various types of return products belong to one product group, e.g., electronic products or cars. The problem situation at hand is reflected in Fig. 1.

The determination of a recovery plan involves optimizing some objective function with respect to a set of decision criteria. It may be necessary to engage in trade-offs among these criteria, e.g., a trade-off between profit and amount of recycled content. In this paper, a combination of two models is presented that can serve as a managerial tool for ICM professionals involved in these types of issues. Although the mathematical formulas may be dense at times, the practical implications of the various modeling steps will be explained. The remainder of the paper is built up as follows. In Sec. 2 an outline of the research is carried out; in Sec. 3 relevant literature is reviewed and the writers' research is positioned; in Sec. 4 a model is described for determining recovery strategies for single product types; in Sec. 5 a model for determining recovery strategies in a multiproduct situation is presented, where these products are part of a coherent product group; finally, in Sec. 6 models and case results are discussed and conclusions are drawn.


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2 PROBLEM DEFINITION

First, the definition of some concepts used are as follows:

- **Product**—single-type manufactured equipment, built up from components in multiple assembly layers.
- **Product group**—multiple type collection of coherent products.
- **PRD strategy**—product recovery and disposal strategy for a single product.
- **GRD policy**—group recovery and disposal strategy for a product group, where a PRD strategy is assigned to each product part of the product group.
- **Assembly**—a product or a part.

Now, let us analyze the problem at hand. Formulating a recovery plan means formulating decision rules with respect to: (1) determining an optimal level of disassembly for return products; and (2) assigning optimal recovery and disposal (RD) options to the product or its released components. The recovery-decision process is reflected in Fig. 2.

Although legislation is the initial driving force behind the return flows, the main goal is to exploit commercial opportunities, i.e., maximize net profit from recovery. However, many constraints may obstruct this endeavor, e.g., environmental laws. In general, the formulation of a recovery strategy is based on technical, commercial, and ecological decision or feasibility criteria, which express the technical, commercial, and environmental feasibility for application of reuse, recycling, or disposal. It should be noticed that these feasibility criteria are applicable at two levels: the product level and the product group level (Krikke et al. 1996). For example, the technical state of a return assembly is a factor to be considered at the product level, because it determines the feasibility of reuse options for that particular product (or parts released from it after disassembly). On the other hand, criteria like legislative recovery targets are defined for entire product groups, e.g., electronics. Examples of these criteria are given in Table 1.

The main difference between the two levels lies in the possible compensation or substitution effects at the product group level. For example, if one type of product fails to meet certain recovery targets, it can be compensated by another product. Similarly, two different types of cars may have been equipped with the same type of motor. If the PRD strategy for both cars implies revision of the engine, then they compete in the same (secondary) market. Also in processing capacity, optimization at the product group level is required, because reverse logistic facilities may be used for multiple product types. The distinction of two decision levels for product type and product group is therefore quite natural as a form of hierarchical decomposition. For this reason, the optimization is performed in a two-phase procedure. The following text describes the two steps in the procedure.

In the first step, PRD strategy at the product level is determined. In Krikke et al. (1997), a model is developed that determines a PRD strategy for one product type with maximal net profit, taking into account all relevant technical, ecological, and commercial feasibility criteria at the product level. As a case example, a PRD strategy for a TV was determined, named TV-X, of which the disassembly tree is reflected in Fig. 3.

This disassembly tree consists of nine assemblies in three layers, where each layer reflects a disassembly level. Each assembly, which refers to the product as well as its parts, can be found in quality class \( q = 1 \) (good) or \( q = 2 \) (poor) with a certain probability. These probabilities are conditional, i.e., the chance of finding an assembly in a certain class \( q \) depends on the class of the parent assembly. For instance, if the parent assembly is returned in good quality, one is more likely to find the children of this assembly in good quality than when the parent has a bad quality. Thus, the model requires a disassembly tree, a quality classification scheme, and conditional probabilities as input. Moreover, disassembly costs and recovery revenues (both also conditional on classes \( q \)) are additional input parameters. In the optimization, the assignment of optimal disassembly and RD options is now dependent on the quality classes; hence, a PRD strategy is formulated as a set of conditional assignment rules to support disassembly and RD decisions. In addition to an expected net profit, the output consists of an expected rate of disassembly, recovery, and disposal operations. A profit-optimal PRD strategy for a case example is shown in Fig. 4.

The PRD strategy of Fig. 4 optimizes a tactical recovery strategy on net profit for a single product and may be less preferable in view of criteria on the product group level, e.g., environmental recovery targets. Therefore, an alternative strategy with a higher recovery score and possibly less profit may be desirable. In addition, limited volumes of secondary end markets or restricted capacity of recycling and disposal facilities may also require alternative strategies. In general, alternative strategies at the product level are needed to deal with feasibility criteria at the product group level. The overall idea is to determine multiple PRD strategies for every product.
from generators not assigned to recycling, are disposed of to some landfill with capacity $X$ (there is only one landfill in the model). The model is used to determine the least costly assignment of recycling options and landfill operations, given a life span $T$ of the landfill. At the end of its life span, the landfill is closed and replaced by another one at a certain cost. By varying the landfill's economic lifetime $T$---of course within a range of possible lifetimes---a cost-optimal life span of the landfill and corresponding assignment of recycling options can be found. Jacobs and Everett (1992) developed an extended version of this model that allows for multiple landfills and they investigate additional aspects, e.g., the appropriate service life of consecutive (future) landfills and the effects of landfill (tipping) fees.

### 3.2 Physical Network Models

Caruso et al. (1993) consider an Urban Solid Waste Management System (USWMS), which is structured into four phases, namely, collection, transportation, processing, and landfill. They developed a location-allocation model to find the number and location of the processing plants, given the location of the waste generators and landfills. For each processing plant, the technology incineration, composting or recycling, the amount of waste processed as well as the allocation of service users (waste sources) and landfills (waste sinks) are determined. No more than one facility may be located in one geographic zone and there are maximum capacities for all facilities and landfills. The model is single period and has a multicriteria objective function, with components for economic cost, waste of resources, and ecological impact. Efficient heuristics are developed to solve the problem.

