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A simulation-optimization model for sustainable product design and efficient end-of-life management based on individual producer responsibility

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ABSTRACT

This paper integrates two decision problems, namely, the design alternative selection and EOL option determination, for a family of products based on individual producer responsibility in the entire life cycle considering possible uncertainties. To address three pillars of sustainability (economic, environmental, and social), three objectives are considered: the maximization of the producer's profit, the minimization of the environmental impact, and the maximization of the social impact. Two constraints to control recovery and recycling rates are considered, which are usually imposed by legislative directives. A simulation-optimization model is developed to formulate and solve the model. An example based on a real-world case is provided to illustrate the application of the model. The proposed model is a useful tool for producers to evaluate the EOL performance of their products and to analyze the effect of EPR goals or regulations on their profitability, and for policy makers to predict the response of producers to a given package of circular-economy strategies.

1. Introduction

Responsible consumption and production is one of the 17 goals considered for Sustainable Development (SD) (UN, 2015). In order to reach this goal, traditional manufacturing disciplines should be changed. The current paradigm of production is mainly based on the linear economy, that is, “take, make, and dispose”. However, the circular economy additionally considers the recovery phase to close the global energy and material loops. This can be achieved by designing products and services that reduce waste and minimize negative sustainability impacts.

In order to make European businesses and consumers shift towards a stronger level of the circular economy, the European Commission (EC) has adopted a new action plan named Circular Economy Package. This promotes closing the loops of product lifecycles and brings benefits for both economy and environment (by extracting the maximum value from raw materials, products, and waste; fostering energy savings; and reducing Green House Gas emissions). In 2015, the package was amended to include eco-design rules to make products more recyclable, and new targets were assigned for recycling and landfill rates. The EC presented an action plan, and introduced new targets for some directives by adding new legislative proposals; for more details see Bourguignon (2016). Such legislations make manufacturers responsible for the End-Of-Life (EOL) stage (Mascle, 2013).

Another driver for companies is to consider Extended Producer Responsibility (EPR), which integrates SD principles into their business. The EPR implicates that a producer is responsible for the environmental impacts of its products during their entire life cycles (Nnorom and Osibanjo, 2008). The EPR can be implemented as either individually or collectively, called the Individual Producer Responsibility (IPR) and the Collective Producer Responsibility (CPR). Under the IPR, each producer individually bears the cost of EOL treatment of its own brand products, while under the CPR, multiple producers cooperatively share the costs of managing all of their EOL products (Massarutto, 2014). Under the IPR, a producer may have sufficient interest to invest in designing more sustainable products, which are more easily and cheaply recyclable. However, under the CPR there is not enough incentive for such investment as the other producers benefit from this improvement at the EOL stage while they do not share the required investment (Lindqvist and Lifset, 2003). In fact, under the CPR there is no incentive for producing products with more recyclability features if all producers pay the same recycling fee based on their market share (Nnorom and Osibanjo, 2008). The European Union (EU) converted the principle of the EPR to regulations in 2003 by introducing the Waste Electric and Electronic Equipment (WEEE) directive, which was recast in 2012 (Favot, 2014).
As discussed above, integrating EOL-management issues with decisions made at the design stage is advantageous under the IPR. However, a remarkable issue in this integration at the design stage is the presence of uncertainty on what will occur at the EOL stage. Product units with identical design will have different statuses when reaching the EOL stage. Customers in various market segments may have different consumption behaviors. They may be careful or careless when using a product, which results in different quality levels at the EOL stage. In addition, they may be likely to return or not to return the used product units to EOL facilities or after-market sales. Hence, the relevant uncertainty should be considered to control the possible future risks in integrating design and EOL decisions.

The aim of this study is to develop a multi-objective stochastic optimization model that simultaneously integrates two problems of selecting design alternatives and planning EOL options for a family of products produced by a single producer under the IPR, where each product part can have finitely many design alternatives and EOL options. The objectives are maximizing the producer’s total profit, minimizing the environmental impact, and maximizing the social impact while satisfying two constraints on the recovery and recycling rates. Fig. 1, schematically illustrates the components of the developed model.

Because of the complexity caused by the uncertain quality of EOL product units, the functions used in the objectives and constraints have no closed-form formulas and they are estimated by a simulation model. To find approximate Pareto optimal solutions of the model, the multi-objective Simulated Annealing (SA) is used (Rosen and Harmonosky, 2005; Ahmed and Alkhamis, 2009). To illustrate the applicability of the proposed model, it is applied to a hypothetical case study on a cell phone, and trade-offs among the three objectives are analyzed.

In addition to producers, policy makers can also use our proposed model for evaluating the effectiveness of alternative policies. They can simulate and predict a producer’s behavior when facing their new regulations or policy strategies such as introducing new or amending mandatory targets, taxes/subsides, penalties, and collection schemes. In our numerical study, it is shown how the model can be a useful instrument for studying the effect of new circular-economy regulations on producers.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the problem definition and mathematical formulation. Section 4 explains our solution method based on simulation-based optimization. Section 5 provides a hypothetical case study, and Section 6 concludes the research results.
2. Literature review

The EPR emphasizes on the responsibility of producers for their products at the EOL phase. In order to achieve a more efficient EOL management, producers should move towards enhancing the efficiency of the recovery processes of their products by integrating EOL-management considerations at the product design stage. This section reviews papers that incorporate EOL-related decisions into the design stage of a product.

A classical approach in the literature to incorporate EOL considerations into the design stage is to adapt Design For X (DFX) methods, such as design for disassembly (Soh et al., 2014), design for reuse (Sabbaghi et al., 2015), and design for remanufacturing (Li and Liang, 2012). Most of these studies have focused on design for disassembly (Esmailian et al., 2016), where the aim is to minimize disassembly time (Santochi et al., 2002), to find the most efficient disassembly sequence (Huang et al., 2015), or to plan disassembly sequences (Behdad and Thurston, 2012). These papers typically do not determine EOL options for each part in a product and only consider EOL-related issues, for example, by decreasing negative environmental impacts (Ameli et al., 2017; Lu et al., 2018) or by easing the disassembly procedure (Vanegas et al., 2018). In the following, a few of these studies that consider optimizing EOL options are reviewed. Li et al. (2008) proposed a fuzzy graph-based modular DFX method that considers product lifecycle objectives guided by the design-for-environment method. Their model suggests modular formulation for a product where the parts in each module are planned to have an identical EOL option. Kwak and Kim (2010) studied the potential role of product design in overcoming difficulties of e-waste recovery by integrating disassembly and EOL planning. Their proposed framework analyzes how design changes affect product recoverability and what architectural characteristics are desirable from the EOL perspective. For better design evaluation, they presented an optimization-based model, which considers product design and recovery network design simultaneously. Joshi et al. (2017) developed a mathematical programming model to evaluate design alternatives for a product with respect to a disassembly factor, and also to determine the number of EOL product units that should be disassembled, remanufactured, recycled, and left untouched. Their model considers the uncertain conditions of received EOL products. Both studies showed the advantage of integrating EOL options.

