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Abstract

Sustainability in products has gained increasing attention, and engineering community is exploring ways to employ sustainability principles without jeopardizing cost or manufacturability advantages. To this end, we propose a framework that brings sustainability considerations to the conceptual design stage of product development. In the framework, two types of sustainability indices, interval and deterministic, are adopted to work with other design and manufacturability factors. Data envelopment analysis (DEA) is introduced to the proposed framework as the major decision making tool. In the proposed framework, the best concept decision is selected using a two-phase decision process. Two types of DEA models, interval and assurance region (AR), are applied in different phases to evaluate different criteria. The interval DEA is applied to the first phase to handle ambiguous data sets in the beginning of the conceptual design stage, while the AR model is introduced to the second stage to incorporate with decision makers' preferences for solving definite criteria in reaching the best design. The proposed framework can benefit manufacturers in choosing the best product concept that not only fulfills all the functional and manufacturing considerations, but also accounts for the environmental concerns.

Keyword
Sustainability, Data Envelopment Analysis, Product Development Process, Conceptual Design

1. Introduction
To design and manufacture sustainable products, manufactures need to select cleaner processes and materials that cause less impact on the environment. While minimizing the potential environmental impacts, however, manufacturers still have to offer products with high performance and cost efficiency to maintain market competitiveness. Accordingly, to generate a better product design from the get-go and to exploit potential efficiencies, manufacturers should integrate sustainability concerns into the early stages of the product development process.

Life cycle assessment (LCA) is a widely used tool that can evaluate the potential environmental impact of a product throughout its entire life cycle [1, 2]. However, at the initial product development stage, it is difficult to implement LCA evaluation since it requires detailed product information, and is time consuming [3, 4]. Therefore, in this study, we propose a new concept selection framework using a two-phase design decision making process with simplified sustainability indices. The conceptual design stage is a critical stage in the product development process. In this stage, products are embodied from a set of sub-systems, and the major functions and specifications are determined [5]. Integrating sustainability criteria into the conceptual design stage with other manufacturing or functional criteria can ensure that the product is properly designed in order to reduce or prevent from the future modifications.

In this new framework, we divide the conceptual design stage into two sections, the front end stage, and the back-end stage. Two different decision making processes are proposed by applying different data envelopment analysis (DEA) models for each of the two stages. Also, two different sustainability indices are used for evaluating the relative sustainability degree for each of the stages. For the front-end, since most of the detailed design criteria are still undetermined, we apply interval DEA to evaluate interval criteria as a pre-screening process to eliminate product candidates with inferior efficiencies. This pre-screening process can effectively reduce the complexity of assessing the entire product candidates. This pre-screening action can also benefit manufacturers in cost and time savings in comparison to a full assessment. The remaining product candidates after this pre-screening process will be expanded with more detailed information and evaluated at the back-end stage of the conceptual design process. A deterministic DEA model, the assurance region DEA model, is used for selecting the best product concept at the back-end stage.

2. Literature Review

Below we provide brief literature reviews on sustainability indices and DEA.

2.1. Sustainability Index

To evaluate the sustainability issues, proper sustainability performance indices are necessary. However, sustainability consideration is complex, and it involves a wide range of aspects. Therefore, multiple criteria from various perspectives should be taken into account when assessing sustainability. In addition, owing to different product structures and composition, sustainability criteria might vary from one industry to another.

Khan et al. [6] proposed a life cycle index system, LInX, as a product life cycle assessment (LCA) evaluation tool in process and product development and decision making. The LInX system involves four main groups, including environment, cost, technical feasibility and socio-political; and each group contains several basic attributes. A 0-10 scoring system is used to evaluate the performance of each attribute, where higher values represent a greater penalty level. Hur et al. [7] measured the green productivity (GP) of a product system or process. GP index is acquired by the ratio of two indices, productivity of a system over its potential environmental impact. The two indices integrate the indicators from life cycle assessment (LCA) and total cost assessment (TCA). The GP index can provide decision makers a comparable basis in making better managerial decisions.

Singh et al. [8] developed a composite sustainability performance index (CSPI), which involves five groups of indices to assess the sustainability issues during conceptual design for steel industry. They categorized 60 key indicators into five groups, including: 1) organizational governance, 2) technical aspects, 3) economic, 4) environmental, and 5) society. A 0-10 scale is used to assess each key indicator. Sun et al. [4] proposed a new material group based environmental impact drivers by grouping 594 materials from the Eco-indicator 99 H/A [9]. These simplified drivers consider material mechanical and physical properties with life cycle assessment (LCA), and can enable users to quantitatively evaluate materials' environmental impact in the early stages of the product design process.