In Ossenbruggen and Ossenbruggen (1992) a computer package for solid waste management (SWAP) and the underlying LP-model are presented. The model describes a waste management district as a network, where nodes represent waste sources, intermediate (capacitated) processing facilities, and destinations (sinks) on given locations. Sources, sinks, and intermediate stations can be of multiple (technology) types. Decision variables are the amount of waste to be processed by each facility and the magnitude of flows between the facilities. Implicitly, the applied technologies are determined. Constraints follow from technically allowed processing sequences and capacity limitations. The algorithm finds a cost-optimal solution, where the cost function only includes vari-

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**FIG. 5. Two-Phase Optimization Procedure to Determine GRD Policy**

A two-stage procedure explains the use of two models. A heuristic procedure is used to generate alternative PRD strategies at the product level (Sec. 4). Subsequently, an MILP model assigns the PRD strategies at the product group level (Sec. 5).

### 3 LITERATURE REVIEW

Relevant literature can be classified in two classes: scheduling models and physical network models. These are discussed in Sec. 3.1 and 3.2, respectively. In Sec. 3.3, there are some notes on the literature in relation to this research.

#### 3.1 Scheduling Models

Lund (1990) developed an LP-model to find the least cost schedule of solid waste recycling and disposal for multiple planning periods. The decision variables are $R_{ij}$, representing the number of waste generators of class $i$ (e.g., households in a certain area), to be subjected to recycling option $j$ (e.g., newspaper recycling) in period $t$. Waste volumes $y_t$ coming...
able costs per waste unit, e.g., kilogram. These unit costs incorporate tipping fees, shipping costs, and revenues from reuse.

Pugh (1993) describes the HARBINGER model, which gives decision support for the long-term waste management planning of a city or county. The waste management system involves collection, transportation, treatment, and disposal or reuse of a community’s waste stream. These systems tend to be very complicated, which explains the need for mathematical analysis. The heart of HARBINGER lies in the multiperiod allocation submodel, which determines a cost-optimal assignment of waste from the sources to treatment and disposal facilities on given locations, within constraints set by the user (e.g., for capacity). Optimization occurs on least cost. Other submodels of HARBINGER are used to specify the input for the allocation submodel and for postoptimality analysis.

### 3.3 Notes on Literature

The two models have clearly different approaches. The scheduling models determine optimal recovery and disposal options for a waste stream, without considering the physical network, while the physical network models focus on location-allocation aspects, thereby implicitly determining optimal recycling technologies. Both kinds of models are in line with the second step of our optimization procedure, particularly the scheduling models that deal with the assignment of recycling options within linear constraints. They give valuable insight in the inevitable trade-offs between various criteria, relevant in assigning recovery and disposal options to waste streams. LP models prove to be very suitable for determining a recovery and disposal plan, because they are relatively easy to model and solve and give possibilities for sensitivity analysis. However, the preceding models do not fit the problem definition for two major reasons.

First, a distinction lies in the definition of waste. Both the scheduling and the physical network models deal with a mixed (urban) waste stream and not with durable assembly products. Therefore, no distinction is made between optimization at the product level and the product group level nor does one allow for product and component reuse and disassembly aspects. Second, the definition of recycling options is different. In the scheduling models, recycling options are coupled to identified substreams: one can only assign one recycling option to each waste stream for each class of waste generators. The physical network models, however, combine the assignment of recovery options with the design of the physical network. This may lead to great modeling and computational complexity in a GRD-policy situation, in which various disassembly levels and RD options for multiple product types are allowed for. For consumer products, the problems of recovery planning and physical network design should be decoupled. Now, the GRD policy should be seen as one of the input parameters of the physical network design. Hence, a stronger use of decomposition is proposed here, which results in higher simplicity. Some simplifications are made on the following aspects. To avoid high uncertainty in parameter values, a multiperiod planning approach is not used; just one (tactical) planning period is implemented. Moreover, there is no distinguishing between different classes of waste generators at the GRD level, but instead, quality classes are incorporated in the alternatives at the product level. Operation management of the reverse logistics is also considered as a decoupled problem that can be addressed after the network design. As a consequence, the GRD policy is determined on a market level, i.e., the physical design aspects of the reverse logistic system are neglected. The main underlying assumption is that the cost and revenue functions are the same for all locations in the system. This may not always be the case. For example, the profitability of applying an RD option might partly depend on transportation costs. However, regional differences between various sources of return products can easily be captured in the writers model by considering them as different products. This will be discussed in Sec. 6.

### 4 Generating Set of PRD Strategies at Product Level

This section is organized as follows. In Sec. 4.1 the need for alternative strategies will be illustrated with an example of TV-X. In Sec. 4.2 a heuristic procedure is developed, which can determine such an alternative strategy; in Sec. 4.3 this procedure is applied to a case example.

#### 4.1 Need for Alternative PRD Strategies

As we explained in Sec. 2, the PRD strategy is determined at the product level and may be suboptimal with respect to feasibility criteria at the product group level, such as environmental impact, market aspects, and needed processing capacity. In this subsection, situations are considered where the profit-optimal strategy falls short on some of these criteria.

Consider the PRD strategy $x_0$ for TV-X in Fig. 4. It results in a net profit of $218$ per TV and meets product level constraints, see Krikke et al. (1997). However, as mentioned earlier, additional product group level criteria determine the overall feasibility of a PRD strategy. For example:

- The amount of reused and recycled contents (to meet legislative recovery targets).
- The needed capacity (because processing capacity may be a critical constraint).
- The resulting secondary products (because sales volumes of secondary markets may be restricted).

Now, take a closer look at legislative recovery targets. These targets require that a minimal level of reuse ($e_1$), material recycling ($e_2$), and metal recycling ($e_3$) is achieved, usually expressed in terms of percentages of the mass of the return flow.

### TABLE 2. Weights and Amounts of Recycled Contents of Materials for One Disassembled TV-X

<table>
<thead>
<tr>
<th>Material</th>
<th>Amount (1)</th>
<th>Plastics (2)</th>
<th>Iron (3)</th>
<th>Copper (4)</th>
<th>Aluminum (5)</th>
<th>Platinum (6)</th>
<th>Glass (7)</th>
<th>Toxins (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Present in TV (kg)</td>
<td>1.6</td>
<td>1.25</td>
<td>0.8</td>
<td>0.7</td>
<td>0.7</td>
<td>3.0</td>
<td>0.15</td>
<td>0</td>
</tr>
<tr>
<td>Recycled (kg)</td>
<td>0.05</td>
<td>0.5</td>
<td>0.8</td>
<td>0.6</td>
<td>0.525</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

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• \( \varphi(e2, s_0) = 0.5 \times (0.05 + 0.5 + 0.8 + 0.6 + 0.525 + 0.2) = 1.3 \) kg (amount of recovered materials).

