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Optimizing Sustainability Performance through Component Commonality for Multi-Generational Products

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ABSTRACT

Increasing frequency of new product introduction reduces the potential to implement closed-loops and repurpose serviceable end-of-use resources, causing sub-optimal resource utilization. Furthermore, it hinders the transition to sustainable manufacturing and circular economy. Although careful planning of inter-generational design compatibility allows implementing sustainable closed-loops even in fast-paced multi-generation systems, designers currently lack the product sustainability performance (PSP) forecasting methods required for such planning. Thus, this paper presents a new design methodology that forecasts and maximizes the closed-loop dynamic PSP by identifying the optimal component-level commonality between successive design generations. The proposed method employs the Norton-Bass diffusion model to forecast multi-generation demand and utilizes the Non-dominated Sorting Genetic Algorithm II to identify the optimal design configurations. The representative PSP objectives used in this work are: maximization of manufacturer gross profit maximization, minimization of total greenhouse gas emissions, and maximization of product's functional value (for customer). The optimized inter-generational component commonality significantly improved all three objectives considered. The results further demonstrate the potential PSP improvements by optimizing the market introduction timing of successive product generations to increase closed-loop resource management effectiveness.

KEYWORDS:

Multi-generational design; Component commonality; Sustainable manufacturing; Closed-loop resource optimization; Circular economy; Configuration design;

1. Introduction

Manufacturers compete to develop and release the newest generation of their products as fast as possible, leading to diminished *demand cycle*[1] spans. A popular example is the iPhone, which is usually updated almost annually with a new generation (Ewa et al., 2017). On the other hand, increasing focus on sustainable manufacturing (SM) and circular economy (CE) calls for redesigning products to improve *end-of-use*[2] (EoU) resource utilization. Closed-loop productions, by practicing reuse or remanufacture, enable recovery at the product/component level. Thus, closed-loops maximize recuperating embedded value and overall life cycle sustainability benefits and are essential to SM and CE (Hapuwatte et al., 2021). Yet, the diminishing demand cycles (and production timelines) complicate the establishment of effective closed-loops since the EoU resources return after the current product generation's demand dies down. The resulting sub-optimal EoU activities negatively impact product sustainability performance (PSP). Although the frequent introduction of new generations of product design promotes evolutionary designs (i.e., gradual changes) with inter-generational compatibility (especially at the component-level), currently, the economic factors solely decide the compatibility. Deliberate planning of the inter-generational compatibility allows implementing closed-loop productions and promotes more sustainable EoU activities. However, it requires tools for multi-generational performance assessment that can be used during the design stage to forecast the PSP and help identify optimum levels of compatibility between generations.

[1] The term 'demand cycle' refers here to a product's market phases (i.e., *introduction*, *growth*, *maturity*, and *decline*). It avoids confusion with the term 'product life cycle'—which in this paper refers to the product's physical life stages (i.e., *pre-manufacturing*, *manufacturing*, *use*, and *post-use*) following the sustainable manufacturing literature.

[2] The term 'end-of-use' is used here in general to refer to both end-of-use (EoU) and end-of-life (EoL). Nasr et al. (2018) provides a detailed discussion on the differences between these two.

Designing sustainable products requires utilizing multiple *R*s of the 6Rs (reduce, reuse, recycle, redesign, recover, and remanufacture) (Go et al., 2015; Joshi et al., 2006). Consequently, it entails carefully coordinating the production forecasts (based on demand forecast) and closed-loop return flows to strategize the production considering the supply constraints. Such sustainability-focused strategizing requires an accurate life cycle triple bottom line (TBL) assessment that takes PSP's *dynamic* nature into account (Hapuwatte et al., 2021). However, the current dynamic PSP evaluation limits to single-generation productions. But, as Figure 1 shows, the production-return coordination and dynamic PSP forecasting are even more critical in closed-loop multi-generational designs. Those elements enable informed design decisions that improve the successive product generations.

Figure 1 visualizes the production forecast and closed-loop EoU product return curves in a multi-generation product system. The current generation's (Gen-1) returns delay depends on the Gen-1 product's life span and return logistics. The next-generation (Gen-2) product is designed at t_d. Depending on τ_2 (Gen-2's market introduction time) and the Gen-1's return delay, it is evident that diminishing demand cycle spans can lead to considerable amounts of Gen-1 EoU resources return during (or after) the Gen-1's production declines. Thus, to design Gen-2 at t_d and predict its dynamic PSP over time, in addition to sustainability evaluation, the designer-support tools must forecast production (i.e., demand cycle) curves.

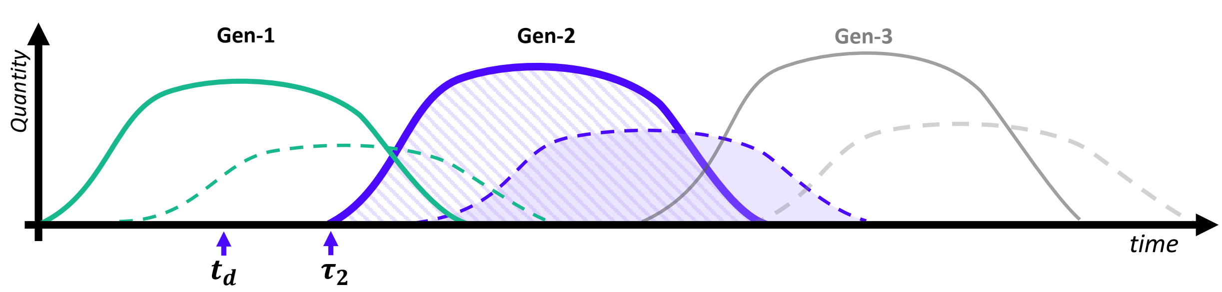

Fig. 1 Production forecast (solid lines) and return (dashed lines) flows in a closed-loop multi-generation system (t_d = time when Gen-2's design decisions are taken, τ_2 = time of Gen-2's market introduction)

Therefore, the purpose of the work presented in this paper is to develop a design-stage tool that maximizes the dynamic PSP over the entire production timeline by identifying the optimum component-level compatibility between successive design generations. This would help identify the specific Gen-2 components to be made common with Gen-1 design (i.e., decision variables) to optimize Gen-2's PSP. Overall, it would provide the opportunity to establish closed-loop productions in fast-paced multi-generational systems, thus improving the CE prospects.

For simplicity, this paper uses the term 'components' to identify independent functional units within a product (e.g., modules, sub-assemblies, parts). Section 2 provides a brief background for this work. Section 3 details the development of the proposed method using configuration design. The proposed method employs a multi-objective optimization approach maximizing manufacturer's gross profit, minimizing greenhouse gas emissions, and maximizing product's functional value. These representative objectives were chosen since they consist of metrics involving all TBL dimensions and all primary stakeholder categories (i.e., manufacturer, customer, and society-at-large). The case study presented in Section 4 demonstrates the optimized inter-generational component commonality significantly improving the Gen-2 PSP. Furthermore, the Pareto front results show an overall improvement of all three objectives.

2. Background

SM recognizes the importance of holistic consideration of economic, environmental, and social dimensions (i.e., TBL) (Moldavska and Welo, 2017). Besides the increasing significance of CE (Ellen MacArthur Foundation, 2013; Hapuwatte and Jawahir, 2021), closed-loop systems are becoming indispensable to manufacturers also due to the expanding 'extended producer responsibility' regulations (EPR Canada, 2017; European Parliament, 2012) to curtail TBL impacts.

Comprehensive PSP evaluations are necessary for designing sustainable products (Hapuwatte et al., 2021). Conventionally, TBL and life cycle perspective (International Organization for Standardization, 2015; United Nations Environment Programme, 2012) are considered integral to PSP. Recently, Hapuwatte and Jawahir (2021) re-emphasized the importance of 6Rs, total life cycle (TLC) considerations (Jawahir et al., 2006), and primary stakeholder view (PSV) for comprehensive PSP evaluations.

The production forecast mimics the demand. The EoU returns follow the production curve with a delay (Debo et al., 2006; Östlin et al., 2009). Therefore, it is essential to forecast the demand when planning PSP. Meade and Islam (2006) provided a comprehensive review of the diffusion models forecasting demand. Bass diffusion (Bass, 1969) is the most commonly used model.

In studies on EoU planning, Wang et al. (2017b) utilized Bass diffusion to strategize component remanufacture; Subramanian et al. (2013) analyzed how consideration of the remanufacture option can reverse the component commonality decisions; and Geyer et al. (2007) modeled closed-loop systems with remanufacturing, considering component durability limits. However, these prior works focused heavily on the economic aspect and single generation product systems. More recently, Badurdeen et al. (2018) and Aydin and Badurdeen (2019) incorporated broader TBL metrics in the diffusion dynamics-based component commonality studies, albeit for single generation systems.

Notably, Wang et al. (2017a) presented foundational work on component commonality in multi-generation systems. However, it was again limited to the economic dimension and remanufacturing. Moreover, they investigated commonality between product generations by studying the probabilistic obsolescence of components. While their work provided valuable insights, there still exists a gap for multi-generation design support tools to assess specific product design alternatives (i.e., configurations) available to the designers.

The proposed method uses the configuration design method (Wielinga and Schreiber, 1997) to examine the exact component alternatives. In configuration design, the designer selects a unique set of modular components from a library to match the customer requirements and specifications. Additionally, the Genetic Algorithm technique was utilized in multiple previous studies (Aydin and Badurdeen, 2019; Badurdeen et al., 2018; Chapman et al., 1994; Li et al., 2006) to optimize configuration designs.