A class of recent studies directly integrate EOL planning problems with design optimization decisions. Kwak et al. (2009) introduced a framework for analyzing design architecture of a product with respect to the EOL process. Their framework provides a plan for disassembling product and applies a proper EOL option to each one of the resulting disassemblies. They considered environmental regulations by setting a limit on the maximum disposal rate. Umeda et al. (2013) proposed a design support method for improving the recyclability of electrical and electronic products with the change of material composition and EOL treatment scenarios. Their method can be used for analyzing and modifying the design of a product based on given EOL scenarios, while it cannot be used for products with a large number of material combinations or EOL scenarios. Ardent et al. (2015) studied the relations between product design and EOL treatment. Their analysis was based on a case study of commercial refrigerating appliances. They used the information extracted from the literature and interviews with the selected experts to develop their method; which first identifies difficulties and criticalities in the EOL-treatment process, and then addresses them using required modifications in the design phase. Finally some possible solutions at the product design level were suggested. Ziout et al. (2014) provided a multi-criteria method to consider different stakeholders. Their model considers political, economical, social, technological, environmental, and legal criteria. The decision method is built around AHP method and ranks EOL options to select the best solutions. Designers can benefit from their work by understanding the probable future of their products. However, the implementation of this method is practically impossible when many design alternatives or EOL options are available.

Favi et al. (2017) presented a design-for-EOL method to help designers for evaluating product EOL performance, which can be used to modify the product design structure. The aim of the method is to maximize reusing and remanufacturing product components as well as the material recycling. Parajuly et al. (2016) provided a method to study the product characteristics and EOL processing of the Robotic Vacuum Cleaner (RVC), in order to understand the future outcome of recovering different materials and the impact of product design on the recoverability. The above-mentioned studies do not provide a model to select design and EOL option for the parts, but evaluated the EOL performance of a product design for given EOL scenarios.

The above methods did not consider design alternatives and EOL options for parts of a product. Ameli et al. (2016) recently proposed a simulation-based method to improve the EOL management by considering life cycle issues at the product design stage. The objectives are the maximization of the total profit and the minimization of the product’s environmental impact, subject to regulatory restrictions. However, their solution method is enumerative and only applicable for that there are few design-EOL scenarios for the combination of design alternatives and EOL options of main parts of a product.

There are a few studies on integrating EOL and design phases for a product family. Kwak and Kim (2011) attempted to examine the product family design with the EOL-phase considerations. To evaluate a given design of a product family, they proposed a mixed-integer programming model that identifies an optimal take-back (amount, type, and condition of a core that should be taken back) and recovery strategy (amount, type, and condition of a core for each one of disposal and recovery options; disassembly level of a core; and recovery and disposal options for each part). Environmental regulations are also considered as constraints on collection and recovery targets. The model can be used to assess the profitability of any family design from a set of available ones. However, they did not incorporate uncertainties of real-world decisions and integration of EOL, design, and manufacturing stages. Wu et al. (2016) used a bi-objective mixed-integer programming to determine the configurations of both new and remanufactured products in a family of products. The objectives are the minimization of the product cost and the maximization of the total market share. Their optimization problem is solved by implementing Non-dominated Sorting Genetic Algorithm II (NSGA II).

The above literature review shows that integrating EOL consideration into the design stage has recently become an interesting and active research area. However, the current studies overlook social impacts, and mostly ignore EOL uncertainty. Moreover, their methods can only be used when a few design alternatives and EOL options are available, and they cannot be applied to products with many designable parts. In fact, by considering EOL activities the problem becomes more complex and only simple products can be processed by human intuition without accessing detailed life cycle information. Therefore, one can identify the lack of an optimization method for integration of design and EOL decisions, which can be used in large scales while considering economical, environmental, and social impacts in an uncertain environment. This research gap is addressed in this paper.

3. Problem definition and formulation

In many industries, manufacturers produce a family of products in order to offer a variety of options to the market economically. A family of products is a group of similar products with the same platform (Kwak and Kim, 2011). The set of products in a family is presented by $F$, indexed by $i$. The set of parts included in the product $s$ is shown by $P^s$, which is indexed by $j$. Each part $i$ included in $P^s$ may have various design alternatives. The set of these available alternatives are $D^i_j$, indexed by $j$. Here, for simplicity, we assume that for each product only one design architecture is available, while this can easily be relaxed.
using the modeling approach applied by Ameli et al. (2017). The products in the family share common parts that are called “the core” and the related set is denoted by $P^{core}$. The set of possible EOL options for part $i$ under design alternative $j$ in product $s$ is denoted by $E^i_{s,j}$. If design alternative $i$ is selected for a part, an EOL option should be assigned to it from a given set $E^i_s$ of available EOL options. Four possible EOL options are defined as follows: REU = (reuse · remanufacture · recycle · dispose), REM = (remanufacture · recycle · dispose), REC = (recycle · dispose), and DIS = (dispose). As an illustration, when REM is selected as the EOL option for a part, if that part of a returned product unit has acceptable quality for remanufacturing, it is first sent for remanufacturing operation; otherwise, if it has sufficient quality for recycling, it is recycled, else, it is sent for disposal operation. In some cases, some EOL operations may not be applicable. This may occur because the quality of an EOL part is not acceptable for some operations or due to the technical limitations existing for some parts. For example, assume that REM is assigned as the EOL option for a Printed Circuit Board (PCB). Then, the remanufacturing operation is not typically considered for a PCB because of technical aspects. It means that if the quality of a returned PCB unit meets customer’s requirements, it will be reused; otherwise, it will be recycled. The set $E^i_s$ may contain one, two, or several possible EOL options. Each part in the core should have the same design alternative and EOL option in all products of the family. The product units are then produced and sold. After finishing the use phase and reaching to the EOL phase (each product has its own probability distribution for the use-phase duration), products may be collected in different ways: mail-in, drop-off, one-day events, or pick up (other methods can also be considered, if any). Collected product units are then sent to EOL facilities.