Overall, sustainability indices can aid in producing more sustainable products. However, most sustainability indices are relative measures and lack a standardized comparison basis. In this study, we apply the environmental impact drivers from Sun et al. [4] and generate two different types of sustainability indices which can easily be used in the conceptual design stage.

2.2. Data Envelopment Analysis

Data envelopment analysis (DEA) is a linear programming based multi-criteria decision making tool proposed by Charnes et al. [10]. The first DEA model is the CCR (Charnes-Cooper-Rhodes) model. DEA is a widely used performance evaluation tool that can tackle multiple criteria. It measures the relative productivity efficiency among a set of decision making units (DMUs). DEA has the advantage that exempts decision makers from assigning weights for each criterion. In fact, DEA is based on the Pareto optimality and automatically generates the best set of weights for each DMU to reach its highest efficiency score. However, since the weights are assigned by the system, weights are uncontrollable and the efficiency score might only depend on few criteria. Thompson et al. [11] proposed the DEA assurance region (AR) model that sets weight restrictions to increase discrimination power and also enable management input. They applied the AR model to select the best laboratory site among six candidates. Thompson et al. [12] later applied the AR model to evaluate the efficiency and profitability of 14 major companies in U.S.

Traditionally, DEA can only solve deterministic data sets. Cooper et al. [12] first proposed the imprecise DEA (IDEA) to handle imprecise data. IDEA performs a series of complex linear transformation and rescaling of variables, and generates a deterministic efficiency value for each DMU. Despotis et al. [13]

proposed an alternate way that simply applies transformations on variables. The proposed model is called interval DEA. The interval DEA method generates a set of boundary efficiency values for each DMU. Wang et al. [14] introduced a modified interval DEA model to solve interval or fuzzy input/output problems. The proposed method improves from the interval DEA and attempts to compare all the DMUs based on a common reference set. A minimax regret-based approach (MRA) is later used to compare and rank all the DMUs. Kao [15] constructed a two-level mathematical model to acquire the upper and lower bounds of efficiency scores. After introducing linear transformation techniques, for each DMU, the initial pair of non-linear formulations is simplified resulting in interval efficiencies. Interval DEA has been applied to a variety of areas in solving problems involving uncertainty. Smirles et al. [16] used interval DEA to evaluate DMUs containing missing values. Missing values are replaced by interval bounds obtained by statistical or experiential techniques. Thus interval DEA can generate interval efficiency bounds for those DMUs with missing data. A more recent example is by Toloo et al. [17], who presented a framework using interval DEA to measure overall profit efficiency from indices involving interval data.

Despite DEA is a superior decision making tool, it was seldom applied to solve product design related problems. In this study, we propose a new framework with two-phases and use two different DEA models, the interval DEA model and the AR model as the decision making approaches. In addition, a case study implementing the proposed framework to an electrical toothbrush concept selection problem is provided in the last part of this study.

3. Problem Definition

The case study in this article is extended from the previous work of our research team on the concept selection of electronic toothbrushes [14]. We study two consumer electronic toothbrushes, Oral-B™ Vitality Series (Dual Clean), and Crest™ Spin Brush Pro. Both products are dissected and grouped into six categories of functional modules: Brush head, Coupler/De-coupler, Actuator, Oscillation generator, DC motor and Battery. In the case study, we demonstrate a two-phase concept selection decision making process for choosing a new electronic toothbrush product from all the product candidates. All the components come from the two existing electronic toothbrushes mentioned before. Accordingly, we have two alternatives for each of the six functional modules with a total of $2^6 = 64$ combinations of concepts. In the next section, we introduce the newly proposed concept selection framework.

4. Methodology

We propose a two-phase framework to solve concept selection problems. As we mentioned before, in this study, we divide the entire conceptual design stage into two sub-sections, the front-end stage, and the back-end stage. For the front-end stage, interval DEA is adopted to solve several interval criteria. This stage can be regarded as a pre-screening process to filter non-competitive product candidates. After this pre-screening process, the remaining product candidates are brought to the back-end stage of the conceptual design to collect more detailed and complete information for further consideration. For the back-end stage, since all the information for each product candidate is available, DEA AR model evaluates all the remaining product candidates and selects the best one to carry to the next product design stage. In the following sections, we explain each of these phases in detail.