3. Proposed methodology

For each design configuration (i.e., the product design alternatives compared), the proposed method's first step models and simulates the diffusion of products and their EoU returns. Then it forecasts the allocation to each EoU stream (reuse, remanufacture, recycle, sale, and disposal), and the total production's material and processing requirements, using the simulation results. By employing these forecasts and design configuration-specific life cycle data, the model estimates each Gen-2 design configuration's overall PSP by calculating a set of TBL metrics. Finally, an optimization procedure finds the optimal design configurations that maximize the PSP. Figure 2 illustrates these steps.

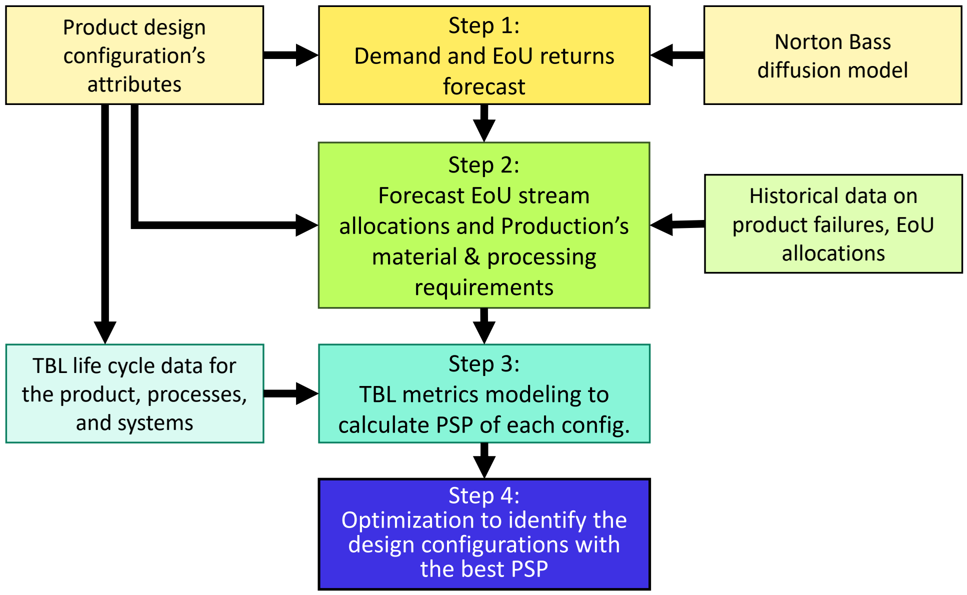

Fig. 2 Major steps in the proposed methodology to identify the optimal product design for Gen-2

Following general assumptions, relevant factors were considered in developing the proposed methodology. The proposed model assumes that the newly-manufactured (brand-new) and rebuilt products (products containing at least one reused or remanufactured component) are equal—including the price—and made to exact specifications. Therefore, the customers do not differentiate between them. Furthermore, the returns due to premature failure are assumed to be negligible, as shown by Hapuwatte et al. (2021) that the Monte Carlo technique can incorporate uncertain product returns. Since the calculations represent values over time, the model adjusts economic metrics to the present value (taking τ_2 as the present time) using an appropriate discount rate. In contrast, the marketing influences and similar external factors affecting product sales are beyond the scope of this paper, and therefore are not modeled. It is also important to note that the proposed method considers the multi-life cycle flow (i.e., utilization of EoU resources in the same generation) in addition to the multi-generational flow. More specific assumptions are provided within the respective sections.

3.1. Developing product demand models

3.1.1. Multi-generational diffusion

The Norton-Bass (NB) diffusion model (Norton and Bass, 1987) examines the dynamic behavior of sales in multi-generational problems. Eqs. (1) and (2) describe the demand variations $D_1(t)$ and $D_2(t)$ for Gen-1 and Gen-2. $F(t)$ is the probability that an individual adopts the product by the time period t, and m_1 and m_2 are Gen-1 and Gen-2 market potentials. τ_1, τ_2, and τ_3 are the market introduction times of Gen-1, Gen-2, and Gen-3, respectively. τ_1 also marks the start period of the analysis. An approximate value for τ_3 is assumed to be provided by the manufacturer.

$$D_1(t) = F(t)m_1[1 - F(t - \tau_2)] \tag{1}$$

$$D_2(t) = F(t - \tau_2)[m_2 + F(t)m_1][1 - F(t - \tau_3)] \tag{2}$$

When p is the coefficient of innovation and q is the coefficient of imitation, as described by Bass (1969),

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}\ ,\ t \geq 0. \tag{3}$$

Although later NB model adaptations incorporated concepts such as leapfrogging and switching (Jiang and Jain, 2012), those add little value for the two-generation system discussed here. For this paper’s intention to evaluate and forecast PSP (rather than retrospectively studying sales) in multi-generation systems, the original NB model (Norton and Bass, 1987), with the extensions described in Section 3.1.2 are more apt.

3.1.2. Price-utility adjustments

The product price or utility change can vary its diffusion curve. Eq. (2) forecasts the Gen-2 baseline design's diffusion. Since the proposed model tests many Gen-2 design configurations to find the optimal ones, their diffusion (and the resulting return) curves could also change, as illustrated in Figure 3.

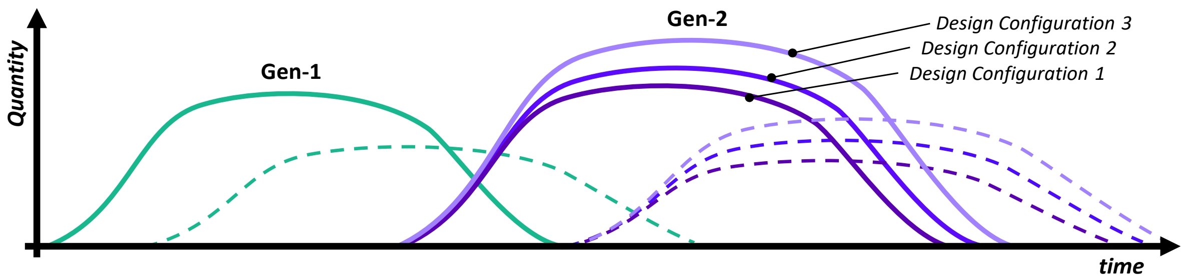

Fig. 3 Incorporating the effects of product design configurations to multi-generation diffusion modeling

Several prior publications discussed different methods to integrate price as an explanatory variable in the NB model. In particular, Speece and MacLachlan (1992) and Tsai (2013) detailed utility-adjusted pricing. The proposed method adapts those methods to form Eq. (4). It integrates the utility-adjusted pricing function $G_2(P)$ and the price elasticity parameter of market potential γ.

$$D_2(t) = F(t-\tau_2)[m_2 + F(t)m_1][1 - F(t-\tau_3)]G_2(P)^{\gamma} \tag{4}$$

$G_2(P)$ adjusts the baseline market potential by comparing the price (P_2^{config}) and utility rating (U_2^{config}) of each product configuration with the respective values of the baseline design, as expressed in Eq. (5). Section 3.4.1 details the calculation of P_2^{config} and U_2^{config}.

$$G_2(P) = \left[\frac{P_2^{config}/P_2^{base}}{U_2^{config}/U_2^{base}}\right] \tag{5}$$

3.1.3. *Estimating the diffusion modeling parameters*

The parameters discussed in Sections 3.1.1 and 3.1.2 can be estimated based on historical data, using the nonlinear least square approach (Srinivasan and Mason, 1986). Additionally, Lee et al. (2014) employed machine learning to relate product attributes (e.g., price, technology newness, industry competition) to forecast the diffusion parameters for pre-launch products. Some NB applications suggested using generation-specific p and q parameters (Islam and Meade, 1997; Jiang and Jain, 2012), whereas others (including original NB model) consider p and q to be the same over generations. Since forecasting these parameters is beyond the scope of current work, the baseline parameter values, including p, q, m_1, m_2, and γ are assumed to be given by the marketing department (based on historical or market survey data).

3.2. Modeling the production numbers

The proposed method sets up Gen-2's configuration design framework as follows to standardize and apply the NB model. The product design consists of a set number of *component-types* (indexed '*c*') indicating its major functional modules. e.g., For a 'printer,' these include modules relating to paper feeding, cartridge movement, casing, Wi-Fi connectivity, etc. Then, the *component-variants* (indexed '*v*') are the individual choices available for each component-type. The product's performance, costs, and life cycle impacts vary according to the designer's choice of variants for each component-type. To make Gen-2 capable of fulfilling Gen-1's demand, the component-types needs to be consistent between the generations.

Since this study is on design of the Gen-2 product, the component-variants choices are for Gen-2. The inter-generational commonality level is decided by identifying which Gen-2 component-types use the same component-variants as the Gen-1.

3.2.1. Modeling the end-of-use (EoU) appropriations

Eq. (6) provides the number of Gen-i recovered products in time ($t+u$). u is the average useful life of the product. For mathematical simplicity, the model assumes the time spent in forward and return logistics is negligible (or, it is incorporated in u). The return curve mimics the demand (thus, also production) curve shape but follows with a delay of u (Debo et al., 2006). The return rate for Gen-i (R_i) is the fraction of products that is returned to the manufacturer (or its EoU-agent) out of the total number of products that reaches EoU in each period.

$$N_i^{recov}(t+u) = D_i(t)R_i, \qquad i = 1, 2 \tag{6}$$

In a closed-loop production system, return happens at the product-level. The manufacturer then disassembles these EoU products into component-level during recovery. Hapuwatte et al. (2021) demonstrated allocating the EoU components into different EoU streams and calculating the production-mix for a single-generation product system. In this paper, the 'EoU appropriations' (Eqs. (7-11)) are the initially expected allotment ratios for each EoU stream (e.g., reuse, remanufacture, recycle, sale, and disposal). In contrast, the term 'EoU allocation' signifies the final distributions to each EoU stream, calculated using the simulation results, which consider the periodic needs. Unlike in single-generation systems, the multi-generation systems modeling requires incorporating identifiers for recovered component's generation and their compatibility with products from other generations to calculate the correct production-mix.