Note that since EOL treatment is carried out only during the time interval $(t_0, t_1)$, if a product unit is returned after $t_0$ or before $t_1$, it is disposed of or stocked, respectively. Moreover, it is not accepted after $t_0$. The model is based on the IPR, and the producer is the only stakeholder that is responsible for its EOL treatment. The notation used in the model is given in Table 1.

Decision variables of our models are defined as follow:

- $x^i_{s,j}: A$ binary variable that equals 1 if design alternative $j$ is selected for part $i$ in product $s$; otherwise, it equals 0, $i \in P^i$, $j \in D^i$, $s \in F$.
- $y^i_{s,j}: A$ binary variable that equals 1 if EOL option $k$ is selected for part $i$ under design alternative $j$, in product $s$; otherwise, it equals 0, $i \in P^i$, $j \in D^i$, $k \in E^i_{s,j}$, $s \in F$.

$X$ and $Y$ denote vectors that include all decision variables $x^i_{s,j}$ and $y^i_{s,j}$, respectively. Furthermore, $\xi$ is a random vector that includes all uncertain factors of our proposed model (e.g., use phase-duration, the quality and return time of the EOL product, as well as cost or revenues of its treatment). The Total Profit (TP), Environmental Impact (EI), Social Impact (SI), ReCoVery (RCV) rate and ReCycling (RCY) rate, which are functions of $X$ and $Y$, are defined by $TP(X, Y, \xi)$, $EI(X, Y, \xi)$, $SI(X, Y, \xi)$, $RCV(X, Y, \xi)$, and $RCY(X, Y, \xi)$, respectively. Due to its dependency on random vector $\xi$, these functions are random variables. In order to quantify these random variables, their expected values are used (for a given random variable $W$ with finite mean, the expected value is denoted by $E(W)$).

Considering the notation and description provided above, the mathematical formulation of our decision problem becomes as follows:

\[
\sum_{j \in D^i} x^i_{s,j} = 1 \quad s \in F, i \in P^i. \tag{6}
\]

\[
\sum_{k \in E^i_{s,j}} y^i_{s,j,k} = x^i_{s,j} \quad s \in F, i \in P^i, j \in D^i. \tag{7}
\]

\[
x^i_{s,j} = x^s_{i,j} \quad s, s' \in F, i \in P^i, j \in D^i. \tag{8}
\]

\[
y^i_{s,j,k} = y^s_{i,j,k} \quad s \in F, i \in P^i, j \in D^i, k \in E^i_{s,j}. \tag{9}
\]

\[
x^i_{s,j} \in \{0, 1\} \quad s \in F, i \in P^i, j \in D^i. \tag{10}
\]

\[
y^i_{s,j,k} \in \{0, 1\} \quad s \in F, i \in P^i, j \in D^i, k \in E^i_{s,j}. \tag{11}
\]

The first objective function (1) maximizes the expected value of producer’s profit. The profit resulted from selling new and reused product units; plus revenues gained from reselling, remanufacturing, and recycling parts after cost deduction. The second objective function (2) minimizes the expected value of the total environmental impact, here measured by the total amount of CF produced in the entire life cycle of the family of the products. The third objective function (3) maximizes the expected value of the total social impact, here measured by the number of created jobs. Constraints (4) and (5) control the recovery and recycling rates, where $E[RCV(X, Y, \xi)]$ and $E[RCY(X, Y, \xi)]$ are expected values of the recovery and recycling rates, respectively. Constants $F^i_{s,j}$ and $F^i_{s}$ are the minimum acceptable values for the mean recovery and recycling rates. These values are usually set based on environmental regulations such as WEEE directive, or, in the absence of obligatory regulations, based on the best practices of the industry or the producer itself. Constraint set (6) ensures that just one design alternative for each part is selected. According to constraint set (7), exactly one EOL option is assigned to the selected design alternative for each part. Constraints (8) and (9) are included in the mathematical model to guarantee that design and EOL options of the core parts in different products of the family are the same. Constraint (10) and (11) impose integrality restrictions on the decision variables.

The next section provides a solution method to tackle the above complex model.

4. Simulation-based optimization algorithm

Our proposed mathematical model is a very challenging optimization problem. As the number of parts included in a product and their design alternatives increases, the complexity of the model grows exponentially. Assume there is a product in the family that includes only five parts where two design alternatives exist for each part. If four EOL options are available for each design alternative, then there are $2^5 \times 4^5 = 32768$ potential solutions. Adding a part to the assumed product increases the number to $2^6 \times 4^6 = 262144$. On the other hand, in Eqs. (1)–(5), the expected values do not have closed-form formulas in terms of the decision variables. These expectations can only be estimated based on samples generated by a simulation model. Accordingly, applying the simulation-based optimization method (also known as the simulation-optimization method) seems to be the best way to design a solution algorithm to (approximately) solve our model (Amaran et al., 2016). The procedure of this method is depicted in Fig. 2 (April et al., 2003).

As shown in Fig. 2, to apply the simulation-based optimization method, a simulation model is required to estimate the five complex expectation-based performance measures appeared in (1)–(5) for the values selected for our decision variables. This simulation model should sufficiently be replicated such that the expected values of the performance measures can be estimated with an acceptable accuracy level. Our sensitivity analysis on the number of replications indicates that estimated values based on 3000 replications remain unchanged when extra replications are added. As our optimization problem belongs to
Table 1
The notation of the proposed model.