• \( \varphi(e3, s_0) = 0.5 \times (0.5 + 0.8 + 0.6 + 0.525) = 1.2 \) kg (amount of metal recycled).

Furthermore, it is given that metals account for 4/10th of all materials and that the total weight of TV-X is 8.2 kg. The relative recovery scores are calculated as follows:

- For material recycling: \( 1.3 \times 0.5 \times 8.2 = 0.32 \), where \( T(e2) = 0.70 \).
- For metal recycling: \( 1.2/0.5 \times 8.2 \times 0.4 = 0.73 \), where \( T(e3) = 0.95 \).

Hence, the writers fall short on the targets \( T(e2) \) and \( T(e3) \). Therefore, an alternative strategy is required to improve material recycling scores. Analogously, the amount of reuse \( \varphi(e1) \) can be analyzed. It is assumed that the achieved reuse score of 0.53 is satisfactory; hence, no alternative strategy is needed for the benefit of target \( T(e1) \).

Again it is stressed that alternative strategies are generated at the product level to comply better with criteria at the product group level. Recovery targets are only one example of these criteria. Any feasibility criterion \( c \) may be analogously included to the preceding ones, for example, for market or capacity reasons. Alternative strategies are generated for each product type part of the product group.

Note that \( \varphi(c, s) \) can be negative. This may occur, for example, when applying a certain RD option generates a market demand for another RD option. An example of this is in the PRD strategy \( s_0 \) in Fig. 4, second-hand TVs are reused. Suppose that the TVs are sold at the second-hand market \( m1 \), then \( \varphi(m1, s_0) = 0.50 \) TVs. Now, assume the repair of the TVs requires a certain (refurbished) part, which was also recovered after return and for which an external market \( m2 \) exists independent from \( m1 \). Then, this part is withdrawn from the external market \( m2 \) for the benefit of \( m1 \) and \( \varphi(m2, s_0) = -0.50 \) is set. Hence, if a constraint \( T(m2) \) is imposed on the refurbished parts market (because of a restricted market volume), this constraint is relaxed by applying \( s_0 \) to TV-X. In Thierry et al. (1995), the interrelationship of product recovery options is discussed.

In conclusion, alternative strategies are generated on a number of (combination of) criteria \( c \). It is logical to formulate one alternative strategy for a combination of product group level criteria of which synergy is to be expected in generating an alternative strategy. For example, improving the metal recycling score of TV-X also improves the overall material recycling score, which justifies the clustering of criteria \( c \) in a cluster \( CL(k) \). This is done for all products \( i \) part of the product group. The ultimate result is a set \( S_i \), where \( S_i = \{ s_0, s_{1n}, \ldots, s_{kn} \} \), with \( K \) the number of clusters of product group level criteria \( c \) that require the generation of alternative strategies. The sets \( S_i \) form the input for the second optimization step: assigning the PRD strategies to each product type in a GRD policy. This will be discussed in Sec. 5.

### 4.2 Procedure for Generating Alternative PRD Strategies

In this section, a general procedure for generating a set of alternative PRD strategies is described. The core of the procedure is a heuristic algorithm. The heuristic algorithm works basically as follows. The starting point is the profit-optimal PRD strategy \( s_0 \) with an expected net profit and expected scores on product group level criteria \( c \). The writers wish to improve the scores on criteria of some cluster \( CL(k) \). Assume that this cluster concerns the recovery scores. Environmental unfriendly alternatives from the set of RD options are removed. Hence, the recovery scores are increased by favorably modifying the sets of feasible RD options \( R_0(j, q) \). If the recovery improvements are not harmed, options are removed in favor of other clusters, which are given less priority. After modification of the set \( R_0(j, q) \), the PRD strategy is recalculated with the dynamic programming (DP) model described in Krikke et al. (1997). Analogously, alternative strategies for other clusters can be determined (e.g., markets), where the recovery cluster is given a lower priority. This way, for every cluster \( CL(k) \) an alternative PRD strategy \( s^*_k \) is determined. These alternative PRD strategies all consist of conditional assignment rules. Before this heuristic can be applied, however, some steps must be taken.

First, all RD options that can potentially improve the score on any criterion \( c \) must be added to the set of feasible RD options \( R_0(j, q) \). For example, in the original stochastic DP model of Krikke et al. (1997), it is only allowed for one recycling option per assembly \( j \) per class \( q \), where a subprocedure determines which recycling option is optimal. Here, all recycling options that are applicable must be taken into account, even the most non-profitable ones. Second, the criteria must be clustered in \( K \) sets \( CL(k) \), according to the rule of thumb described in Sec. 4.1.

Now, the full optimization procedure can be constructed, which is visualized in Fig. 6. It generates alternative PRD strategies with increasing performance on product group level criteria by iteratively “jumping” between the product and the product group level. The heuristic algorithm is described in detail in Appendix I.

### 4.3 Alternative PRD Strategies for TV-X

Now, the case is continued and two alternative PRD strategies for TV-X are determined. In the first alternative strategy, the scores on \( e2 \) (material recycling) and \( e3 \) (metal recycling) are improved. Reuse \( (e1) \) should not get worse. In the second alternative strategy, the market volume \( m1 \) for second-hand TVs is restricted. Only one out of four TVs can be upgraded for sale, while in the PRD strategy of Fig. 4 one out of two TVs is assigned to this option as follows.

![FIG. 6. Full Optimization Procedure for Determining Set of Alternative PRD Strategies](image-url)
Firstly, we cluster criteria $c$. Two clusters $k$ are formed. The first cluster includes the recovery criteria $e_1$, $e_2$, and $e_3$. Inclusion of $e_1$ is allowed, because only scores on reuse are dependent on quality class $q$. Hence, no improvement on $e_2$ and $e_3$ can be realized by changing the amount of product or part reuse ($e_1$). The second cluster consists of only one criterion, namely, market volume for second-hand TVs. The parameter settings are summarized in Appendix I.