Component-Variant Index (v): This paper uses the following indexing convention for the design configurations. Since Gen-1's design is already finalized, v is fixed at '1' (i.e., only a single variant) for all Gen-1 component-types. For Gen-2, v takes an integer value from 1 to V_c (where V_c is the total number of variants available for the component-type 'c'), representing the component-variant chosen for the specific design configuration. The number of component-types (c) ranges from 1 to C_0. For notation purposes, a component-variant indexed by '1' in Gen-2 always denotes that component-type's design is unchanged from Gen-1's. Thus, the Gen-2 component-types that use variants indexed '1' are compatible with a Gen-1 reused or remanufactured component.

$N_{i,c,v}^{recov}(t)$ represents the quantity of Gen-i's component-type c, variant v, recovered in time t. When the appropriation fractions for reuse ($\gamma_{i,c,v}^{reuse}$), remanufacture ($\gamma_{i,c,v}^{reman}$), recycle ($\gamma_{i,c,v}^{recyc}$), and sale ($\gamma_{i,c,v}^{sale}$) are known for each component-type c and variant v, the available number of components for each EoU stream is,

$$N_{i,c,v}^{reuse}(t+1) = \gamma_{i,c,v}^{reuse} N_{i,c,v}^{recov}(t) \ , \quad (7)$$

$$N_{i,c,v}^{reman}(t+1) = \gamma_{i,c,v}^{reman} N_{i,c,v}^{recov}(t), \quad (8)$$

$$N_{i,c,v}^{recyc}(t+1) = \gamma_{i,c,v}^{recyc} N_{i,c,v}^{recov}(t), \quad (9)$$

$$N_{i,c,v}^{sale}(t+1) = \gamma_{i,c,v}^{sale} N_{i,c,v}^{recov}(t), \quad (10)$$

$$N_{i,c,v}^{dispo}(t+1) = 1 - [N_{i,c,v}^{reuse}(t+1) + N_{i,c,v}^{reman}(t+1) + N_{i,c,v}^{recyc}(t+1) + N_{i,c,v}^{sale}(t+1)] \ , \quad (11)$$

i = 1, 2, c = 1,2, …, C_0, $v \in \{1, …, V_c\}$ and $N_{i,c,v}^{recov}(1) = 0$.

The parameters R_i and $\gamma_{i,c,v}^{x}$ are calculated using historical data and component attributes (e.g., common failure modes, failure rates, materials used). Section 3.2.2 calculates the actual allocations to each EoU stream—which depends on the production requirement.

3.2.2. Modeling the actual allocations for each end-of-use (EoU) stream

When the production capacity can handle the demand levels predicted by the diffusion model, the number of components produced in each period t is,

$$N_{i,c,v}^{prod}(t) = D_i(t)\lambda_{i,c}, \quad i = 1, 2, \quad c = 1, \ldots, C_0, \quad \text{and } v \in \{1,\ldots, V_c\}, \tag{12}$$

where $\lambda_{i,c}$ is the number of component-type c in a single product of Gen-i. Otherwise, the production capacity will cap the actual production number.

After the initial EoU appropriations are determined from Eqs. (7-11), these values are compared to the demand values predicted for each successive period. In specific time ranges where there are two generations in the system with possible returns (particularly after (τ_2+u)), the model checks if each Gen-2 component-type's variant is compatible with Gen-1 (i.e., v = 1). The sustainable activity hierarchy (European Commission, 2008) provides the initial basis for identifying the most efficient recovery paths (i.e., requiring the least change to embedded value and additional work). It prioritizes reuse and remanufacture. When a component-type uses the same design in both generations, the reuse/remanufacture in the same generation gets priority. Since this paper focuses on the Gen-2 design, the equations below primarily present expressions for Gen-2.

For each time t, to fulfill Gen-2 component-type c demand ($N_{2,c,v}^{prod}(t)$), first the Gen-2's reuse appropriation ($N_{2,c,v}^{reuse2to2}(t)$) is taken. If that is inadequate and v = 1, then the Gen-1's excess reusable components ($N_{1,c,1}^{reuse\_excess}(t)$) are taken to fulfill the rest of Gen-2 demand ($N_{1,c,1}^{reuse1to2}(t)$). If that is still not adequate, the Gen-2's remanufacturable components ($N_{2,c,v}^{reman}(t)$) are taken to fulfill the demand (termed $N_{2,c,v}^{reman2to2}(t)$). If there is further shortfall, and v =1, then Gen-1's excess remanufacturable components (termed $N_{1,c,1}^{reman\_excess}(t)$) are taken to fulfill the rest of Gen-2 demand (termed $N_{1,c,1}^{reman1to2}(t)$). If the demand cannot be fulfilled using all these strategies, then components are newly manufactured to fulfill the Gen-2's residue demand (termed $N_{2,c,v}^{newm}(t)$).

After fulfilling Gen-2 demand ($N_{2,c,v}^{prod}(t)$) (and if $v = 1$ for the component-type c, then also fulfilling any unfulfilled Gen-1 demand: $N_{1,c,1}^{prod}(t)$), any excess components that were initially appropriated for reuse or remanufacture are assumed to be allocated for recycling (i.e., the next most effective EoU activity). For Gen-2, the total number of components actually allocated for recycling ($N_{2,c,v}^{recyc*}(t)$) is,

$$N_{2,c,v}^{recyc*}(t) = N_{2,c,v}^{recyc}(t) + [N_{2,c,v}^{reuse}(t) - N_{2,c,v}^{reuse2to2}(t) - N_{2,c,v}^{reuse2to1}(t)] + [N_{2,c,v}^{reman}(t) - N_{2,c,v}^{reman2to2}(t) - N_{2,c,1}^{reman1to2}(t)], \tag{13}$$

$$c = 1, 2, \ldots, C_0; \quad v \in \{1, \ldots, V_c\}; \text{ and}$$

$$\text{in all } v \neq 1\text{: } N_{1,c,v}^{reuse2to1}(t) = 0 \text{ and } N_{1,c,v}^{reman2to1}(t) = 0.$$

3.2.3. Modeling the production-mix

The 'production-mix' for a specific production period is the total number of newly manufactured (i.e., brand-new), reused, and remanufactured components produced in that period. Figure 4 summarizes the different production possibilities and their respective production-mix calculations considering the allocations discussed in Section 3.2.2. The general expression for Gen-2 production-mix is,

$$N_{2,c,v}^{prod}(t) = N_{2,c,v}^{newm}(t) + N_{2,c,v}^{reuse2to2}(t) + N_{1,c,v}^{reuse1to2}(t) + N_{2,c,v}^{reman2to2}(t) + N_{1,c,v}^{reman1to2}(t), \tag{14}$$

$$\text{where, } c = 1, \ldots, C_0; \ v \in \{1, \ldots, V_c\}; \text{ and}$$

$$\text{in all } v \neq 1\text{: } N_{1,c,v}^{reuse1to2}(t) = 0 \text{ and } N_{1,c,v}^{reman1to2}(t) = 0.$$

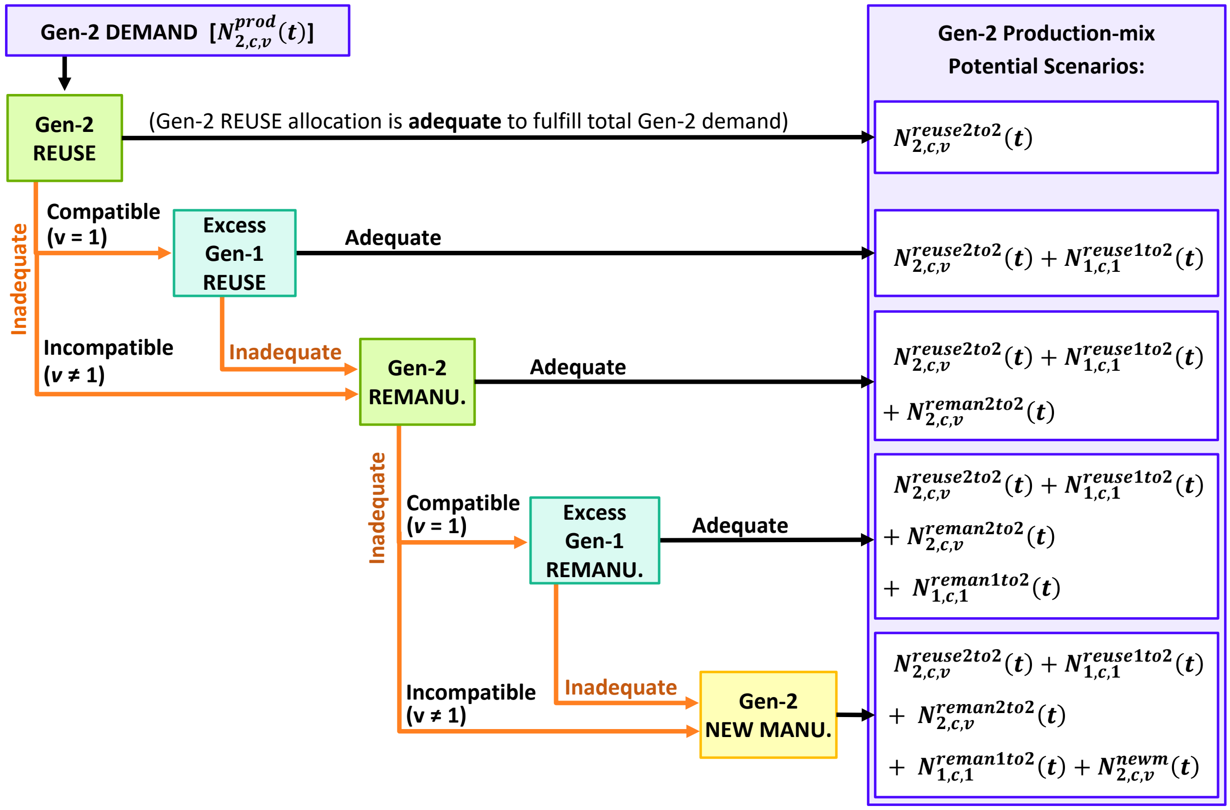

Fig. 4 Potential scenarios in Gen-2 production-mix calculation for component-type c, considering the EoU allocation possibilities. For a given period, only one of them will be true.