Sets and variables:
- \( F \) The set of products in a family, indexed by \( s \), \( |F| = f \)
- \( P^* \) The set of parts in the product \( s \), indexed by \( i \), \( |P^*| = n^* \)
- \( D^*_i \) The set of design alternatives for part \( i \) of product \( s \), indexed by \( j \), \( |D^*_i| = m^*_i, i \in P^* \)
- \( D^* \) The set of core parts in a family
- \( E^*_l \) The set of possible EOL options for part \( i \) of product \( s \) under design alternative \( j \), indexed by \( k \)
- \( A \) The set of take-back policies for a product at its EOL, indexed by \( l \)
- \( x^*_t \) A binary variable that equals 1 if design alternative \( j \) is selected for part \( i \) of product \( s \), otherwise it equals 0, \( i \in P^*, j \in D^*_i, s \in F \)
- \( y^*_t \) A binary variable that equals 1 if EOL option \( k \) is selected for part \( i \) under design alternative \( j \), in product \( s \), otherwise it equals 0, \( i \in P^*, j \in D^*_i, k \in E^*_l, s \in F \)
- \( Y^*_t \) A vector that includes all decision variables, \( y^*_t, i \in P^*, j \in D^*_i, k \in E^*_l, s \in F \)
- \( X \) A vector that includes decision variables, \( x^*_t, i \in P^*, j \in D^*_i, k \in E^*_l, s \in F \)
- \( Y \) A vector that includes decision variables, \( y^*_t, i \in P^*, j \in D^*_i, k \in E^*_l, s \in F \)
- \( \xi \) A random vector that includes all stochastic parameters of the model

Functions:
- \( TP(X, Y, \xi) \) The total profit of production and EOL activities for a product unit; a random variable
- \( EI(X, Y, \xi) \) The environmental impact of production and EOL activities for a product unit; a random variable
- \( SI(X, Y, \xi) \) The social impact of producing and EOL activities for a product unit; a random variable
- \( RCV(X, Y, \xi) \) The recovery factor for a product unit; a random variable
- \( RCY(X, Y, \xi) \) The recycling factor for a product unit; a random variable
- \( E(W) \) The expected value of random variable \( W \), which is one of \( TP(X, Y, \xi), EI(X, Y, \xi), SI(X, Y, \xi), RCV(X, Y, \xi) \) and \( RCY(X, Y, \xi) \)

Parameters:
- \( (b_1, b_2) \) The EOL treatment period
- \( \theta_t \) The end of EOL planning horizon; returned products will not be accepted after \( \theta_t \)
- \( t_{in} \) The return time of a product unit
- \( \hat{\xi}_i^f \) The minimum acceptable recovery rate for the product
- \( \hat{\xi}_i^F \) The minimum acceptable recycling rate for the product
- \( w_i^f \) The weight of part \( i \) of product \( s \) under design alternative \( j \)
- \( c_{x,s,dis}(i,2) \) The disposal cost of product \( s \), which is returned after \( t_2 \)
- \( c_{x,s,h}(i,2) \) The holding cost of product \( s \) per time unit, which is returned before \( t_1 \)
- \( c_{x,s,ins} \) The inspection cost of product \( s \) at the EOL
- \( c_{x,s,dis,q} \) The disposal cost for a low quality product unit at the EOL after inspection
- \( k_{x,s,ins} \) The remanufacturing cost for product \( s \) under design alternative \( j \)
- \( c_{x,s,rem} \) The remanufacturing cost for part \( i \) of product \( s \) under design alternative \( j \)
- \( \hat{\xi}_i^q \) The revenue of reusing part \( i \) of product \( s \) under design alternative \( j \)
- \( \hat{\xi}_i^q \) The revenue of remanufacturing part \( i \) of product \( s \) under design alternative \( j \)
- \( \hat{\xi}_i^q \) The recycling cost for part \( i \) of product \( s \) under design alternative \( j \)
- \( \hat{\xi}_i^q \) The revenue of recycling part \( i \) of product \( s \) under design alternative \( j \)
- \( \hat{\xi}_i^q \) The environmental impact of manufacturing part \( i \) of product \( s \) under design alternative \( j \)
- \( E_{i,dis}(i,2) \) The environmental impact of collecting a product at the EOL under take-back policy \( l, i \in A \)
- \( E_{i,dis}(i,2) \) The environmental impact of storing product \( s \), which is taken back before \( t_1 \)
- \( E_{i,dis}(i,2) \) The environmental impact of disposing of a unit of product \( s \), which is taken back after \( t_1 \)
- \( E_{i,ins} \) The environmental impact of inspecting a unit of product \( s \) at the EOL
- \( E_{i,ins} \) The environmental impact of disposal of a low-quality unit of product \( s \) at the EOL after inspection
- \( E_{i,ins} \) The environmental impact of reusing a unit of product \( s \)
- \( E_{i,dis,ins} \) The environmental impact of disassembling a unit of product \( s \)
- \( E_{i,dis,ins} \) The environmental impact of inspecting part \( i \) of a unit of product \( s \) under design alternative \( j \)
- \( E_{i,dis,ins} \) The environmental impact of disposing of part \( i \) of a unit of product \( s \) under design alternative \( j \)
- \( E_{i,dis,ins} \) The environmental impact of reusing part \( i \) of a unit of product \( s \) under design alternative \( j \)
- \( E_{i,dis,ins} \) The environmental impact of recycling part \( i \) of a unit of product \( s \) under design alternative \( j \)
- \( E_{i,dis,ins} \) The social impact of manufacturing part \( i \) of a unit of product \( s \) under design alternative \( j \)
- \( E_{i,dis,ins} \) The social impact of collecting a product at the EOL under take-back policy \( l, i \in A \)
- \( E_{i,dis,ins} \) The social impact of storing product \( s \) that is taken back before \( t_1 \)
- \( E_{i,dis,ins} \) The social impact of disposing of a unit of product \( s \) that is taken back after \( t_1 \)
- \( E_{i,dis,ins} \) The social impact of inspecting a unit of product \( s \) at the EOL
- \( E_{i,dis,ins} \) The social impact of disposal of a low-quality unit of product \( s \) at the EOL after inspection
- \( E_{i,dis,ins} \) The social impact of reusing a unit of product \( s \)
- \( E_{i,dis,ins} \) The social impact of disassembling a unit of product \( s \)
- \( E_{i,dis,ins} \) The social impact of inspecting part \( i \) of a unit of product \( s \) under design alternative \( j \)

(continued on next page)
the complexity class of NP-hard (as it is a very complex version of the knapsack problem), a metaheuristic method is used here as the optimizer. The simulation model and the metaheuristic method are explained in the following subsections.