Secondly, the heuristic algorithm is used to generate two alternative PRD strategies for TV-X, one for cluster $CL(1)$ with improved recovery scores and one for cluster $CL(2)$ with less TVs to be sold at the second-hand market. The ultimate result is a set of alternative strategies $S = \{s_0, s_n, s_m, s_k\}$. In Fig. 7, $s_n$ is depicted. The main difference compared to the profit-optimal strategy is that disposal is replaced by recycling as an optimal RD option for both assemblies 5 and 6. In this option, these assemblies are shredded and the materials are separated for recycling and sales, including the toxins. The scores on $e_2$ and $e_3$ are improved to 0.76 and 0.88, respectively, while the targets were 0.70 and 0.95. Net profit has sunk from 218 to 201. Target $T(e_3)$ is still not met, but no more recycling options are available for further improvement. A detailed description of the application of the algorithm is also in Appendix I.

5 MIXED INTEGER LINEAR PROGRAMMING (MILP) MODEL FOR DETERMINING GRD POLICY

After generating a set of alternative PRD strategies for each product type, an optimal strategy is assigned to each product type part of the product group. This is done by an MILP model, which is described in Sec. 5.2. In Sec. 5.3, a TV case is discussed as an example using the model. First, the problem in Sec. 5.1 is formulated. The notation used is the same as in the previous sections, except that an $i$ is added for identifying separate product types in a multiproduct situation.

5.1 Problem Formulation

The aim of a GRD policy is to find an optimal assignment $f_{ik}$ of PRD strategies $s$ to all products $i$. Optimal means on the one hand optimizing net profit and on the other hand it means dealing with constraints $T(e)$ imposed on product group level criteria. The writers distinguish between three categories of criteria $c$: environmental criteria $e (e = 1 \ldots E)$, market criteria $m (m = 1 \ldots M)$, and capacity criteria $p (p = 1 \ldots P)$. These criteria are of an entirely different nature and can be incompatible. To avoid infeasibility, the constraints are considered as soft and the writers strive for minimizing the deficit with respect to the constraints. The relative importance or weight of the decision criteria can vary, depending on several factors. For example, the market weight may depend on price-elasticity of the market, buy-back contracts with suppliers, or the possibilities for market expansion. Weights for recovery targets may depend on consumer behavior and penalties to be expected from the government. In practical situations, additional categories may be distinguished.

At the product level, for each product type $i$, a set $S_i$ of alternative PRD strategies $s$ is available. All strategies have a certain expected net profit $w_{ik}$ and an expected rate of applied disassembly, reuse, recycling, and disposal operations: each combination $(i, s)$ results in a flow $\varphi(e, i, s)$ per single product of relevant criteria $c$ at the product group level. It is assumed that in the next planning period $F$ types of products $i$ are returned in quantities $n_i$. The total number of products is $N$, with $\Sigma_{i} n_i = N$. All $N$ return products must be processed for disposal or reapplication within the planning period. Every product type can only be processed by only one PRD strategy. It is also assumed that all parameters remain constant within the planning period and that the required data or reliable estimates are available.

5.2 Model Construction

Because in a GRD policy it is the intention to balance between net profit and product group level constraints, the writers specify the minimal net profit (target) level $FP$ and the deviation variables $d_e, d_m$, and $d_p$, which reflect the deviation to the product group level constraints. Weights $g_e, g_m$, and $g_p$ are assigned to the variables to reflect their importance. The aim is to penalize violations to the targets $T(e), T(m)$, and $T(p)$, so $\sum_{i} z_e, \sum_{m} z_m$, and $\sum_{p} z_p$ are formulated. Now, the following MILP model is constructed:

\[ \text{MIN} \sum_{e} g_e \times z_e + \sum_{m} g_m \times z_m + \sum_{p} g_p \times z_p \]  

\[ \text{(minimize deviation variables)} \]  

subject to

\[ \sum_{i} \sum_{k} f_{ik} \times w_{ik} \times n_i \geq TP \quad \text{(net profit target)} \]  

\[ \sum_{i} f_{ik} \times \varphi(e, i, s) \times n_i = T(e) \times TM \times mf(e) \]  

\[ \times (1 - d_e) \forall e \quad \text{(recovery targets)} \]  

\[ \text{J. Environ. Eng. 1998.124:368-379.} \]
\[ \sum \sum f_o \times \varphi(m, i, s) \times n_i = T(m) \times TM \times mf(m) \]

\[ \times (1 + d_m) V_{\text{mn}} \quad \text{market volumes} \quad (4) \]

\[ \sum \sum f_o \times \varphi(p, i, s) \times n_i = T(p) \times TM \times mf(p) \]

\[ \times (1 + d_p) V_{\text{mp}} \quad \text{capacity constraints} \quad (5) \]

\[ \begin{align*}
    z_e &= d_e \\
    z_e &= 0 \\
    z_m &= d_m \\
    z_m &= 0 \\
    z_p &= d_p \\
    z_p &= 0
\end{align*} \]

\[ \text{logical constraints} \quad (6) \]

\[ \sum f_o = 1 \forall i \quad \text{entire flow should be processed} \quad (7) \]

\[ f_o = 0, 1 \forall i \forall s \quad \text{one strategy per product type} \quad (8) \]

• The writers model has similarities with a knapsack problem and a product-mix or blending problem. But there are some differences. Compared to a knapsack problem there is not one, but a number of constraints. This makes it a generalized knapsack problem. Compared to a product-mix problem, the decision variable is a boolean and not a continuous variable. Of course, as a variant of the problem, the decisionmaker may wish to assign mixed strategies to one product type i. Then, f_o becomes a fraction and the problem is now solved as an LP problem. In Sec. 6.1 this subject will be further discussed.

• Other relevant decision criteria may be included in the model if necessary. For example, in addition to a maximum capacity, a minimum level of turnover may also be required for certain processing capacities. Any general feasibility criterion c can be fitted into the model, as will be seen in Sec. 5.3.

• As a result of using deviation variables, constraints (3), (4), and (5) are soft. This way, one can always find a feasible solution by properly manipulating TP. This way of modeling is chosen because in practical situations it may be hard to fully meet all constraints T(c). However, if desired, one can define some decision criterion as a hard constraint and remove the deviation variable from the objective function. One could also formulate the objective function as maximization of net profit, subjected to the hard constraints T(e), T(m), and T(p), but again, it is emphasized that no feasible solution may be found.

• The general model is formulated such that all constraints are linear (except for the 0,1-constraint). However, in practical situations nonlinear constraints may occur, as seen in Sec. 5.3.