To identify and account the resulting TBL impacts (discussed in Section 3.4.1), the multi-generation systems require tracking which generation components are allocated where.

3.3. Modeling the material requirements

Deciphering the closed-loop resource flow and its TBL impacts over the entire product life cycle requires understanding the material requirements for the total production. Once the production-mix and forecast for recycling ($N^{recyc*}_{2,c,v}(t)$) are known, Eqs. (15-19) estimate the amounts of secondary material available (from closed-loop recycling) and primary (i.e., virgin) material needed for each period. Let the material-type index be *m* which ranges from 1 to M_0

(where M_0 represents the number of materials in the system). If the material-type *m*'s mass in component-type *c*, variant *v*, of Gen-*i* is $M_{i,c,v,m}$, the total material *m* mass in a Gen-*i* product is,

$$Mp_{i,m}^{newm} = \sum_{c=1}^{C_0} M_{i,c,v,m}\lambda_{i,c}, \quad i = 1, 2; \quad m = 1, \ldots, M_0; \text{ and } v \in \{1, \ldots, V_c\}. \tag{15}$$

Similarly, if the fraction of material *m* necessary (relative to a newly manufactured component) to remanufacture a component-type *c*, variant *v* of Gen-*i* is $\phi_{i,c,v,m}$, the mass of each material *m* necessary to remanufacture a component is,

$$M_{i,c,v,m}^{reman} = M_{i,c,v,m}\phi_{i,c,v,m}. \tag{16}$$

Reused components are assumed to require no additional material (i.e., reuse requires only minor processing such as cleaning and quality assurance). Based on Eq. (14), Gen-2's total material mass requirement in each material-type *m* for time *t* is,

$$M_{2,m}^{req}(t) = N_{2,c,v}^{newm}(t)M_{2,c,v,m} + N_{2,c,v}^{reman2to2}(t)M_{2,c,v,m}^{reman} + N_{1,c,v}^{reman1to2}(t)M_{1,c,v,m}^{reman}, \tag{17}$$

$$c = 1, 2, \ldots, C_0; \ v \in \{1, \ldots, V_c\}; \text{ and in all } v \neq 1: N_{1,c,v}^{reman1to2}(t) = 0.$$

The total mass of recycled material type *m* available at time *t* is,

$$M_{2,m}^{recyc\_tot}(t) = \sum_{c=1}^{C_0} M_{2,c,v,m}N_{2,c,v}^{recyc*}(t), \quad m = 1, \ldots, M_0, \text{ and } v \in \{1, \ldots, V_c\}, \tag{18}$$

assuming the total material in a component is recyclable. If not, a 'recyclability fraction' incorporated into Eq. (18) can account for the scrappage in recycling.

Eq. (19) estimates the amount of primary material required ($M_{2,m}^{pr\_req}(t)$) or the amount of excess recycled material available for sale ($M_{2,m}^{recyc\_s}(t)$) beyond the closed-loop (i.e., cascade flow).

If $M_{2,m}^{recyc\_tot}(t) > M_{2,m}^{req}(t)$, (19)

$$\text{then } M_{2,m}^{recyc\_s}(t) = M_{2,m}^{recyc\_tot}(t) - M_{2,m}^{req}(t), \text{ and } M_{2,m}^{pr\_req}(t) = 0,$$

otherwise,

$$M_{2,m}^{pr\_req}(t) = M_{2,m}^{req}(t) - M_{2,m}^{recyc\_tot}(t), \text{ and } M_{2,m}^{recyc\_s}(t) = 0, m = 1, \ldots, M_0.$$

3.4. Formulating the multi-objective optimization model for multi-generational design

This section discusses the TBL metrics-based PSP estimation for all tested product design configurations, and the multi-objective optimization modeling procedure to identify the optimal design configurations.

3.4.1. Modeling the product sustainability performance (PSP)

This study takes the TBL metrics-based evaluation method suggested by Hapuwatte et al. (2021) as the basis to estimate the PSP of each design configuration. Their work developed a design-stage oriented (i.e., forecasting-based) PSP evaluation, compared to the common retrospective evaluation methods that are best suited to assess finalized designs.

The following three (conflicting) objectives are used to present the proposed method and results succinctly. These objectives were selected to represent metrics involving all TBL and Primary Stakeholder Value (PSV) elements. Their specific TBL dimension and primary beneficiary/impacted PSV stakeholder category (SC) are specified within brackets. In applications, it is advisable to use as many critical metrics (listed in (Hapuwatte et al., 2021)) as possible. The hotspot analysis (United Nations Environment Programme, 2017) can screen for the critical metrics.

i. Maximize manufacturer's TLC gross profit - TGP^{Mftr} (SC: Manufacturer; TBL-dimension: Economic)

ii. Minimize TLC greenhouse gas (GHG) emissions - $TGHG^{SaL}$ (SC: Society-at-large; TBL-dimension: Environmental)

iii. Maximize product functional value score - $PFVS^{Cust}$ (SC: Customer; TBL-dimension: Social)

As detailed next, the proposed method models these metrics over the demand cycle, based on the five basic measurement categories introduced by Hapuwatte et al. (2021). The Gen-2 demand cycle spans from τ_2 till T_2 (the maximum number of periods studied). The model sets T_2 sufficiently large to include all periods with Gen-2 demand plus additional time (>u), making sure that the analysis includes all remaining Gen-2 products. Furthermore, the component variant index 'v' is the optimization's primary decision variable, which takes integer values from 1 to V_c for each component-type 'c'.

Objective-1 (TGP^{Mftr}) takes the difference between the manufacturer's total revenue (TR^{Mftr}) and cost (TC^{Mftr}) for Gen-2, for all life cycle stages, and aggregates over the demand cycle.

$$TGP^{Mftr} = TR^{Mftr} - TC^{Mftr} \tag{20}$$

The revenue expands as,

$$TR^{Mftr} = \sum_{t=\tau_2}^{T_2} \{D_2(t) P_2^{config} + \sum_{c=1}^{C_0} [N_{2,c,v}^{sale}(t) P_{2,c,v}^{comp}] + \sum_{m=1}^{M_0} [M_{2,m}^{recyc\_s}(t) P_m^{mat}]\}, \tag{21}$$

where $v \in \{1, \ldots, V_c\}$ for each component-type c,

aggregating the sales revenue from products, excess recovered EoU components, and excess recycled material. $P_{2,c,v}^{comp}$ is the sale price of a component-type c variant v sold beyond the closed-loop (e.g., for reuse in other applications, external recycling). P_m^{mat} is the per unit mass price of recycled material *m*, sold beyond the closed-loop. Product price (P_2^{config}) is configuration specific (and can be determined parametrically using the attributes of each configuration and the profit margin) and assumed constant over time. If Gen-2's future pricing is known, Eqs. (5) and (21) can incorporate pricing as a time-dependent variable.

Manufacturer's total cost (TC^{Mftr}) aggregates cost elements over TLC, where,

$$TC^{Mftr} = \sum_{t=\tau_2}^{T_2} [C^{Material}(t) + C^{Processing}(t) + C^{Labor}(t) + C^{Logistics}(t) + C^{Capital}(t)] + C^{Fixed}. \tag{22}$$

Each cost element ($C^X(t)$) needs further expansion considering other variables (e.g., number of components produced, unit costs) pertaining to the specific application. The material cost element of Eq. (22) expands to,

$$C^{Material}(t) = \sum_{m=1}^{M_0} M_{2,m}^{pr\_req}(t) Um_m^{cost}, \tag{23}$$

where Um_m^{cost} is the material *m*'s unit cost. The processing cost element of Eq. (22) is,

$$\begin{aligned} C^{Processing}(t) = \sum_{c=1}^{C_0} \{ & N_{2,c,v}^{newm}(t) Up_{2,c,v}^{newm\_cost} + [N_{2,c,v}^{reuse2to2}(t) \\ & + N_{1,c,v}^{reuse1to2}(t)]\, Up_{2,c,v}^{reuse\_cost} + [N_{2,c,v}^{reman2to2}(t) \\ & + N_{1,c,v}^{reman1to2}(t)] Up_{2,c,v}^{reman\_cost} + N_{2,c,v}^{recyc*}(t) Up_{2,c,v}^{recyc\_cost} \\ & + N_{2,c,v}^{sale}(t) Up_{2,c,v}^{sale\_cost} + N_{2,c,v}^{dispo}(t) Up_{2,c,v}^{dispo\_cost} \} \end{aligned} \tag{24}$$

where $v \in \{1, \ldots, V_c\}$ for each component type *c*.