4.1. Phase I

In the conceptual design stage, initially when all the product candidates are defined, all the detailed information may not be collected yet. In this situation, it is difficult to fully review all the product candidates. However, of all the product candidates, some of them may be unworkable or uncompetitive, and should be eliminated. Carrying all these inappropriate product candidates throughout the conceptual design stage is costly and time consuming since they might require the product design team to spend undue effort. Therefore, in our new framework, we suggest using a pre-screening process at the beginning of the conceptual design stage. Interval DEA is selected to be the decision making approach for the phase one. Eq. (1) indicates the formulation of the interval DEA [13].

$$
\begin{aligned}
&Max \quad T_{k_0}^U = \sum_{r=1}^{s} u_r y_{rk_0}^U \\
&s.t. \quad \sum_{i=1}^{m} v_i x_{ik_0}^L = 1, \\
&\quad \sum_{r=1}^{s} u_r y_{rk_0}^U - \sum_{i=1}^{m} v_i x_{ik_0}^L \le 0, \\
&\quad \sum_{r=1}^{s} u_r y_{rk}^L - \sum_{i=1}^{m} v_i x_{ik}^U \le 0, \ k = 1,.....,n \ \ k \ne k_0, \\
&\quad u_r, v_i \ge \varepsilon > 0, \ \forall r, i.
\end{aligned}
\qquad
\begin{aligned}
&Max \quad T_{k_0}^L = \sum_{r=1}^{s} u_r y_{rk_0}^L \\
&s.t. \quad \sum_{i=1}^{m} v_i x_{ik_0}^U = 1, \\
&\quad \sum_{r=1}^{s} u_r y_{rk_0}^L - \sum_{i=1}^{m} v_i x_{ik_0}^U \le 0, \\
&\quad \sum_{r=1}^{s} u_r y_{rk}^U - \sum_{i=1}^{m} v_i x_{ik}^L \le 0, \ k = 1,...,n \ \ k \ne k_0, \\
&\quad u_r, v_i \ge \varepsilon > 0, \ \forall r, i.
\end{aligned}
\tag{1}
$$

Interval DEA model generates the upper and lower bound efficiency scores for each DMU, thus it includes two sub-models. Eq. (1) shows both the interval DEA upper bound model and lower bound models.

For this phase, we use three interval indices as inputs for the interval DEA model. The three indices are as follows:

A. *Interval Cost Index*: For the cost index, we estimate the cost value for each product candidate as an interval value set. It is a relative index, and is set to be an input index.
B. *Interval Sustainability Index*: We use the environmental impact drivers to roughly estimate the sustainability level of each product candidate. For each product candidate, we review all the possible materials used, and set the lowest and highest environmental impact drivers to be the lower and upper bound values of its interval sustainability index values. Interval sustainability index is also an input index in phase I.
C. *Control Index*: For the phase I, we create a control index to enable manufacturers to input their preferences. A simple five-level scale is used (0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, and 0.8-1). The control index is the only output index for phase I.

After taking all the three indices into the interval DEA model, each product candidate receives a pair of efficiency scores. In fact, interval DEA has the ability to cluster all the DMUs into three different efficient tiers. For the highest tier E^{++}, $E^{++} = \{k \in K / T^U = T^L = 1\}$. For the second tier of DMUs, $E^{+} = \{k \in K / T^L < 1$ and $T^U = 1\}$. For the DMU with the worst performance, $E^{-} = \{k \in K / T^U < 1\}$. Only product candidates that belong to the E++ tier will be taken to the next phase.

4.2. Phase II

In the back-end stage of the conceptual design process, all the remaining product candidates are critically evaluated with detailed product criteria, including economical and manufacturing factors. Only the best candidate can progress to the next design stage. In phase II, we employ the DEA AR model to be the decision making approach. AR model is based on the CCR model, but it allows decision makers to set additional weight restrictions for specific usage. When applying this phase II of the method, we suggest decision makers to use any decision making tool, such as analytical hierarchy process (AHP) to generate the weights. In phase II, five criteria are considered in the decision making process:

A. Design for Assembly (DFA) Index: The DFA index is an indicator of the degree of assembly easiness of the components. The DFA index is derived from the ranking system first developed by Rampersad [18]. 13 criteria are used to score and represent the relative assembly easiness in generating the DFA index [19]. For each single component, DFA index ranges from 0 to 10, and the higher the value represents the more assembly difficulty. Eq. (2) shows the formula for acquiring the DFA index:

$$\text{DFA index} = 10\,(\sum P_i - \sum V_{min,\,j})\,/\,(\sum V_{max,\,j} - \sum V_{min,\,i}) \tag{2}$$

P_i : point value for each criterion, i = 1…..13.
$V_{min,i}$: minimum value for each criterion.
$V_{max,i}$: maximum value for each criterion.