5.3 Case: Determining an GRD Policy Mix for Three TVs

To illustrate the working of the MILP model, the writers calculate a TV case for three different types of TVs and the assignment of PRD strategies in a GRD policy at the product group level. Calculations were made with the help of the solver LINGO on a Switch 486 computer. Data related to product composition are derived from Bink (1995), whereas volumes, numbers, etc., are randomly generated. Note that solutions found by the model are not intended to be a representative practical situation, but should provide insight in the potential applicability of the concepts developed.

5.3.1 Case Description and Modeling

Suppose an OEM takes back three types of TVs: A, B, and C in various quantities. At the product level, an optimal PRD strategy s1 has been determined for each type of TV. At the product group level, the following constraints must be taken into account:

• Recovery targets, formulated similarly but not equivalent to European regulations, are as follows:
  \[ T(e1): \text{at least 25 mass }\% \text{ should be reused as product/ component,} \]
  \[ T(e2): \text{at least 70 mass }\% \text{ of all materials should be recycled.} \]
  \[ T(e3): \text{at least 95 mass }\% \text{ of the metals should be recycled.} \]
• The market volume T(m1) for second-hand TVs is limited to 500 TVs.
• The disposal capacity for landfill T(p1) is limited to 7,500 kg.

Note that three kinds of product group level constraints \( c \) are present in this case. They have been clustered in three clusters \( k \). Therefore, three alternative PRD strategies have been determined for each product type. Hence, there are four strategies for each type of TV. Flow \( \varphi(c, i, s) \) is calculated per product per PRD strategy for \( c = e1, e2, e3, m1, \) and \( p1 \). The assignment of weights is a management decision itself. In this case, management wants to put emphasis on the recovery targets, because it fears repercussions from the government and customers. Therefore, a weight of 3 is assigned to \( z_{e1}, z_{e2}, \) and \( z_{e3} \). The market and disposal constraints are taken less seriously, and so a weight of 1 is assigned to \( z_{m1} \) and \( z_{p1} \).

Relevant data can be found in Appendix II. Note that none of the TVs resembles the TV-X used as an example in the previous section. The general model of Sec. 5.2 has to be tailor-made for this problem. The interested reader can find a detailed explanation and model description in Appendix III. Since the model is conceptually equivalent to the general model an analysis of the results continues.

5.3.2 Case Results

In a product recovery situation, the writers are interested in the behavior of the deviation variables as a function of net profit. For example, how the amount of recycled contents correlates with profit is analyzed, i.e., does recycling go down if profit goes up, or not? Note that variables \( d_e \) reflect the positive and negative deficit to constraints \( T(c) \), while \( z_e \) only reflects the positive deficits. This distinction was made because negative deficits, or ‘margins’ in common language, should not be penalized nor rewarded in the objective function. As a managerial indicator, \( d_e \) is the most fitting since it is interesting to know both slack and shortcomings to constraints. For the case at hand, the behavior of the deviation variables is analyzed by varying the minimal required net profit TP, which results in different assignments of PRD strategies to products and, thus, in different scores for the deviation variables \( d_e \) as well as the actual net profit.

Table 3 should be interpreted as follows. The variables \( d_{e1}, d_{e2}, d_{e3}, d_{m1}, \) and \( d_{p1} \) reflect the relative deficit for the constraints \( T(e1), T(e2), T(e3), T(m1), \) and \( T(p1) \). As long as they are nonpositive, the constraint is satisfied. A value lower than zero reflects the relative slack. A positive value implies that the constraint is violated. This is penalized in the objective function by \( z_e \). It is observed that most product group level constraints are met if \( TP = 180,000 \), since the deviation variables are nonpositive. The real profit is then 213,500. There
is one exception to this: the secondary TV market \( m1 \), whose volume is exceeded by a 100%. Therefore, the weight \( g_{m1} \) is varied with steady \( TP = -100,000 \); \( g_{N} \) remains 3 \( \forall e \); and \( g_{tp} \) remains 1. The results of this scenario are reflected in Table 4.

The results in Fig. 8 are summarized. On the x-axis, the total net profit of the GRD policies involved is shown. On the y-axis, the corresponding values for the deviation variables are shown. Thus, the function of the (dependent) deviation variables and the (independent variable) net profit is obtained. It is very difficult to decrease the overload on the secondary TV market. This means that the market needs to be expanded; otherwise no GRD policy can be implemented. If one would succeed in doubling the market volume, an optimal GRD policy would be an assignment of \( (s_4, s_2, s_1) \) to the products A, B, and C with a total profit of 213,500. If no market expansion can be realized, one will have to go back to the product level and reduce the amount of product reuse for at least one of the A, B, or C products. An alternative PRD strategy with no product reuse will be generated, after which the MILP optimization is repeated. It can also be seen that in the high-profit GRD policies, processing capacity becomes a critical constraint, while material recycling scores slightly deteriorate.

In general, an analysis like that reflected in Fig. 8 provides the decision maker with insight with respect to the impact of GRD policies on various feasibility criteria. It can be determined which criteria are critical, whether these are recovery targets, market volumes, or processing capacities. Necessary steps can be undertaken, such as market or capacity expansion, redetermining PRD strategies, selecting alternative RD options, or negotiating with governments on environmental legislation.

## 6 DISCUSSION AND CONCLUSIONS

The discussion is presented in three sections. In Sec. 6.1 the modeling issues are discussed, in Sec. 6.2 the use of the model in relation to other managerial fields in product recovery is discussed, and in Sec. 6.3, conclusions are drawn.

### 6.1 Modeling Issues

The length of the planning period depends mainly on the availability of data and stability of the parameter settings. In principle, the model is developed for the tactical management level, which implies a planning horizon of approximately 1–3 years. In the writers’ opinions, it is not very realistic to extend the planning horizon to multiple periods because this requires data on all future parameter settings. For example, if a multiperiod problem with four periods of 3 years were to be solved, this would require estimates for a timespan of 12 years on the number, types, and quality of the products/components returned; volume and prices in secondary markets; cost prices for recovery and disposal; availability of (new) recovery/disposal techniques; legislation, etc. This may be very difficult. Therefore, a more practical approach is taken, which, in short, boils down to “look where we stand now” and “see where we should be heading to.” Of course, a decision maker may wish to include the effects of historic decisions. For example, if a facility, established in a former period, is available in the coming planning period, then the cost prices of RD options using this facility might be lower than RD options requiring new facilities. Also, a certain processing capacity is available to these RD options, which is a product group level criterion. In general, effects of historic decisions should be incorporated in the cost and revenue functions at the product level and the constraints at the product group level.