The parameters $Up_{2,c,v}^{newm\_cost}$, $Up_{2,c,v}^{reuse\_cost}$, $Up_{2,c,v}^{reman\_cost}$, $Up_{2,c,v}^{recyc\_cost}$, $Up_{2,c,v}^{sale\_cost}$, and $Up_{2,c,v}^{dispo\_cost}$ denote unit processing costs per component, for a single component-type *c* variant *v*, in new-manufacture, reuse, remanufacture, sale, and disposal, respectively. These parameters are estimated from the manufacturer's production data. The model uses similar expansions for labor, logistics, capital, and fixed cost elements.

Objective-2 ($TGHG^{SaL}$) aggregates the TLC GHG emissions over the demand cycle, as

$$TGHG^{SaL} = \sum_{t=\tau_2}^{T_2}[GHG^{newm}(t) + GHG^{reuse}(t) + GHG^{reman}(t) + GHG^{recyc}(t) + GHG^{sale}(t) + GHG^{dispo}(t)], \tag{25}$$

where each element ($GHG^{X}(t)$) refers to the subtotals of emissions in new-manufacture, reuse, remanufacture, recycle, sale, and disposal streams for time *t*. Considering the number of components produced it expands to,

$$TGHG^{SaL} = \sum_{t=\tau_2}^{T_2}\sum_{c=1}^{C_0}\{N_{2,c,v}^{newm}(t)Uc_{2,c,v}^{newm_{GHG}} + \left[N_{2,c,v}^{reuse2to2}(t) + N_{1,c,v}^{reuse1to2}(t)\right]Uc_{2,c,v}^{reuse_{GHG}} + \left[N_{2,c,v}^{reman2to2}(t) + N_{1,c,v}^{reman1to2}(t)\right]Uc_{2,c,v}^{reman_{GHG}} + N_{2,c,v}^{recyc*}(t)Uc_{2,c,v}^{recyc\_GHG} + N_{2,c,v}^{sale}(t)Uc_{2,c,v}^{sale\_GHG} + N_{2,c,v}^{dispo}(t)Uc_{2,c,v}^{dispo\_GHG}\}, \tag{26}$$

where the parameters $Uc_{2,c,v}^{newm\_GHG}$, $Uc_{2,c,v}^{reuse\_GHG}$, $Uc_{2,c,v}^{reman\_GHG}$, $Uc_{2,c,v}^{recyc\_GHG}$, $Uc_{2,c,v}^{sale\_GHG}$ and $Uc_{2,c,v}^{dispo\_GHG}$ denote per component GHG emissions, in new-manufacture, reuse, remanufacture, recycle, sale, and disposal, respectively. These parameters are estimated using the life cycle data.

Objective-3 ($PFVS^{Cust}$) is a product-specific 'score' that integrates the utility rating and product configuration's cost, specifically from the customer's perspective. A general form of this score can be expressed as,

$$PFVS^{Cust} = \frac{U_2^{config}}{TCU^{config}}, \tag{27}$$

where U_2^{config} is the aggregated utility rating of Gen-2 product configuration (used in Eq. (5)), and TCU^{config} is its total cost for the customer. The model defines the utility rating as,

$$U_2^{config} = \sum_{c=1}^{C_0} U_{c,v}^{comp} w_c, \text{ and} \tag{28}$$

$$\sum_{c=1}^{C_0} w_c = 1,$$

where $U_{c,v}^{comp}$ is the functional utility of the component-type *c* variant *v*. w_c is a relative weight (i.e., relative customer preference) assigned to that functionality. w_c is assumed to be available from prior market research. For products with negligible usage cost compared to the purchase price (P_2^{config}), Eq. (28) simplifies into,

$$PFVR_2^{Cust} = \frac{U_2^{config}}{P_2^{config}}. \tag{29}$$

All the above expressions expanding the objective functions are application-specific. They require adapting to the individual case and metrics. Hapuwatte et al. (2021) described *parametric* and *detailed* modeling techniques to estimate such metrics.

3.4.2. Accounting and allocating the TBL impacts in multi-generation product systems

In a multi-generation closed-loop product system that shares the common EoU recovered components, the PSP calculation requires defining how the TBL impacts are accounted and allocated to each generation. Therefore, the TBL impact elements allocated to Gen-2's PSP in this model (also visualized in Figure 5) are:

- From Gen-1 returns, the EoU processing-related TBL impacts due to the portion of components utilized for Gen-2 production
- All TBL impacts due to Gen-2 production (including the forward logistics)
- All TBL impacts due to Gen-2 return logistics

- From Gen-2 returns, the EoU processing-related TBL impacts due to the portion of components utilized for Gen-2 production

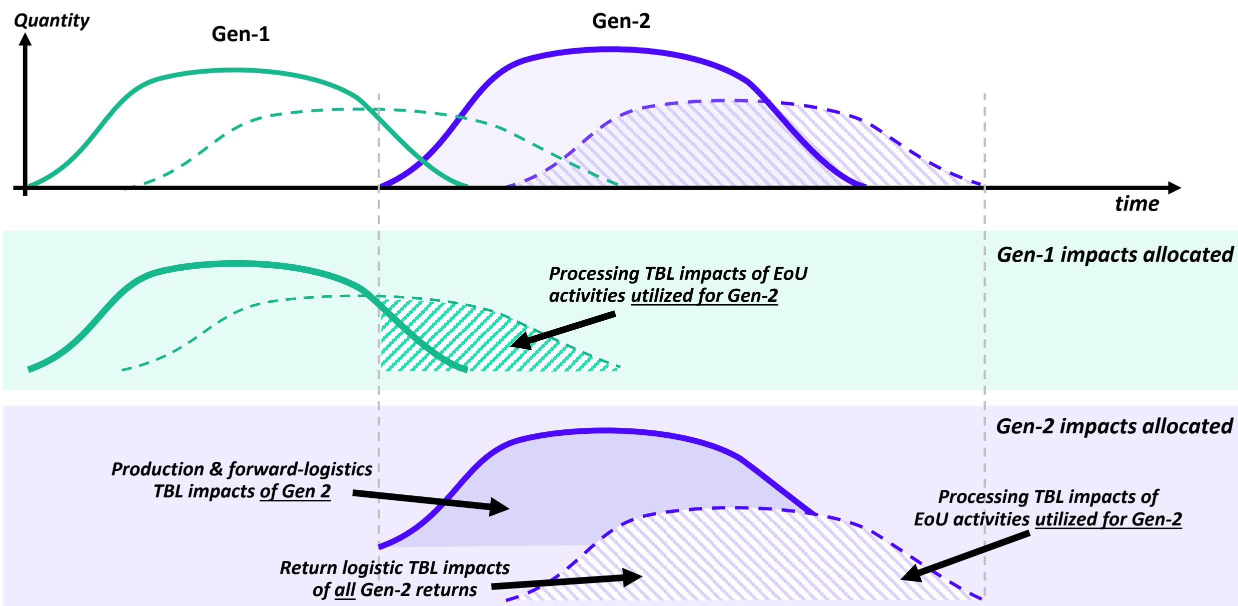

Fig. 5 TBL impact portions allocated towards Gen-2's product sustainability performance (PSP)

3.4.3. Multi-objective optimization using the NGSA-II method

Since this is a multi-objective problem, evolutionary algorithm optimization techniques (such as the genetic algorithm) are more appropriate due to their efficiency in finding non-dominated solutions. It is instrumental in product design as it provides the designer multiple design configurations that are non-dominated within the entire solution space (i.e., a Pareto front—PF). Thus, each PF solution is optimal for different cases. Considering other factors and objective priorities, the designer can pick the final product design from the PF.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) provides a computationally efficient, fast, and elitism-based optimization (Deb et al., 2002). It finds PFs with better solution spreads (through crowding distance assignment) and more-convergent to the true PF. Recently, NSGA-II was applied in product design configuration problems (Aydin and Badurdeen, 2019; Badurdeen et al., 2018). Thus, this method uses NSGA-II. Additionally, the simulated binary crossover (SBX) (Deb and Agrawal, 1999) extension provides control over the 'child solutions' spread, allowing them to be more diverse initially, but becoming more focused as the population converges. It also provides the ability to incorporate additional constraints—an advantage for certain applications (e.g., to set compatibility requirements between component-variants).

With the Eqs. (20-29), the optimization becomes:

$$\text{Maximize } f_1 = TGP^{Mftr}$$

$$\text{Minimize } f_2 = TGHG^{SaL}$$

$$\text{Maximize } f_3 = PFVS^{Cust},$$

with the primary decision variable: $1 \leq v \leq V_c$, for each $c = 1, \ldots, C_0$,

and, the additional decision variable (used in Case-2 below): $\tau_2^{min} \leq \tau_2 \leq \tau_2^{max}$, where τ_2^{min} and τ_2^{max} are the allowable minimum and maximum Gen-2 introduction times.

As illustrated in Figure 6 algorithm flowchart, once the optimization parameters are set, it first generates a random population (of size N_{pop}) and calculates the sustainability metrics to evaluate the three objective functions. Then the parent population is sorted by ranking and crowd distance, and an offspring population is created applying crossover and mutation. The metrics are calculated for the combined populations, which are then used in sorting and identifying a new population. This process is recursively applied, as depicted in Figure 6, for i_{max} times. Finally, the PF is identified from the non-dominated solutions.