A. **Functionality Index**: The functionality index relates to the concept of Quality Function Deployment (QFD) matrix. It represents the potential customer satisfaction for varying product candidates. The functionality index ranges between 1 and 9. Since functionality index is to measure the fulfillment of customer requirements, we want to maximize its value. Accordingly, functionality index is set as an output index.

B. **Cost Index:** If decision makers have actual cost data for each product concept, they should be used. If not, we recommend decision makers to use a 1-9 scoring system to arrive at relative cost indicators. We assign 1 to the module with the lowest cost and 9 to the most expensive one. The overall cost index for a product candidate is aggregated by summing up all the cost scores from its components, and it is normalized to a 1-9 scale. Cost index is an input index since the lower the value is superior.

C. **Compatibility Index:** For each product concept, we need to consider the compatibility issue of all its components. In this study, we develop a new compatibility index. We set up the compatibility matrix and evaluate all components in a pairwise fashion by using a three-level weight system. If two components are perfectly matched, they receive a score of "2". If two components are incompatible, they receive a "0" score. Otherwise, a score of "1" is assigned. By multiplying all the compatibility values among all the components, we first obtain a compatibility value for the certain product candidate. Further, we eliminate incompatible product concepts. To scale the remaining concepts into a proper level, we take them into a base-2 logarithm function, and add 1 to the result. Compatibility index is also an output index since the higher the value indicates the more chance to be carried out.

D. **Sustainability index:** We adopt the sustainable index from Sun et al. [4]. The sustainability index is calculated by summing up each material's weight multiplied by its relative environmental impact driver in a product candidate. Sustainability index is set as an input index since lower values indicate a higher level of sustainability in a product.

5. Case Study

In this case study, initially we have 64 conceptual designs. As a result of phase I, only 34 candidate designs are brought to the phase II. After computing the compatibility index, we further eliminate 13 incompatible product candidates. Therefore, there are total of 21 product candidates to be input to the DEA AR model. The weight restrictions for this study can be expanded to be: $u_1:u_2:v_1:v_2:v_3$ = 6:3:2:3:1, where u_1,u_2,v_1,v_2 and v_3 are, in order, the weight of functionality index, compatibility index, DFA index, cost index and the sustainability index. In Table 1, we can see that candidate design 8 is the overall best candidate, which receives the highest efficiency score. The detailed component information for the best product candidate, candidate 8, is revealed in Table 2. For each of the components, we review the lowest material level and include accurate weight information.

Table 1: Phase II DEA AR result

Product Candidate	DEA Efficiency Score	Ranking
5	0.863679966	7
8	1	1
9	0.907530099	4
12	0.75204723	15
16	0.85952239	8
17	0.925436412	3
20	0.757869029	14
21	0.885793738	5
25	0.929079815	2
28	0.768883517	10
29	0.746704889	16
32	0.879708577	6
37	0.7630811	12
41	0.764286203	11
44	0.633151145	20
45	0.613183573	21
48	0.721539382	18
49	0.763073914	13
53	0.731832476	17
57	0.778783979	9
60	0.644804654	19

Table 2: Detailed component information for the best product candidate

Product Candidate	Battery	Actuator	DC Motor	Oscillation generator	Coupler/Decoupler	Brush head
8	Crest	Crest	Crest	Crest	Oral-B	Oral-B
	Alkaline	ABS plastic (2.4g)	Metal (30.83g)	ABS plastic (2.4g)	ABS plastic (10.2g)	Nylon/ABS plastic (7.75g)

6. Conclusion

In this study, we propose a new two-phase framework for solving conceptual design problems. By adding a pre-screening phase I, the proposed method can effectively reduce the complexity of the final concept selection process. Also, by adopting the DEA AR model, it integrates decision makers' preferences into weight constraints but still fairly evaluate all the performance of each design candidate. The result indicates that the proposed method can be effectively applied to problems in conceptual design stage.

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