4.1. Simulation model

This sub section explains the simulation model that is conducted to estimate the expected values in Eqs. (1)–(5). These values are approximated after replicating the simulation model 3000 times. The product-unit flow in the simulated model is illustrated in Fig. 3. For better understanding of the simulation procedure, the following points are useful:

- For each part, the design alternative and initial EOL option are given in advance (inputs of the model).
- The parts of each product unit are modeled as entities.
- Attributes assigned to each entity are weight, production cost, sales revenue, EOL cost, and EOL revenue.
- After merging entities, product units are assembled and sold. The probability distribution of the use-phase duration of each product in the family follows a Normal distribution.
- Based on the return time, each collected product unit may go through four different routes:
  1) If a product unit is returned before \( t_1 \), it is stored until the EOL treatment period begins and an inventory holding cost is paid.
  2) Product units that are returned after \( t_2 \) and before \( t_H \) are sent directly to the disposal facility.
  3) The stored product units and those returned during \( (t_1, t_2) \) are sent to the EOL facility.
  4) The product units that are returned after \( t_H \) are rejected.
- Product units returned before \( t_1 \) are sent for reuse, disposal, or disassembly based on their quality class, which is distributed according to a discrete distribution. Each product unit is first inspected; and if its quality is satisfactory, it is reused. If its quality is poor, it is disposed of; and in the other cases, the product unit is disassembled and the EOL options are implemented.
- In the disassembly facility, parts (entities) of the product units are separated.
- Each part is inspected, and based on its quality and initial EOL option the final EOL option is determined.
- EOL revenues and costs are generated from uniform distributions on intervals whose bounds depend on the quality of the returned parts.

- \( T_P(X, Y, \xi) \), \( E_l(X, Y, \xi) \), \( S_l(X, Y, \xi) \), \( RCV(X, Y, \xi) \) and \( RCY(X, Y, \xi) \) are calculated in each replication, where \( \xi \) denotes the sample of random vector \( \xi \) in the rth replication.
- The simulation model is replicated 3000 times to estimate the quantities in (1)–(5), as \( E[T_P(X, Y, \xi)] \), \( E[E_l(X, Y, \xi)] \) and \( E[S_l(X, Y, \xi)] \), \( E[RCV(X, Y, \xi)] \), and \( E[RCY(X, Y, \xi)] \) where \( \xi \) is a discrete random vector that takes each one of samples \( \xi_r \), \( r = 1, \ldots, 3000 \) with equal probabilities of 3000\(^{-1}\).

Table 1 (continued)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>( u_{ij}^{rem} )</td>
<td>The social impact of remanufacturing part ( i ) of a unit of product ( s ) under design alternative ( j )</td>
</tr>
<tr>
<td>( u_{ij}^{reu} )</td>
<td>The social impact of reusing part ( i ) of a unit of product ( s ) under design alternative ( j )</td>
</tr>
<tr>
<td>( u_{ij}^{rec} )</td>
<td>The social impact of recycling part ( i ) of a unit of product ( s ) under design alternative ( j )</td>
</tr>
<tr>
<td>( p^{sl} )</td>
<td>The probability of returning a product unit under take-back policy ( l )</td>
</tr>
<tr>
<td>( c^{sl} )</td>
<td>The cost of returning a product unit under take-back policy ( l )</td>
</tr>
</tbody>
</table>

4.2. Simulated Annealing

To solve the proposed optimization problem, because of the complexity of the performance metrics used in (1)–(5), one needs to run the simulation model presented in Section 4.1 to estimate the metrics associated with a given solution, which consists of a design and its EOL options for a family of products. This procedure should be used by an optimization method to determine a good solution, although it is very time consuming. For the sake of computational efficiency, we need to use a local-search-based metaheuristic that cerates only one new solution in each iteration, and consequently needs to run the simulation model once per iteration. Indeed, population-based metaheuristics such as NSGA II and Multi-Objective Particle Swarm Optimization (MOPSO) are not appropriate for our problem.

In this research, a multi-objective Simulated Annealing (SA) is applied, which is considered a popular local-search-based metaheuristic for large-scale discrete optimization (Alrefaei and Diabat, 2009; Suman, 2003; Ehsrgott, 2006; Bechikh et al., 2017).

The SA is an optimization method inspired by the annealing process in metallurgy, where a material is heated and then cooled gradually in order to increase the size of its crystals and to reduce their defects. Both the temperature and the thermodynamic free energy are affected by heating and cooling. In the SA, the cooling procedure is modeled by slowly decreasing the probability of accepting bad solutions when exploring the solution space. This mechanism is used to escape local optima by allowing moves that worsen the objective function value in the hope of finding a global optimum. The SA gives good results for a wide spectrum of optimization problems specially when the search space is discrete (Rosen et al., 2008). The words “Boltzmann factor”, “temperature”, and “cooling schedule”, which are used in the rest of the

Fig. 2. A schematic representation of the simulation-based optimization algorithm.
From an initial solution, an SA algorithm proceeds in several iterations. At each iteration, a random neighborhood solution ($S'$) of the current solution ($S$) is generated. Moves that improve the objective function are always accepted, while a non-improving one is accepted only when the acceptance probability $P(\Delta E, T)$ associated with $S'$ becomes greater than a random number $R$, which is drawn from a uniform distribution on the interval (0,1). The probability $P(\Delta E, T)$ is defined based on the Boltzmann factor ($K$), current temperature ($T$), and the variation of the objective function ($\Delta E$), as follows:

$$P(\Delta E, T) = e^{-\frac{\Delta E}{KT}}.$$

As an SA algorithm progresses, the probability of accepting non-improving moves decreases. The temperature is used as a control parameter for this purpose. The temperature is gradually decreased according to a cooling schedule such that only a few non-improving solutions are accepted at the end of the search. The geometric schedule is the most popular cooling function that updates the temperature by using the equation

$$T = \alpha T,$$

where $\alpha \in (0, 1)$ is a predetermined decreasing rate. Computational experience has shown that $\alpha$ should be between 0.5 and 0.99. The search can be stopped after reaching a specific number of unchanged solutions, a final temperature $T_F$, or a predetermined number of total iterations (Talbi, 2009).