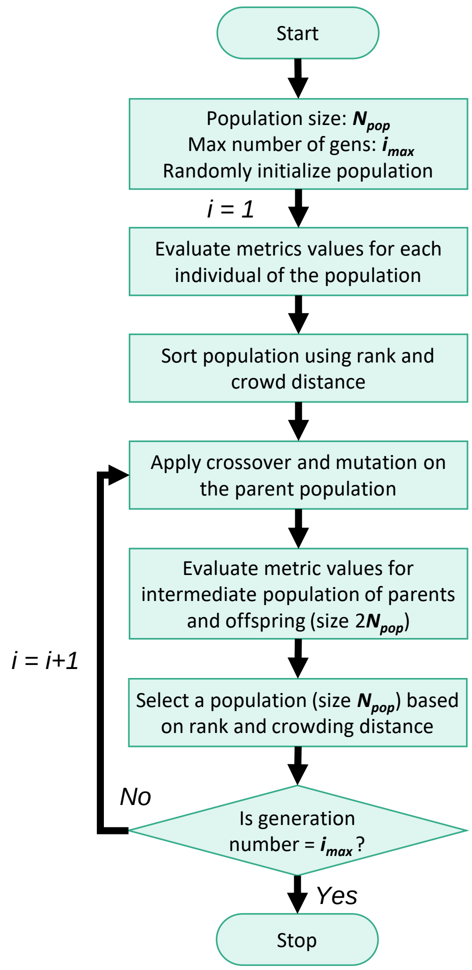

Fig. 6 Algorithm flowchart for the NSGA-II method

4. Results and discussion

In a product like iPhone, designers can enlist the crucial modules (i.e., component-types) in a similar optimization procedure to identify the optimally sustainable upgrade path by distinguishing the component-types to be kept common in each successive annual generation update. In such an example, the *component-types* are the modules (e.g., rear camera module, audio module, etc.) and the *variants* are the alternative choices designers have for each module (e.g., for the camera module: wide angle + telephoto lenses, wide + ultra-wide + telephoto, wide angle only, etc.).

Since the primary objective of this section is to demonstrate the application of the proposed methodology and understand the multi-generational sustainable product design concept, a simpler theoretical product is used here. The case study uses a product with a design configuration of 6 component-types, and 7 variants for each component-type, representing typical number of major modules in a consumer electronics product. The coding and simulation utilized the MATLAB R2020a. Table 1 summarizes the major parameters and the optimization setup used. Other parameters, and life cycle and production input data used in the simulation are listed in the *Supplementary document*. This example uses EoU return time and return rate parameters representative of typical consumer electronics product with an established closed-loop. However, the parameter values listed in Table 1 depend on the exact product and the market. Following Section 3.2.1's convention, the study indexes all Gen-1 component variants as 'v = 1'.

Table 1 Parameters and their values common to Case-1 and Case-2

Gen.	Parameter	Symbol	Value(s)
Gen-1	Component-type index	c	1 to 6
	Component-variant index (for each c)	v	1
	Gen-1 introduction to market (period#)	τ_1	1
	Total market potential of Gen 1 (in product units)	m_1	50,000
	Use and return logistics time (in periods)	u_1	24
	EoU product return rate	R_1	0.6
Gen-2	Component-type index	c	1 to 6
	Component-variant index (for each c)	v	1 to 7
	Additional market potential of Gen 2	m_2	15,000
	Use (and return logistics) time (in periods)	u_2	24
	EoU product return rate	R_2	0.6
	Product price	P_2^{config}	Cost*1.25
Gen-3	Gen-3 introduction to market (in period)	τ_3	48
Common parameters:			
	NB model: Coefficient of innovation	p	0.04
	NB model: Coefficient of imitation	q	0.65
	Discount rate for present value calculation	6% APY	
NSGA-II optimization setup parameters			
	Population size (N_{pop})	200	
	Number of generations (i_{max})	200	
	Distribution index	20	
	Cross index	1	
	Mutation probability	0.5	

Section 3.1.3 of this paper identified the NB model parameter estimation methods. Based on a comparable product design studies (Aydin and Badurdeen, 2019), reasonable p and q values were chosen (Table 1). The optimization setup parameters (Table 1) were based on Deb and Agrawal (1999). Additionally, the objective values were examined during the NSGA-II loops to verify convergence.

4.1. Case study assumptions

This study makes the following assumptions to simplify modeling. The Gen-2 product price (P_2^{config}) is static for each design configuration and is set using a multiplier of the respective configuration's production cost (i.e., 25% profit margin). It also assumes there are no duplicates of each component-type in the product (i.e., for all six component-types, $\lambda_{i,c}$ =1). The study defines $\gamma_{i,c,v}^{x}$ factors at the component level, assuming variants of each component type will have similar EoU appropriation values.

4.2. Analysis of the results

This section summarizes and discusses the results of the two simulated cases. Case-1 demonstrates the importance of considering inter-generational commonality during product design and the potential improvements possible through the use of the proposed method. Case-2 discusses the impact of the timing of the successive generation's market introduction to further maximize the PSP benefits of component commonality.

4.2.1. Case-1: Comparing the optimum Gen-2 design configurations found with and without considering the inter-generational commonality potential

Case-1A simulates the baseline scenario: the designers do not consider closed-loop sourcing of Gen-1 excess resources to the Gen-2 production when choosing Gen-2 configuration. Thus, for simulation purposes, the Gen-1 return rate (R_1) is set to 0.

Case-1B simulates the same conditions as Case-1A but considers potential sharing of EoU resources—available due to inter-generational component commonality. Thus, the R_1 is set to the current value (i.e., R_1 = 0.6).

For both cases, the Gen-2 market introduction time (τ_2) is set to Period 24. An alternative method (instead of R_1 = 0 for baseline) to disregard the Gen-1 component-variants for Gen-2 design is constraining 'v' to vary between 2 and 7 for all component-types. However, setting R_1 = 0 allows the Gen-1 component-variants to be available as choices for the Gen-2 (i.e., 1A and

1B design spaces are the same). Notably, it permits Gen-1 components to be still chosen (due to reasons others than closed-loop benefits). Thus, R_1 = 0 presents a more general baseline scenario.

The Case-1's (both 1A and 1B) total design space consists of 117,649 solutions. For Case-1A, the NSGA-II finds 194 unique non-dominated solutions in the PF, whereas for Case-1B, it finds 152. Figures 7 (a.) and (b.) visualize the non-dominated solutions of Case-1A and 1B. Figures 7 (c.) and (d.) view Case-1B's PF's two objectives at a time. The GHG emissions generally improve (i.e., minimizes) with the increasing manufacturer gross profits. The product's utility score (for customers) generally diminishes with the increasing manufacturer gross profits. Thus, the objectives are conflicting and multi-objective optimization is necessary to balance the trade-offs.

Table 2 lists three Gen-2 design configurations each for Case-1A and Case-1B (design configurations #1A-1 to #1B-3) that provide the best values for each objective individually. It also lists the variants selected (i.e., '*v*' values) for each configuration's component-types 1 to 6.

For the purpose of comparing solutions of Case-1A and Case-1B, the objective values of all design configurations were normalized (using min-max scaling (Jain et al., 2005)), and the three objectives were equally weighted to obtain a single score. Table 2 lists the resulting highest scoring solutions as the 'Best configuration (using equal weighting)' for Case-1A and Case-1B. Table 2 also compares the relative change of objective values between the 'best configurations' of Case-1A vs. Case-2B. In real applications, the designer can appropriately weight each objective based on their relative importance/preference. Furthermore, a sensitivity analysis can be utilized to analyze the stability of the optimal solution and the resulting impacts on the designer decisions.