The model does not distinguish between different parameter settings for products of one type, returned from different geographic areas. This can be easily repaired, if necessary. For example, the profitability of RD options might partly depend on transportation costs; hence, on the physical distance between supply points, facility locations, and demand points. This can be solved by defining product subtypes \( i \) on the basis of regions (e.g., TV-X from France), and RD suboptions by market locations (e.g., TV reuse for second-hand markets in Nigeria), and adapt net profits accordingly. Again, differences are incorporated in the cost and revenue functions and this may lead to considering different options.

A major assumption in this research is that only one decision maker determines the GRD policy. The writers believe that this is the best approach for analytical purposes, but it is also applicable in practical situations. Even if responsibility is scattered all over the reverse chain, it is useful to determine a GRD policy that is globally optimal as a starting point for discussions or negotiations. If this GRD policy prejudices

---

### Table 3. GRD Policies for Various TP, \( g_{m1} = 3 \) \( \forall e, g_{tp} = 1, g_{tp} = 1 \)

<table>
<thead>
<tr>
<th>TP (1)</th>
<th>GRD policy (2)</th>
<th>( d_{m1} ) (3)</th>
<th>( d_{s2} ) (4)</th>
<th>( d_{s1} ) (5)</th>
<th>( d_{m2} ) (6)</th>
<th>( d_{m3} ) (7)</th>
<th>Profit (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>A:s4 B:s2 C:s4</td>
<td>-0.60</td>
<td>-0.60</td>
<td>-0.06</td>
<td>0</td>
<td>0</td>
<td>-0.44</td>
</tr>
<tr>
<td>80,000</td>
<td>A:s4 B:s2 C:s2</td>
<td>-0.60</td>
<td>-0.60</td>
<td>-0.06</td>
<td>0</td>
<td>0</td>
<td>-0.44</td>
</tr>
<tr>
<td>180,000</td>
<td>A:s4 B:s2 C:s1</td>
<td>-0.60</td>
<td>-0.60</td>
<td>-0.06</td>
<td>0</td>
<td>0</td>
<td>-0.44</td>
</tr>
<tr>
<td>220,000</td>
<td>A:s4 B:s3 C:s1</td>
<td>-0.60</td>
<td>-0.60</td>
<td>-0.06</td>
<td>0</td>
<td>0</td>
<td>-0.44</td>
</tr>
<tr>
<td>230,000</td>
<td>A:s4 B:s1 C:s1</td>
<td>-0.60</td>
<td>-0.60</td>
<td>-0.06</td>
<td>0</td>
<td>0</td>
<td>-0.44</td>
</tr>
<tr>
<td>260,000</td>
<td>A:s1 B:s3 C:s1</td>
<td>-1.00</td>
<td>-1.00</td>
<td>-1.00</td>
<td>2</td>
<td>0</td>
<td>267,500</td>
</tr>
<tr>
<td>270,000</td>
<td>A:s3 B:s1 C:s1</td>
<td>-1.00</td>
<td>-1.00</td>
<td>-1.00</td>
<td>2</td>
<td>0</td>
<td>267,500</td>
</tr>
<tr>
<td>285,000</td>
<td>A:s1 B:s1 C:s1</td>
<td>-1.00</td>
<td>-1.00</td>
<td>-1.00</td>
<td>2</td>
<td>0</td>
<td>267,500</td>
</tr>
</tbody>
</table>

### Table 4. GRD Policies for Various \( g_{m1} \), TP = 100,000, \( g_{m1} = 3 \) \( \forall e, g_{tp} = 1 \)

<table>
<thead>
<tr>
<th>( g_{m1} ) (1)</th>
<th>GRD policy (2)</th>
<th>( d_{m1} ) (3)</th>
<th>( d_{s2} ) (4)</th>
<th>( d_{s1} ) (5)</th>
<th>( d_{m2} ) (6)</th>
<th>( d_{m3} ) (7)</th>
<th>Profit (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A:s4 B:s4 C:s4</td>
<td>-0.34</td>
<td>0.11</td>
<td>0.24</td>
<td>0.7</td>
<td>0.04</td>
<td>26,000</td>
</tr>
<tr>
<td>100</td>
<td>A:s4 B:s4 C:s4</td>
<td>-0.34</td>
<td>0.11</td>
<td>0.24</td>
<td>0.7</td>
<td>0.04</td>
<td>26,000</td>
</tr>
<tr>
<td>1,000,000</td>
<td>A:s4 B:s4 C:s4</td>
<td>-0.34</td>
<td>0.11</td>
<td>0.24</td>
<td>0.7</td>
<td>0.04</td>
<td>26,000</td>
</tr>
</tbody>
</table>
some channel members, a compensation scheme should be established. Although this is a very interesting subject, it is beyond the scope of this research.

In the MILP formulation only one PRD strategy is assigned to each product type. This is not the case when an LP formulation is used, which is in fact a relaxation of the MILP formulation. For example, if the LP model for the parameters is solved as given in the first scenario of Sec. 5.3, then an optimal assignment is (11, s1), (2, 0.1 s1/0.9 s2), and (3, s1), with a net profit of 218,000 and deviation variables values \( d_1 = 0.6, d_2 = 0.01, d_3 = 1, \) and \( d_4 = -0.29. \)

In conclusion, there are no important changes in results due to LP relaxation in this case. However, differences strongly depend on the parameter settings; hence, this kind of analysis can certainly be worthwhile. One should be aware of the fact that modeling the problem as an LP problem requires fractional assignments of PRD strategies. This complicates the implementation, because multiple strategies are assigned to one product type. There are several ways to deal with this:

- Establishing a mixed GRD policy per product, i.e., multiple PRD strategies can be assigned to one type of product where, e.g., half of the number of products returned is processed by a profit-optimal strategy and the other half by some alternative strategy. Presumably, this is difficult to implement in practice.
- Assigning PRD strategies to geographically distinct supply points, such that the overall assignment within the GRD policy must be realized.
- Establishing operational decision rules, in which fluctuations in inventory level, demand and supply, available resources, etc., determine the actual assignment of PRD strategies in time. Of course, in the end, the tactical assignment should be realized.
- Reformulate the PRD strategies. For example, try to generate an alternative strategy that leads to a mixture of s1 and s2.

The formulation as an LP problem also enables sensitivity analysis, which can be very useful in testing the robustness of solutions. However, these issues need further exploration.