When the optimization problem has more than one objective function, the objective functions (each objective function is denoted by $f_i$) are weighted by the decision maker ($w_i$) and aggregated into a single measure ($f$) to calculate the probability of accepting a non-improving
Inputs: $X, Y$, deterministic parameters, and a sample of random vector $\xi$ (including all stochastic parameters) given in Table 2.

With a little abuse of notation, samples of stochastic parameters are denoted by the same notation used for the stochastic parameters.

Initialize:
Let the index $j$ designate the selected design alternative for a part.
Set the initial values of $TP$, $EI$, $SI$, $RCY$ and $RCY$ as follows:
$$TP = \sum_{i} E_{i}, \quad EI = \sum_{i} E_{i}, \quad SI = \sum_{i} S_{i}, \quad RCY = 0, \quad RCY = 0.$$ count$_{rec} = 0, \quad count_{dis} = 0$. 

For $s=1$: 
If the product unit is returned to an EOL-collection centre then:
$$TP = TP - \sum_{i} P_{i}^{\text{rec}}, \quad EI = EI + \sum_{i} P_{i}^{\text{rec}}, \quad SI = SI + \sum_{i} S_{i}^{\text{rec}}.$$ 
Else if $t_{rec} > t_{dis}$ terminate
Then:
$$TP = TP - C_{i}^{\text{dis}}(t_{s}), \quad EI = EI + E_{i}^{\text{dis}}(t_{s}), \quad SI = SI + S_{i}^{\text{dis}}(t_{s}).$$
If $t_{dis} > t_{rec}$ terminate
Then:
$$TP = TP - C_{i}^{\text{rec}}(t_{s}), \quad EI = EI + E_{i}^{\text{rec}}(t_{s}), \quad SI = SI + S_{i}^{\text{rec}}(t_{s}).$$
Else if $t_{dis} = t_{rec}$ terminate
Then:
$$TP = TP - C_{i}^{\text{dis}}, \quad EI = EI + E_{i}^{\text{dis}}, \quad SI = SI + S_{i}^{\text{dis}}.$$ 
End.

The parameters of our SA algorithm are listed below:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{0}$</td>
<td>The initial temperature</td>
</tr>
<tr>
<td>$(X_{0}, Y_{0})$</td>
<td>The initial solution</td>
</tr>
<tr>
<td>$(X', Y')$</td>
<td>A solution that is generated in the neighborhood of $(X, Y)$ at each iteration</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>The decreasing rate of the cooling schedule</td>
</tr>
<tr>
<td>$T_f$</td>
<td>The final temperature</td>
</tr>
<tr>
<td>$I_{\text{it}}$</td>
<td>The maximum number of iterations at each temperature</td>
</tr>
<tr>
<td>$I_{\text{max}}$</td>
<td>The maximum number of total iterations</td>
</tr>
</tbody>
</table>

Fig. 4. The pseudo code of the procedure used for calculating the performance measures based on the simulation model.

move; $\Delta E$ is calculated for this new measure (Suman, 2003).

In our SA algorithm, the procedure of generating a neighborhood solution from the current solution is as follows:

1) Randomly select one of the parts of all the products in the family.
2) Select randomly another design alternative and an EOL option for the selected part.
3) If the selected part is included in the core, then copy the newly selected design alternative and EOL option for that part to the same part in all of the products in the family.
Table 2
The Taguchi inputs for tuning the SA algorithm’s parameters (the selected values are shown in bold).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Symbol</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>μ0</td>
<td>A</td>
<td>15, 20, 25, 30, 35, 40</td>
</tr>
<tr>
<td>α</td>
<td>B</td>
<td>0.9, 0.95, 0.99</td>
</tr>
<tr>
<td>σ</td>
<td>C</td>
<td>0.0005, 0.01</td>
</tr>
<tr>
<td>Itr</td>
<td>D</td>
<td>1, 3, 10</td>
</tr>
<tr>
<td>Itrmax</td>
<td>E</td>
<td>15, 50, 100</td>
</tr>
<tr>
<td>Itrmax</td>
<td>F</td>
<td>1000, 2000, 3000</td>
</tr>
</tbody>
</table>

Table 3
Three extreme Pareto optimal solutions for the case study.

<table>
<thead>
<tr>
<th>Part</th>
<th>Design alternatives</th>
<th>The solution with the best performance in TP</th>
<th>The solution with the best performance in EI</th>
<th>The solution with the best performance in SI</th>
</tr>
</thead>
<tbody>
<tr>
<td>screen</td>
<td>LCD</td>
<td>REM</td>
<td>REM</td>
<td>REM</td>
</tr>
<tr>
<td>housing</td>
<td>plastic</td>
<td>REC</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td></td>
<td>aluminum</td>
<td>DIS</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td>battery</td>
<td>Li ion</td>
<td>REC</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td></td>
<td>Li Polymer</td>
<td>DIS</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td>loudspeaker</td>
<td>loud speaker</td>
<td>REC</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td>ear speaker</td>
<td>ear speaker</td>
<td>REC</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td>front camera</td>
<td>5 mp</td>
<td>REM</td>
<td>REU</td>
<td>REM</td>
</tr>
<tr>
<td></td>
<td>13 mp</td>
<td>REM</td>
<td>REU</td>
<td>REM</td>
</tr>
<tr>
<td>rear camera</td>
<td>12 mp</td>
<td>REM</td>
<td>REU</td>
<td>REM</td>
</tr>
<tr>
<td></td>
<td>23 mp</td>
<td>REM</td>
<td>REU</td>
<td>REM</td>
</tr>
<tr>
<td>home button</td>
<td>without finger</td>
<td>REC</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td></td>
<td>print</td>
<td>DIS</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td></td>
<td>with finger print</td>
<td>REC</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DIS</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td>PCB</td>
<td>PCB</td>
<td>REC</td>
<td>REU</td>
<td>REU</td>
</tr>
<tr>
<td>antenna</td>
<td>antenna</td>
<td>REC</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td>sensors</td>
<td>sensors</td>
<td>REC</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td>CPU</td>
<td>quad-core</td>
<td>REC</td>
<td>REU</td>
<td>REU</td>
</tr>
<tr>
<td></td>
<td>octa-core</td>
<td>REC</td>
<td>REU</td>
<td>REU</td>
</tr>
<tr>
<td>WIFI</td>
<td>WIFI</td>
<td>REC</td>
<td>DIS</td>
<td>DIS</td>
</tr>
<tr>
<td>side keys</td>
<td>side keys</td>
<td>REC</td>
<td>REC</td>
<td>REU</td>
</tr>
<tr>
<td>charger port</td>
<td>Micro USB</td>
<td>DIS</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td></td>
<td>USB-C</td>
<td>DIS</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td>vibrating motor</td>
<td>vibrating motor</td>
<td>DIS</td>
<td>REC</td>
<td>REC</td>
</tr>
<tr>
<td>card tray</td>
<td>1 SIM</td>
<td>REU</td>
<td>REU</td>
<td>REU</td>
</tr>
<tr>
<td></td>
<td>2 SIM</td>
<td>REU</td>
<td>REU</td>
<td>REU</td>
</tr>
</tbody>
</table>