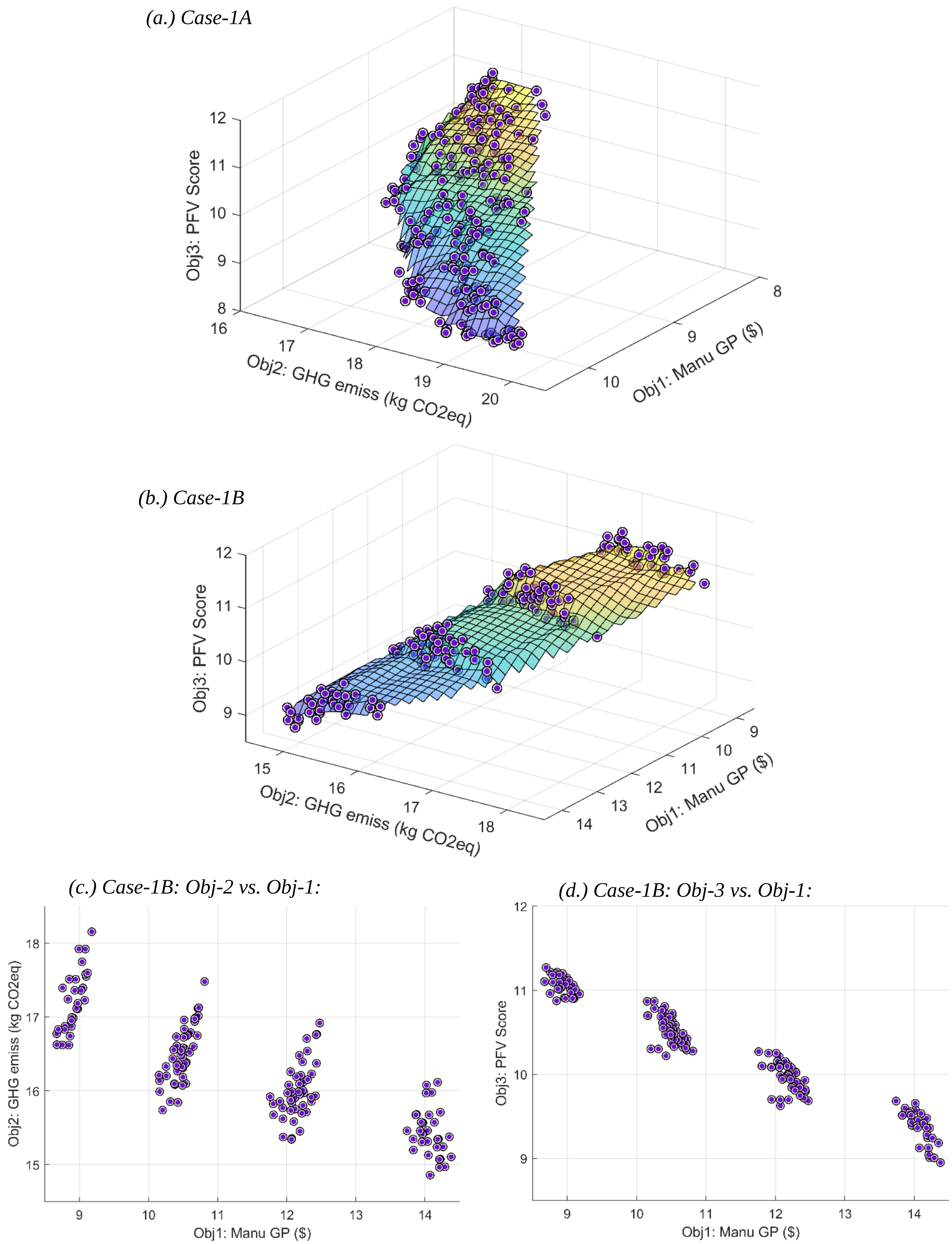

Fig. 7 Pareto front (PF) solutions scatter for (a.) Case-1A and (b.) Case-1B, in terms of the three objectives (surface color visually represents the vertical height). Case-1B's PF visualized taking two objectives at a time: (c.) GHG emissions vs. Manufacturer Gross Profit, and (d.) Product functional value score vs. Manufacturer Gross Profit.

Table 2 Case-1A and Case-1B Pareto fronts' unique solutions summary

	Obj-1: Manu GP	**Obj-2:** GHG Emiss.	**Obj-3:** Funct. Score	Num. of common components
Case-1A (Baseline):				
Design configuration #1A-1: *v* = [7,4,1,3,5,7]	**10.5**	20.0	8.7	1
Design configuration #1A-2: *v* = [2,7,6,2,2,1]	8.8	**16.4**	9.9	1
Design configuration #1A-3: *v* = [5,7,7,6,2,1]	8.3	17.0	**11.3**	1
Individual objective's best values*	10.5	16.4	11.3	-
Best configuration (using equal weighting): *v* = [5,7,6,6,2,1]	8.4	17.0	11.2	1
Objective value averages (for the entire Pareto front)	9.4	18.0	9.8	0.9
Case-1B:				
Design configuration #1B-1 *v* = [2,1,1,1,5,1]	**14.4**	15.1	8.9	4
Design configuration #1B-2 *v* = [2,1,1,1,2,1]	14.1	**14.9**	9.1	4
Design configuration #1B-3 *v* = [5,7,7,6,2,1]	8.7	16.8	**11.3**	1
Individual objective's best values*	14.4	14.9	11.3	-
Best configuration (using equal weighting): *v* = [4,1,1,1,2,1]	13.8	15.2	9.5	4
Objective value averages (for the entire Pareto front)	11.4	16.3	10.2	3.0
Relative change between Case-1B vs. Case-1A:				
in 'Best configuration (using equal weighting)'	+64.7%	-10.4%	-1.7	+3
in 'Objective value averages (for the entire Pareto front)'	+21.3%	-9.6%	+0.4	+2.1

**Objectives 1 and 3 are maximizations. Objective 2 is a minimization.*

Compared to the baseline (Case-1A), Case-1B's 'best configuration' improves the Obj-1 by 64.7% and Obj-2 by 10.4% (i.e., an emission reduction) by utilizing the inter-generational commonality. However, the Obj-3 reduces from 11.2 to 9.5 score-points in the Case-1B. It is due to Case-1B's best configuration employing more component-types that use variant-1 (e.g., for component-types 2, 3, 4, and 6). Therefore, it can repurpose Gen-1 excess returns and reduce costs and emissions (due to reduced material and processing needs) in Gen-2. But, the use of Gen-1 variants averts product functionality improvements available through newer component variants (e.g., from technological advancement), leading to the identified reduction of Obj-3 score. Therefore, if customer's functionality improvement or differentiating the successive design generation are priorities, the designer should choose a different solution from the identified PF that emphasizes the Obj-3.

The ‘objective value averages (for the entire PF)’ lists the averages for each objective by sampling all unique solutions of the PF (i.e., 194 and 152 for Case-1A and 1B, respectively). Comparing these average values for Case-1A and Case-1B (the last row in Table 2) demonstrate how the overall PF benefits by the inclusion of multi-generational design optimization over the standalone optimization. The improvements in average values of Obj-1 by 21.3%, Obj-2 by 9.6%, and Obj-3 by 0.4 score-points confirm that inter-generational component commonality improves the overall PF solutions. Thus, it offers the designer a set of design configuration alternatives with improved PSP to choose from.

Further analysis shows that the average number of common components in PF configurations increases from 0.9 (Case-1A) to 3.0 (Case-1B). As Figure 8 visualizes, the Case-1B PF solutions move to increased concentration (i.e., larger bubbles) in the common component variants (v = 1). This also explains the ‘stepped’ effect seen in Case-1B’s PF (Figures 7). The analysis of the individual design configurations in the PF reveals that each ‘step’ is a cluster of configurations with a similar number of common components. For example, in Figure 7(d), the solutions in the cluster with the highest Obj-3 scores have up to two common components. Solutions in the next clusters to the right have three, four and five common components in the design configurations. If the designers have limits on the commonality with Gen-1 (e.g., to ensure Gen-2 differentiates enough from Gen-1), they can focus on appropriate clusters in the PF.

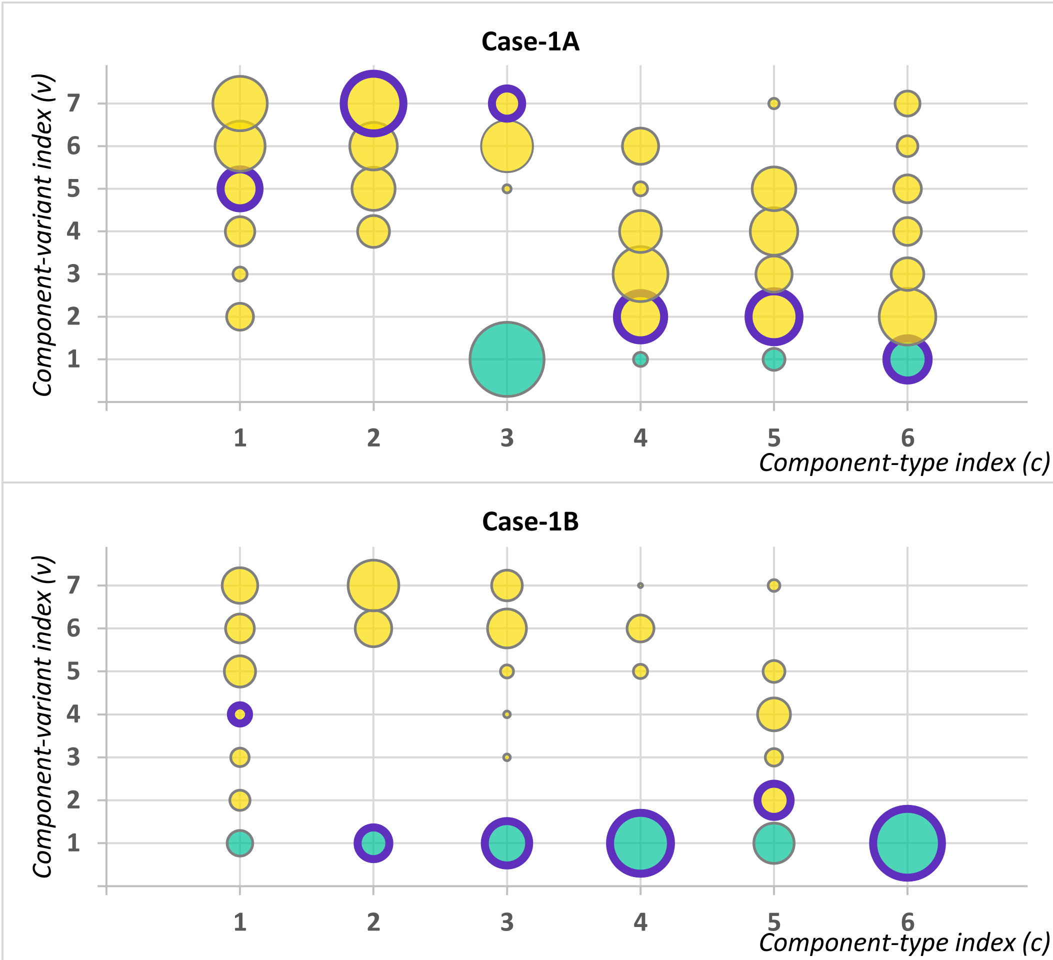

Fig. 8 Distribution of component variants in the Pareto fronts of Case-1A and Case-1B. Size of the bubble visualizes the number of solutions that use the specific component variant.
(Green colored: Common component designs to Gen-1; Purple outlined: 'Equal weighted best configuration')

Component-types 5 and 6 are set as non-performance influencing components (i.e., w_c = 0 in Eq. 28). Figure 8 shows the Case-1B moving all PF solutions to use variant-1 for the component-type 6. In component-type 5, while more Case-1B PF solutions use variant-1, there are still many configurations using other variants. The recoverability differences between component-types 5 and 6 explain this. According to the input data, the returns of component-type 5 are 0% reusable and 10% remanufacturable. And, the returns of component-type 6 are 30% reusable and 40% remanufacturable. Thus, it highlights the importance of including the reusability and remanufacturability ratings of components when deciding on design configuration commonality.