6.2 Use of Models in Relation to Other Managerial Fields in Product Recovery

The use of the models with respect to determining recovery strategies has been discussed extensively in the previous sections. Here, links with other fields in product recovery management will be discussed. On the model input side the following. Mandatory reuse and recycling confronts OEMs with entirely new managerial problems, among which is the determination of recovery strategies for return flows. This paper discusses the determination of an optimal GRD policy for mandatory returned (discarded) durable assembly products of multiple types. It deals with the question of how to handle this return flow in terms of disassembly, recovery, and disposal. The problem is dealt with on a tactical management level because it involves anticipation to management issues like environmental legislation, buy-back agreements with suppliers, developing secondary end markets, and the setup of a logistic network. Some interesting models were found in the literature, but none fits the writers problem definition, which includes aspects like multilevel assembly structures, recovery targets, limited marked volumes, and interrelated RD options. Therefore, a new combination of two models is presented, which enables one to economically exploit compulsorily return flows while meeting given commercial, environmental, and technical constraints as much as possible. A case was calculated to illustrate the applicability of the model. Model assumptions and use were discussed. Subjects for further research include analyzing the robustness with respect to uncertainty in parameters, the operational management of implementing PRD strategies, situations of shared decision responsibilities in the reverse chain, developing forecasting tools and secondary markets, the impact of design for recycling, changing supplier relations, and the mutual impact of GRD policies and logistic network design.

In the writers view, the formulation of a GRD policy is critical in handling compulsory return flows, since it gives decision support in finding solutions for the recovery of these flows that are economically and ecologically sound. Only when both are satisfied will ICM be a success.

APPENDIX I: HEURISTIC PROCEDURE FOR DETERMINING ALTERNATIVE PRD STRATEGIES

Heuristic Algorithm

1. Order all clusters \( CL(k) \) by \[ \sum_{c \in CL(k)} g_{c} \times [T(c) - n \times \psi(c, s)TM \times mf(c)] \]

   [In case of \( > \) constraint, the ordering is done by \( \Sigma_{c \in CL(k)} g_{c} \times [n \times \psi(c, s)TM \times mf(c) - T(c)] \)]

   Set \( O(k) = (k_1, \ldots, k_d) \)

2. Set \( \hat{k} = k_1 \) and \( k := \hat{k} \)

3. Select RD option \( r^{*} \) to be removed
for $r := 1$ to $K$ do $\phi_0(r) := 0$
for all $j, j \in \cup R(c)$, do
for all $q$ do
for all $r, r \in R(j, q)$ and $r \notin \cup R(c)$, do $\phi_1(r) := \phi_0(r) + TM(j) \times p(j, q)$
$r_m := \text{ARGMAX} \phi_1(r)$
if $\phi_1(r) = 0$ then goto i.

iv. If $r_m \in R(j, q)$ then remove $r_m$ from $R(j, q)\forall q$ unless a set becomes void. It that case do nothing.
v. If no changes have been made in $R(j, q)$ for any $(j, q)$ then goto vi. else goto iii.
vi. Set $k := k + 1$. If $k \leq K$ then goto iii. else goto vii.

vii. Determine PRD strategy for $k$. The resulting strategy is $s^i_m$. Set $g_c := 0$ for any $k$, then reininsert removed RD options into $R(j, q)\forall q$ and goto i. else STOP.

Parameter settings for alternative PRD strategies for TV-X:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RD options</td>
<td>$r = 1$ (upgrade), 2 (restore), 3 (recycling), 4 (disposal)</td>
</tr>
</tbody>
</table>

Heuristic Algorithm Applied to TV-X

i. $\sum g_c \times [T_r - n \times \varphi(e, s_0)TM \times mf(e)] = 1.18$ and $g_m \times [n \times \varphi(m1, s_0)TM \times mf(m1) - T(m1)] = 0.25$; hence, $O(k) = (1, 2)$

ii. Set $k := 1$ and $k := 1$

iii. $r_m := 4$ (disposal)

iv. Remove $r = 4$ from $R(j, q)\forall q$
v. Goto iii.

vi. No changes in $R(j, q)\forall q$ v. Goto vi.

vi. Set $k := 2$, goto iii.

APPENDIX II. PRODUCT DATA OF TV A, B, AND C

<table>
<thead>
<tr>
<th>TABLE 5. Composition Return Flow</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 6. Material Composition of Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material</td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>Glass</td>
</tr>
<tr>
<td>Metals</td>
</tr>
<tr>
<td>Plastics</td>
</tr>
<tr>
<td>Toxins</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 7. Net Profits of PRD Strategies per Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product</td>
</tr>
<tr>
<td>---------</td>
</tr>
<tr>
<td>A</td>
</tr>
<tr>
<td>B</td>
</tr>
<tr>
<td>C</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 8. Physical Output $\varphi(c, i, s)$ of Processing One TV of Type A/B/C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criteria</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>e1 (kg)</td>
</tr>
<tr>
<td>e2 (kg)</td>
</tr>
<tr>
<td>e3 (kg)</td>
</tr>
<tr>
<td>m1 (numbers)</td>
</tr>
<tr>
<td>p1 (kg)</td>
</tr>
</tbody>
</table>

APPENDIX III. MILP MODEL TAILOR-MADE FOR CASE

Some complications arise when the general model is applied to the case. The critical reader may have observed that the linearity of the case problem is troublesome. The complications are explained in more detail. The cause of the complication lies in the formulation of the recovery targets for metal recycling (e3) and overall material recycling (e2). These targets are defined for the return flow resulting after reuse (e1). As a result, the constraints for T(e2) and T(e3) become non-linear. 