\[
f_i(X, Y) = E[T_P(X, Y, \hat{\xi})] - \lambda max\{F_1^Y - E[R_{CV}(X, Y, \hat{\xi})]\}, 0] \\
- \lambda max\{F_1^Y - E[R_{CV}(X, Y, \hat{\xi})]\}, 0] \\
f_i(X, Y) = E[\alpha(X, Y, \hat{\xi})] \\
f_i(X, Y) = E[\beta(X, Y, \hat{\xi})] \\
f_i(X, Y) = w_1f_i(X, Y) + w_2f_i(X, Y) + w_3f_i(X, Y)
\]
where \( \hat{\xi} \) is a random vector generated in the simulation model (see Section 4.1 for more details). Note that the first function includes two penalty terms to address the constraints (4) and (5). Here, we set \( w_1 = \frac{1}{\lambda}, i = 1, 2, 3, \) and \( \lambda_1 = \lambda_2 = 35. \)

Using the above notation and description, the steps of our multi-objective SA algorithm can be given as follows:

**Step 1:** Randomly generate an initial solution \((X_0, Y_0)\), set \((X, Y) = (X_0, Y_0)\), and store \((X, Y)\) in the set PS.

**Step 2:** Generate a new solution \((X', Y')\) in the neighborhood of \((X, Y)\) using the procedure explained above.

**Step 3:**
3.1 If the new solution \((X', Y')\) satisfies the constraints (4) and (5) and \((X', Y')\) is not dominated by any solution in PS, then
a. store \((X', Y')\) in PS
b. delete solutions in PS that are dominated by \((X', Y')\), if any.
c. update the current solution as \((X, Y) = (X', Y')\), and go to Step 5;
3.2 otherwise
a. generate a random number \(r\) from the uniform distribution over \((0,1)\),
b. compute \( \Delta E = f_1(X', Y') - f_1(X, Y)\),
c. if \( r < \frac{\Delta E}{\alpha T} \), set \((X, Y) = (X', Y')\).

**Step 4:** If the number of iterations under temperature \( T \) is not greater than \( Itr_{PS} \), go to Step 2.

**Step 5:** Reduce the temperature by the cooling schedule \( T = \alpha T \).

**Step 6:** If one of the stopping criteria: 1) \( T < T_{PS} \) or 2) the number of iteration is greater than \( Itr_{max} \), or 3) the number of unchanged consecutive solutions is greater than \( IS_{max} \), is met; then stop and return PS, else go to Step 2.

The input parameters of the above algorithm should be tuned by running a numerical study based on an appropriate experimental design (see section 5.1 for more details).

5. Case study

In this section, a case of a cell phone is provided to illustrate how the proposed model helps to choose appropriate design alternative and EOL option for each part of a product under uncertain situations. Cell phones have relatively short life cycles. Their reusability makes them the most valuable EEE products found abundantly in waste streams (Silveira and Chang, 2010).

Here, it is assumed that there is one product in the family, and only some parts of the cell phone have more than one design alternative. These parts and their alternatives are shown in Table 3. The information on technical issues, costs, revenues, probability, and quality of returns is gathered from experts working in Iranian mobile-phone service centers and websites that provide services for cell phones such as ETrade Supply.

The total amount of Green House Gas (GHG) emissions, also known as the Carbon Footprint (CF), during the product life cycle, is used as the indicator for the EI. The CF amount for each design alternative of a part is obtained from the studies by Ercan et al. (2013) and Ameli et al. (2016).
The potential to create jobs at the EOL stage of the product is used as the indicator for the SI. It is measured by the approximated number of employees required at the EOL stage. In order to estimate this index, we use the reports that estimate the number of jobs created in waste management activities. These reports state the relation between the weights of waste collected, recovered, or disposed and the jobs created in each activity (Manhart, 2007; Vernon, 2001). Based on these values, we calculate the potential of job creation for each design alternative of a part based on its weight. For example, each 1000 tons of WEEE averagely creates 15 jobs in the recycling sector. The weight of a unit of Aluminum Housing is about 10 g. Therefore, if a unit of this part is recycled, its contribution to the number of created jobs is approximately given by 
\[
\frac{10 \text{ g}}{1000 \text{ tons}} \times 15 \text{ jobs}.
\]
This procedure is implemented for major EOL-treatment tasks, which are collection, disassembly, and inspection, reuse, remanufacturing, recycling, and disposal.

The values of \( F_I^S \) and \( F_S^T \) are extracted from the WEEE directive. There are ten product categories covered by this directive. From 15 August 2015 until 14 August 2018, 80% of WEEE falling within category 3 (information technology and telecommunications equipment) should be recovered, and 70% should be prepared for reuse and recycle (WEEE Directive, 2012). These targets are included in the developed model.

The simulation-optimization procedure given in the previous section was implemented in MatLab R2016a, on a PC with Intel® Core ™ i5-

<table>
<thead>
<tr>
<th>Table 4</th>
<th>The values of the objective and constraint functions for the three approximate Pareto solutions given in Table 3.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The solution with best performance in TP</td>
</tr>
<tr>
<td>TP</td>
<td>428.60</td>
</tr>
<tr>
<td>EI</td>
<td>89.42</td>
</tr>
<tr>
<td>SI</td>
<td>(7.15 \times 10^{-3})</td>
</tr>
<tr>
<td>RCV</td>
<td>0.86</td>
</tr>
<tr>
<td>RCY</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Fig. 5. The RPD analysis results for tuning the SA algorithm's parameters.