4.2.2. Case-2: Incorporating the market introduction time of Gen-2

Case-2 uses Case-1B conditions but with added flexibility (by adding τ_2 as a decision variable in the optimization) to bring forward or delay Gen-2 market introduction by up to 3-periods (i.e., $22 \leq \tau_2 \leq 27$). For Case-2, the optimization finds 163 unique non-dominated solutions (from the total design space of 705,894) as visualized in Figure 9.

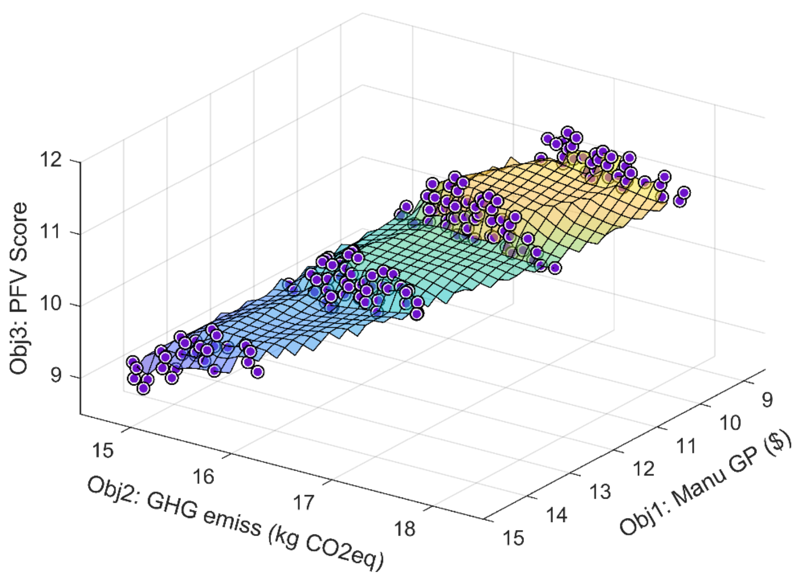

Fig. 9 Case-2 Pareto front design configurations scatter in terms of the three objectives

Table 3 summarizes Case-2 PF solutions. They are very similar to Case-1B but with improved objective values. For the equally weighted solution, Obj-1 and Obj-2 further improve by delaying τ_2 to period 27 (compared to Case-1B's 24). Gen-1's expected returns, starting at period 24 and ramping up over the subsequent periods, explain this. Delaying the Gen-2 introduction time provides more Gen-1 excess returns (after Gen-1 demand declines) available for Gen-2 from the start. Figure 10 confirms this as it analyzes Case-2 PF solution distribution vs

τ_2. Shades of color represent the aggregate number of common components in each PF solution (darker the color, higher the commonality). As the τ_2 advances from period 22 to 27, a higher percentage of solutions become design configurations that include a greater total number of common components (i.e., darker color shade).

Table 3 Case-2 Pareto front solutions summary

	Obj-1: Manu GP	**Obj-2:** GHG Emiss.	**Obj-3:** Funct. Score	Num. of common components
Design configuration #2-1: $v = [2,1,1,1,5,1]$, $\tau_2 = 27$	**14.7**	15.0	8.9	4
Design configuration #2-2: $v = [2,1,1,1,2,1]$, $\tau_2 = 27$	14.4	**14.8**	9.1	4
Design configuration #2-3: $v = [5,7,7,6,1,1]$, $\tau_2 = 22$	9.0	16.8	**11.3**	2
Individual objective's best values*	14.7	14.8	11.3	-
Best configuration (using equal weighting): $v = [1,1,1,1,2,1]$, $\tau_2 = 27$	14.4	15.0	9.4	5
Objective value averages (for entire Pareto front)	11.4	13.9	12.7	2.9
Relative change between Case-2 vs. Case-1A:				
in 'Best configuration (using equal weighting)'	+71.0%	-11.4%	-1.8	+4.0
in 'Objective value averages for entire PF'	+21.2%	-22.9%	+2.8	+2.0

**Objectives 1 and 3 are maximizations. Objective 2 is a minimization.*

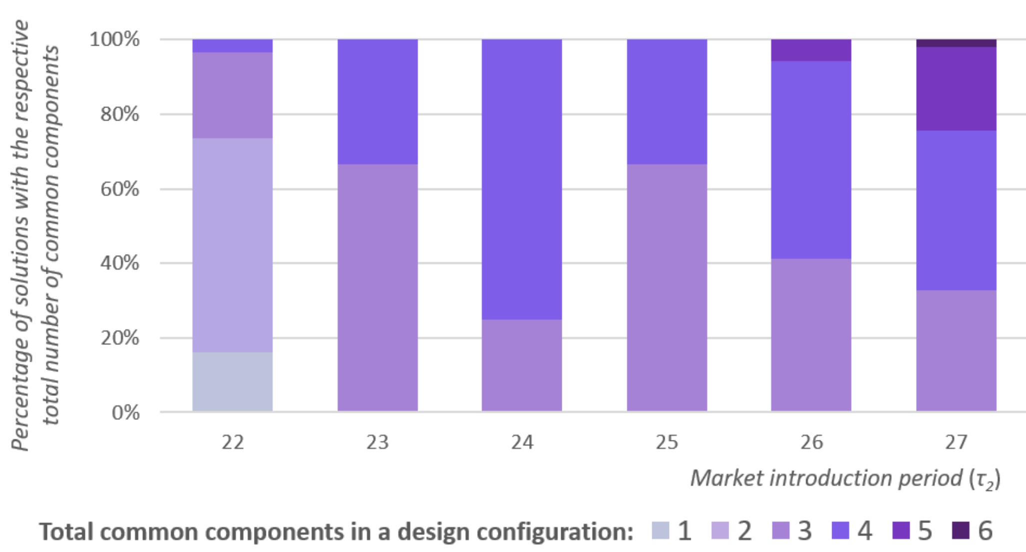

Fig. 10 Variation of the total number of common components (as a percentage out of all solutions for a given τ_2) in Case-2 PF when varying the market introduction time

5. Conclusions

This paper provides a basis for evaluating the PSP in multi-generation product design alternatives and identifying the optimum inter-generational commonality level. It also expands the quantification and modeling of dynamic PSP to multi-generational systems. Consequently, it enables the designers and manufacturers to make component-commonality decisions with a holistic view of sustainability concerns, moving beyond the typical solely cost-reduction focus. Thus, it is a crucial step towards designing products to implement and advance SM and CE objectives.

The case study and the results confirm the need for optimization-based procedures in developing tools for multi-generational design for sustainability due to the conflicting objectives involved. The inclusion of inter-generational commonality in the optimization allowed significant gains for the objective values. This is especially noticeable from the ‘objective value averages (for entire Pareto front)’ measure. It confirms an overall improvement in the entire non-dominated solution set due to the component-level commonality. Thus, the designer can now choose the Gen-2 design configuration from an overall improved set of alternatives. The ‘clustering’ effect in the PF allows the designers to choose from design configurations with similar commonality levels.

The results also demonstrate potential further PSP improvements by using this method to determine the optimal time for the new generation’s market introduction. This is integral to planning EoU activities for closed-loop material flow effectively. In the light of increasing extended producer responsibility regulations, including product take-back options, effective EoU activity and closed-loop planning are major concerns for the manufacturers. Such regulations will inevitably enforce the use of design tools that incorporate resource conservation planning concepts discussed here.

Some applications can involve additional constraints. For instance, in the iPhone example, specific component-types are more ‘obligatory’ to upgrade annually (e.g., camera module) than others (e.g., audio module). Certain modules require periodic updates with industry standards (e.g., connectivity module when 5G network standard was introduced). Since the proposed method was made adaptable to handle such constraints and conditions, the complexities discussed above can be easily incorporated to reach meaningful solutions. Additionally, such real-life applications of this model in future work will also help refine the methodology for greater dissemination of the outcome for a range of multi-generational products in a range of application sectors.

Due to the high customer differentiation between ‘brand-new’ and ‘rebuilt’ in applications such as mobile phones, EoU component-level usability can limit to the manufacturer-serviced repairs. Indeed, many electronics companies utilize ‘reused’ or ‘remanufactured’ components for warranty repairs. In contrast, the proposed framework is directly applicable in product-as-a-service applications (increasingly promoted by the CE). Because, for the customer, the rebuilt products are perfect substitutes for the brand-new ones. Managed print services, rented modem equipment from internet service providers, and leased vehicles, aircraft engines, or heavy machinery are a few already popular such applications. The proposed work enables designing of the products optimally for the required functionality, performance, and sustainability by considering multiple design generations at the early product design stage.

The PSP evaluation and diffusion modeling presented are particularly application-specific. Thus, the assumptions made, and modeling carried out require customization when applying to specific cases. Especially the aspects such as the price-utility adjustment in diffusion modeling require further research and adaptation. In addition, the use of this approach with design methods other than configuration design requires further adaptation. However, the increasing trend to adopt product modularity provides more opportunities to employ this method with configuration design.

Finally, the resulting PFs from the optimization included many non-dominated solutions. Thus, it requires a method to refine the solutions hierarchically. For comparison purposes, the result section applied equal weighting on the sustainability objectives to find the ‘best configurations.’ In practice, designers can filter solutions to a more manageable number of choices using screening (e.g., setting a maximum number of common components between generations and specifying objective target value ranges). The additional optimization objectives in practical applications can also limit the number of PF solutions. The authors plan to expand this work by quantifying the designer preferences and help identify the most preferred non-dominated solution.

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