\[ l_0 = \sum_{i} \sum_{s} \varphi(e1, i, s) \times n_i \times f_o \]

and construct the following model for the case problem:

\[
\begin{align*}
& \text{MIN } 3 \varepsilon_{e1} + 3 \varepsilon_{e2} + 3 \varepsilon_{e3} + \varepsilon_{m1} + \varepsilon_{p1} \\
& \text{subject to } \\
& \sum_{i} \sum_{s} f_o \times n_i \times w_i \geq TP \\
& \sum_{i} \sum_{s} f_o \times n_i \times \varphi(e1, i, s) = 0.25 \times TM \times (1 - d_o) \\
& \sum_{i} \sum_{s} f_o \times n_i \times \varphi(e2, i, s) = 0.70 \\
& \times (TM - l_0) \times (1 - d_o) \\
& \sum_{i} \sum_{s} f_o \times n_i \times \varphi(e3, i, s) = 0.95 \\
& \times 0.4 \times (TM - l_0) \times (1 - d_o) \\
& \sum_{i} \sum_{s} f_o \times n_i \times \varphi(m1, i, s) = 500 \times (1 + d_m) \\
& \sum_{i} \sum_{s} f_o \times n_i \times \varphi(p1, i, s) = 7500 \times (1 + d_p) \\
& \varepsilon_{e1} \geq d_{e1} \\
& \varepsilon_{e1} \geq 0 \\
& \varepsilon_{e2} \geq d_{e2} \\
& \varepsilon_{e2} \geq 0 \\
& \varepsilon_{e3} \geq d_{e3} \\
& \varepsilon_{e3} \geq 0 \\
& \varepsilon_{m1} \geq d_{m1} \\
& \varepsilon_{m1} \geq 0 \\
& \varepsilon_{p1} \geq d_{p1} \\
& \varepsilon_{p1} \geq 0 \\
& \sum_{i} f_o = 1 \quad \forall i = 1, 2, 3 \\
& f_o = 0.1 \quad \forall i = 1, 2, 3 \quad \forall s = 1, 2, 3, 4
\end{align*}
\]

As can be seen, the constraints (12) and (13) are quadratic. To eliminate the term with \(e1\) from the constraints, the amount of reuse \(l_0\) has to be estimated in advance of the optimization. Therefore, it is estimated that a fraction \(C\) of the total return flow will be reused in an optimal solution. 

\[ l_0 = C \times TM \]

is substituted in the constraints (12) and (13), as a result of which the constraints become linear. However, the deviation variables \(d_{e1}\) and \(d_{e2}\) no longer reflect the real deviation to the targets \(T(e2)\) and \(T(e3)\), because the amount of reuse \(l_0\) is prefixed while it is actually an outcome of the optimization. As a consequence, the values of \(\varepsilon_{e2}\) and \(\varepsilon_{e3}\) may become too large or too small, depending on the choice of \(C\), which has an effect on the objective function value and, thus, eventually on the assignment of PRD strategies. Therefore, it is of paramount importance to make a good choice for \(C\), resulting in a substitution for \(l_0\) that comes close to the actual amount of reuse. For this optimization, \(C = 0.25\) is chosen. After the optimization, the real deviation can be retrieved to the targets, denoted as \(d_{e2}\) and \(d_{e3}\), as follows:

\[
\frac{d_{e1}}{TM} - \frac{l_0}{TM} = \frac{e2}{e3} = \frac{l_0}{TM} = \frac{e2}{e3} = \frac{d_{e2}}{d_{e3}}
\]

Of course, linearization can also be achieved by defining the deviation variables as the absolute deviation to the recovery targets. This way, one would avoid the use of \(l_0\). However, since it is impossible to know the absolute magnitude of the flows for \(e1\), \(e2\), and \(e3\), as well as for \(m1\) and \(p1\) in advance of the optimization, there is now the problem of choosing the right weighing factors \(g_{e1}, g_{e2}, g_{e3}, g_{m1}\), and \(g_{p1}\). Moreover, the writers wish to compare the deviation of all five constraints; hence the relative definition of the deviation variables is preferred.

APPENDIX IV. REFERENCES


APPENDIX V. NOTATION

The following symbols are used in this paper:

- \(CL(k)\) = cluster (=set of) criteria \(c\) with index \(k\), \(1 \cdots K\)
- \(c\) = feasibility criterion at product group level, \(1 \cdots C\)
- \(d_e\) = relative deficit of score on criterion \(c\) to target \(T(c)\)
- \(e\) = environmental recovery score
- \(f_o\) = assignment of PRD strategy \(s\) to product \(i\)
\[ r = \text{weight assigned to } c, \text{ reflecting its relative importance}; \]
\[ i = \text{type of consumer product}; \]
\[ J(c) = \text{set of relevant assemblies } j \text{ for criterion } c; \]
\[ j = \text{assembly, } 1 \ldots J; \]
\[ m = \text{secondary market}; \]
\[ m(c) = \text{mass fraction of total return flow associated with } c; \]
\[ N = \text{total number of products in return flow}; \]
\[ n = \text{number of products of product type under consideration}; \]
\[ n_i = \text{number of products of product type } i; \]
\[ O(k) = \text{priority ordering of clusters } CL(k); \]
\[ p = \text{processing capacity}; \]
\[ q = \text{quality class that assemblies can be found in } 1 \ldots Q; \]
\[ R(c) = \text{set of relevant RD options } r \text{ for criterion } c; \]
\[ R(j, q) = \text{set of feasible RD options } r \text{ for assembly } j \text{ in class } q \text{ for alternative PRD strategy}; \]
\[ R_d(j, q) = \text{original set of feasible RD options } r \text{ for assembly } j \text{ in class } q \text{ for profit-optimal PRD strategy}; \]
\[ r = \text{RD option by which assemblies can be recovered, } 1 \ldots R; \]
\[ r^m = \text{RD option to be removed from } R(j, q) \text{ to improve scores on } CL(k); \]
\[ r_o = \text{dummy RD option, indicating no feasible } r^m \text{ exists}; \]
\[ S = \text{set of PRD strategies}; \]
\[ S_i = \text{set of alternative PRD strategies of product } i; \]
\[ S^*_i = \text{alternative PRD strategy with improved score on } CL(k); \]
\[ s_o = \text{(original) profit-optimal PRD strategy}; \]
\[ T(c) = \text{targets set on } c; \]
\[ TM = \text{mass of total return flow}; \]
\[ TM(j) = \text{mass of assembly } j; \]
\[ TP = \text{minimal required net profit}; \]
\[ w_i = \text{net profit of processing product } i \text{ by PRD strategy } s; \]
\[ z_e = \text{positive deficit } d, \text{ to be penalized in objective function}; \]
\[ \phi_d(r) = \text{total improvement on } CL(k) \text{ as result of removing } r \text{ from } R(j, q), \text{ where total improvement is sum of improvements on all } c \in CL(k); \text{ and} \]
\[ \phi(c, i, s) = \text{physical flow bearing on criterion } c, \text{ resulting from applying PRD strategy } s \text{ to one product } i, \text{ e.g., for } c = \text{recycling: amount of recycled materials yielded.} \]