Fig. 6. Approximate Pareto solutions for the case study.
5.1. Tuning the parameters of the SA algorithm

In order to obtain better performance, it is necessary to tune the parameters of the SA algorithm. This can be done by running the algorithm under different combination of parameter values and selecting the combination that makes the best responses. However, it is usually very time-consuming to study all possible combinations. Robust Parameter Design (RPD), sometimes called the Taguchi method, is a powerful tool for parameter tuning (Montgomery, 2017), which has widely been used to reduce the number of experiments needed to appropriately set the parameter values of a metaheuristic algorithm (Adenso-Díaz and Laguna, 2006). In this method, two classes of factors that influence the experiment response are considered: controllable (called signal) and uncontrollable (called noise). The aim of the method is to maximize the signal to noise (S/N) ratio. Table 2 presents the controllable factors of the SA algorithm and the levels of each factor. Although the full-factorial design needs $6^1 \times 3^5 = 1458$ experiments, the RPD method only requires 18 experiments if $L_{18}$ orthogonal array design is used for our case. Fig. 5 graphically shows the results of our RPD analysis. The levels that are selected by the RPD are shown in bold in Table 2.

5.2. An analysis of the numerical results

For the case described above, the approximate Pareto optimal solutions obtained by the proposed SA algorithm are shown in Fig. 6. The decision maker should finally select one of these solutions based on his/her trade-off policy. To illustrate the procedure, Table 3 presents three extreme Pareto solutions with the best performance based on each one of the three objective functions (1), (2), and (3). Table 4 presents the objective- and constraint-function values for these three solutions. For the Pareto solution given in the second column of these tables, the best total profit per product unit is $428.60, with 89.42 kg of CO$_2$ eq per product unit and $7.15 \times 10^{-3}$ employees per product unit. From the solution with the best EI performance, given in the third column, one can see that the company requires to cut $56.01 (about 13%) of its best profit value (obtained under the second-column solution) to achieve the best possible EI performance.

From Table 3 other interesting findings can be observed. For example, in all of the three Pareto solutions, three parts of the product (indicated in bold face) has the same EOL option, which shows the design stability of these parts under different trade-off policies.

5.3. Application of the model to study different polices in circular economy

In this subsection, we discuss about the applicability of the proposed model for simulating the effectiveness and consequences of alternative circular-economy strategies, e.g. the introduction of lower/upper mandatory targets instead of the current directives targets, subsidies/taxes; or different responsibility allocation and collection schemes. In our case study, explained above, we consider WEEE directive’s requirements as constraints. Hence, we are able to evaluate the consequences of changing the targets indicated by this directive for recovery and recycling rates. This analysis may be of interest from a regulatory point of view.
Fig. 7 illustrates the effect of increasing the recovery-rate limit on the solutions. By increasing the expected recovery-rate target, in almost all Pareto solutions the EI values improve, and the SI values worsen. However, the profit values slightly reduce, which shows that the manufacturer losses only a small portion of its profit under the new condition.

Fig. 8 shows the effect of having a stricter recycling-rate target. It can be seen that by increasing this target, EI values decrease and that SI values increase. Nevertheless, the profit values are slightly affected by this change. This again indicates that under the new policy, the manufacturer can have a similar level of profitability because she is able to (re)optimize its design and EOL decisions (using our optimization model) under the newly imposed constraint as well as to cover a part of her recycling expenses by her EOL activities. Moreover, in this case, where the recycling-rate limit has been increased and the recovery rate is remained unchanged, EOL options mostly change to “recycling” instead of “reuse” and “remanufacture” options to meet the new recycling-rate target. This can be a reason for that the EI values worsen and the SI values improve.

Other circular-economy policies can also be analyzed by the same method after adapting or extending our model. Indeed, such models greatly help both producers and policy makers to simulate and analyze the future effects of different policies. A producer can confront the changes and protect its profitability. On the other hand, a policy maker can study the effect of different proposed strategies on producers’ profits and other environmental and social measures, and then decide about the effectiveness of proposals.

6. Conclusions

The application of mathematical models for design-for-EOL problems has recently become a topic of interest because of the growth in the complexity of decision making in this area. However, some simplifications are necessary in modeling these problems to make their mathematical models tractable. Accordingly, after determining solutions from these models, they should be adjusted by experts to meet all real-world aspects. Such models potentially help designers to evaluate suggested product designs and make modifications in order to comply with EOL treatment objectives, if necessary.

This paper proposes a multi-criteria optimization model based on the IPR, which evaluates sustainable design performance of a family of products by integrating two decision problems: design-alternative selection and EOL-option determination. Uncertainties that may appear after the design phase, such as quality statuses, return times, and EOL treatment costs/revenues, are considered in our model. The objectives are maximizing the total profit gained by producing the product family, minimizing the environmental impact, and maximizing the social impact of the product family. Two constraints are considered to meet appropriate recycling and recovery rates, addressed in circular-economy directives, such as WEEE. Since the objective functions and environmental constraints consist of complex expected values that cannot be given in close form, a simulation-based optimization algorithm is used to determine a set of approximate Pareto optimal solutions. The algorithm is developed based on the multi-objective SA where a simulation model is used to estimates the expectations involved in the model.

Finally, a hypothetical case study on a cell phone is provided and solved using our model and algorithm. In the case study, the EI is measured by the total amount of CF emitted during the entire life cycle of the product family and the SI is quantified by the total number of employees required for handling the EOL-management activities of the product family. By using the proposed model a producer will experience an almost-known EOL phase rather than falling into a uncontrolled situation. In such a proactive approach, producers not only may financially benefit from implementing EOL activities but also can improve their corporate image.

Our model may particularly be useful in the evaluation of the effectiveness of alternative circular-economy strategies (e.g., the introduction of stricter/looser mandatory targets and subsidies/taxes, and the possibility of using alternative collection methods). Economic
assessment of regulatory measures, which is mandatory in the EU, can dramatically benefit from the usage of tools of this kind when considering alternative approaches to the design and implementation of the circular-economy package. Here, it is shown how our model is useful to understand the impact of imposing sticker bounds on recovery and recycling rates, which are targets in the WEEE directive.

An important direction for future study is extending our model to capture other strategies. Another challenging future work is to study our integrated problem in a collective responsibility EOL scheme where a number of producers collaborate in the EOL phase of their products.

References